The Dynamics of Local Employment in France

Pierre-Philippe Combes* Thierry Magnac† Jean-Marc Robin‡§

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Abstract

This paper studies the impact of the local economic structure on the local sectoral employment growth. This variable is decomposed into the "internal" growth (the growth of the size of the existing plants) and the "external" growth (the creation of new plants) of local areas. Using panel data methods, we estimate the dynamics of both variables simultaneously. Our observations refer to aggregate of firms of more than 2à employees in 36 manufacturing, trade and services sectors at the 341 French "Employment Area" level from 1984 to 1993.

The persistence of both dependent variables is important in the short run, especially as regards plant size. We show, however, that larger areas benefit from more plant creation simultaneously with larger average plant size. Whereas the number of locally active sectors does not need to be large, having sectors of comparable size favor both internal and external growth. Last, plants appear to get larger and larger in areas where they are more numerous, definitely not in a local monopoly situation, but of uneven size. On the other hand, the number of plants grows faster in places where plants are less numerous and of even size. Thus, large areas endowed with a small number of even size sectors and where are located large leader firms impulsing growth to smaller and numerous plants have larger growth.

*CERAS and Boston University. CNRS researcher also affiliated with the CEPR. Boston University, Economics Department - 270, Bay State Road - Boston, 02215 MA, USA. combes@enpc.fr. http://www.enpc.fr/ceras/combes/.

†LEA-INRA and CREST-INSEE. Also affiliated with the CEPR. ENS - 48, boulevard Jourdan - 75014 Paris, France. Thierry.Magnac@ens.fr. http://www.inra.fr/Internet/Departements/ESR/UR/lea /magnac.htm

‡LEA-INRA and CREST-INSEE. . Also affiliated with the CEPR. ENS - 48, boulevard Jourdan - 75014 Paris, France. Jean-Marc.Robin@ens.fr. http://www.inra.fr/Internet/Departements/ESR/UR/lea/robin.htm

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1 Introduction

Huge amounts of efforts and money are spent in Europe to reduce regional inequalities. In the US, labor mobility is often seen as high enough to make inequalities a secondary problem although the recent increase in regional disparities also leads to the revival of this issue. One of the fundamental questions that emerges in this ongoing debate is to determine whether regional inequalities rapidly and spontaneously vanish or are persistent and have to be tackled through redistribution policies. The purpose of this paper is to present an original methodology permitting the study of regional dynamics and to provide new evidence on the evolution and determinants of regional inequalities in a large European country, France.

The literature on regional income convergence (the "β-convergence", see Barro and Sala-I-Martin [1995]) is prolific. It is not, however, the most relevant theoretical background to the present study. Whereas the geographical level considered in these approaches is, at best, the US states or the NUTS 1 regions in Europe, we consider much smaller geographical units (341 of those for France). It has two major consequences. First, this study refers less to growth theory than to the urban and economic geography literature. Indeed, these frameworks provide explanations more relevant for intra-regional disparities, between cities or between rural and urban areas, for instance. Namely, these inequalities can be large and sometimes more important than inter-regional ones on which the β-convergence literature focuses. The use of less geographically aggregated data is the only way to capture such intra-regional disparities. Second, while β-convergence focuses on total income, we concentrate on sectoral employment inequalities. A secondary reason is that income or production data are not available at the geographical level we consider. More importantly, the study of the employment dynamics is maybe more relevant in the European context. Due to the large persistence of unemployment in Europe, people and politicians are indeed interested more often in the evolution of local employment than in production per capita. Moreover, the data we use is disaggregated by industry (38 sectors) and allow us to study both the local growth dynamics (whether sectoral employment levels converge or not across regions, conditionally or not) and the link of dynamics to local characteristics, mainly related to the local economic structure, as for instance the sectoral composition or the degree of competition.

This study finds its roots in Glaeser, Kallal, Scheinkman and Schleifer [1992] (GKSS below) and Henderson, Kuncoro and Turner [1995] (HKT below). These authors try to link the local long-run sectoral employment growth to the local sectoral specialization (the so-called "MAR externalities") and diversity ("Jacobs externalities"). Combes [2000] replicates the exercise on France, while Henderson, Lee and Lee [2000] and Batisse [2002] study the impact of the same kind of variables on production or productivity growth for Korea and China, respectively. Basically, the employment (or production or productivity) growth over a long period is regressed on the initial level of employment (in the spirit of the convergence literature) and on specialization and diversity indices. GKSS also consider the impact of local competition ("Porter" externalities).

These externalities are due to the fact that the local economic structure affects both pure agglomeration incentives, such as technological spillovers, and market based local interactions. For instance, innovations do not perfectly diffuse across space, as empirically proved by Jaffe, Tratjenberg, and Henderson [1993]. Hence, specialization has a positive impact on local growth if innovations in a given sector mainly benefit to those firms operating in this very sector. By contrast, if cross-fertilization is dominant, innovations in a sector induce larger growth in other sectors, in which case local diversity favors local growth. The sectoral composition also conditions the size of the local markets and the extent of local economies of scale. For instance, if preferences or production functions are CES, agglomeration is stronger in diversified areas, as emphasized in many recent urban economics or economic geography settings (see Fujita and Thisse [1996] for a survey). Again, sectors using a few specialized inputs would on the contrary benefit more from specialization. Duranton and Puga [2001] is a recent example of a theoretical framework emphasizing these different roles of local specialization and diversity, based on both spillovers and market effects. Last, theory shows that local competition also might reinforce both agglomeration and dispersion forces. In terms of market effects, it is well known from Hotelling that competition gives firms incentives to locate in low competition places. However, consumers or input users have by contrast incentives to locate in high competition places. Similarly, on the one hand, competition increases the need to innovate, but, on the other hand, if the sequence of innovations is too fast, innovation incentives decrease, the standard Schumpeterian trade-off. Thus, according to theory, and as more developed in Combes [2000], the effect of the local economic structure on local growth is often ambiguous. The need of empirical studies as our is therefore critical.

The present work is also closely related to Henderson [1997] who uses panel data methods to model the short-run dynamics of local employment and the impact of the local economic structure. Our approach also relies on dynamic panel data analysis since our observations refer to aggregate of plants in local areas and industries over a ten-year period. Apart from the fact that it is based on French data, which provide interesting comparisons between the European and the US regional dynamics, it sensibly differs from Henderson [1997] for three main reasons. First, we aim at restricting the lag structure to a couple of years employing model selection techniques whereas Henderson [1997] considers higher order lags. In our opinion, interpretation is rendered difficult by the fact that the effect of each variable changes from one lag to the other. Second, a common feature of both GKSS and HKT studies is that the effect of local specialization is identified thanks to an assumed non-linear effect of the sectoral employment, which enters the specification both in logarithm and level. To put it another way, if the model were specified only in logarithm, the specialization effect could not be identified from the initial sectoral employment effect (Combes, [1999]). This is all the more problematic when both effects act in opposite directions, as in HKT or Henderson [1997]. We pay attention to some other econometric issues such as endogeneity issues which are carefully considered thanks to the use of dynamic panel data methods. Hence, we set up a robust methodology which we hope is easy to interpret and which could be applied to other contexts. Last and maybe most importantly, decomposing local sectoral employment in the product of local employment per plant and the number of plants is an innovation of our approach. Thus, instead of only working with the dynamics of sectoral employment, we study the dynamics of both variables simultaneously, as embodied in a Vector Autoregression (VAR) setting. Hence, local growth is decomposed into “internal” local growth, defined as the growth of the size of the existing plants of the area, and of “external” local growth, defined as the creation of new plants in the area. For each component, we allow for different dynamics and determinants, which, compared to previous studies, provides new insights into the local growth factors.

We use data on employment in 36 sectors covering manufacturing, trade, and services, available for the 341 French continental ”Employment Areas” (EAs) and observed during

10 years. We first prove the existence of agglomeration economies linked to the global size of the local economy: Larger areas benefit from more plant creation and larger average plant size. This can be attributed to gains due to economies of scale or to strong/high quality technological spillovers. We also refine the verdict regarding the impact of the sectoral composition of the local economy on local growth. Whereas the number of locally active sectors does not need to be large, sectors of comparable size favor both internal and external growth. An interpretation would be that technological spillovers can be cross-sectoral but do not extend to all sectors. Similarly, intermediate inputs are not necessary numerous but equally important. Hence, in both cases, the optimal structure would be small groups of even size sectors. Last, as regards the impact of local competition, it is shown to be non linear. For a given size of the local economy, plants appear to be larger in areas where they are more numerous, definitively not in a situation of local monopoly, but of uneven size. Large leaders, either relying on economies of scale or having research and development units of efficient size, would impulse growth to smaller and numerous plants surrounding them and benefiting for instance from technological spillovers or from large markets and improved matching with their partners. On the other hand, the number of plants grows faster in places where plants are less numerous and of even size. All of these clearly shed new light on the local economic structure which is the most favorable to local growth, even if we also show, besides, the short-run persistence of both components, plant size being even more stable than the number of local plants.

Section 2 is devoted first to a clarification of the theoretical background of this kind of studies and to the presentation of the data we use in our application. Next, Section 3 analyzes some descriptive statistics (sample structure and covariance analysis). Estimation results of static and dynamic VAR models of average plant size and number of plants are presented in Section 4. They are interpreted and discussed in Section 4.3, while Section 5 concludes and opens new lines of research.

2 Economic background and data

2.1 Economic background

The lack of a precisely identified background model is one of the main drawbacks of the studies linking local sectoral growth to local economic structure. Authors estimate descriptive models and not well defined economic models. Indeed, it is a hard task to provide a rigorous setting to these estimations, that have to be viewed, in our opinion, more capable of providing stylized facts than of validating a given theory. The main problem lies in the fact that local growth of a region is linked to the local economic structure of this very region only. As we show below, however, as soon as trade between regions is considered for instance, local growth of a region depends on the characteristics of other regions in a non trivial way. It is for these reasons that we develop in this section a simple framework that helps clarifying the theoretical assumptions lying behind empirical analyses performed in this literature. Next, we show how it can be extended to integrate new features such as, in particular, firm creation.

Let us first consider a setting in which each region z is a closed economy. Only one good is produced, under constant returns to scale, using labor and capital. The production is assumed to be Y_z, given by:

$$Y_z = A_z \left(L_z\right)^{\alpha} \left(K_z\right)^{1-\alpha}, \tag{1}$$

where α is a constant between 0 and 1, and A_z is total factor productivity. If we assume perfect competition both on the good and factor markets, the equilibrium price is obtained as:

$$p_z = \frac{\left(w_z\right)^{\alpha} \left(r_z\right)^{1-\alpha}}{\alpha^{\alpha} \left(1-\alpha\right)^{(1-\alpha)} A_z}, \tag{2}$$

where w_z is the wage and r_z the return to capital. The question is to determine the impact of a productivity shock, $\frac{dA_z}{A_z}$, on the employment growth $\frac{dL_z}{L_z}$. Typically, it is next assumed that the productivity shock depends on regional characteristics, such as specialization, diversity, competition, or total size. Let σ denote the demand elasticity of the good, and ε and ν the supply elasticities of labor and capital, respectively, all being positive constants. By definition, we have:

$$\frac{dY_z}{Y_z} = -\sigma \frac{dp_z}{p_z}, \ \frac{dL_z}{L_z} = \varepsilon \frac{dw_z}{w_z}, \ \text{and} \ \frac{dK_z}{K_z} = \nu \frac{dr_z}{r_z}. \tag{3}$$

Using definitions (3), and differentiating equations (1), (2) and the equalization of labor productivity to real wage:

$$\frac{w_z}{p_z} = \alpha A_z \left(L_z\right)^{\alpha-1} \left(K_z\right)^{1-\alpha}, \tag{4}$$

simple computations leads to:

$$\frac{dL_z}{L_z} = \frac{\varepsilon\left(\sigma-1\right)\left(1+\nu\right)}{\varepsilon\sigma\left(1-\alpha\right)+\alpha\nu\left(\sigma-1\right)+\varepsilon\left(\alpha+\nu\right)+\nu+\sigma} \cdot \frac{dA_z}{A_z}. \tag{5}$$

Many interesting points are worth noting as regards employment growth following a productivity shock. First, the denominator is positive. Hence, a positive productivity shock has a positive effect on employment if and only if the demand elasticity is high enough, more precisely, if it is greater than 1. This is intuitive: if demand does not sufficiently expand following the price decrease due to the productivity shock, employment shrinks since a better productivity implies input savings. The larger the demand elasticity, the larger the production growth, and next the employment expansion. Next, equation (5) also shows that this expansion is larger, the larger the labor and/or capital supply elasticities. At the extreme, if $\varepsilon = 0$, employment does not expand since, even if the wage increases, there is no more free labor in the region. In this case, the productivity gain translates in higher production only thanks to a capital increase. If the capital supply is also inelastic, $\nu = 0$, the production level does not change and neither do labor, capital and the price of the good. The wage and capital real returns increase by the same amount as the productivity shock. Hence, the larger the labor or capital supply elasticities are, the less input prices increase, and thus the more output, and next labor and capital, expand. At the other extreme, if input elasticities are infinite (this is for instance the case of a small region that has access to world input markets), the effect is maximum, equal to $\sigma - 1$. Thus, this simple framework allows to clarify some important aspects regarding the impact of local externalities on employment growth: This effect is positive only if the good demand elasticity is high enough, and the larger input supply elasticities, the greater it is. These points are not mentioned in GKSS, HKT, and Henderson [1997] who interpret their results assuming for instance that a positive productivity shock always induces employment expansion.

GKSS also introduce an index of local competition among explanatory variables. This can be interpreted as a direct effect of competition on the strength of externalities, and thus on employment growth through the productivity shock. However, in the perfect competition setting they assume, the number of competitors is by definition undefined. Moreover, competition may also simultaneously play a role on employment through its impact on price and production levels, if competition is imperfect. Hence, it seems relevant to slightly extend the previous framework to better understand the role that competition may play on local employment growth. We assume imperfect competition to be Cournot with homogenous goods, which leads to intuitive results. Let us first assume a short-run situation in which the number of firms located in the region, N_z, is exogenous. Each firm maximizes its profit with respect to the quantity it produces, taking into account the non-zero demand elasticity and assuming that other firms hold constant their own output. As standard, the quantity best-responses derived from the first-order conditions imply an equilibrium price equal to:

$$p = \frac{\sigma N_z}{\sigma N_z - 1} \cdot \frac{(w_z)^{\alpha} (r_z)^{1-\alpha}}{\alpha^{\alpha} (1-\alpha)^{(1-\alpha)} A_z}, \tag{6}$$

that is to say, a mark-up that depends on the number of firms over the marginal cost. The production function and the equalization of the real wage to productivity still hold and can be differentiated simultaneously with equation (6) to obtain the employment dynamics in this context:

$$\frac{dL_z}{L_z} = \frac{\varepsilon (\sigma - 1)}{\varepsilon \sigma (1-\alpha) + \alpha \nu (\sigma - 1) + \varepsilon (\alpha + \nu) + \nu + \sigma} \left((1+\nu) \frac{dA_z}{A_z} + \frac{\nu}{\sigma N_z - 1} \frac{dN_z}{N_z} \right). \tag{7}$$

If the number of firm remains fixed, $\frac{dN_z}{N_z} = 0$, the effect is exactly the same as under perfect competition, and local competition, here embodied in the local firm number, affects the local employment growth only through its impact on the productivity shock, $\frac{dA_z}{A_z}$. Nevertheless, since in the short-run the number of firms is exogenous and such that profits are non-zero, one may expect some firms to be created and enter the market. In this case, an extra effect is at work. An exogenous increase in the firm number, $\frac{dN_z}{N_z} > 0$, has a negative impact on price. As previously, if the demand elasticity is greater than 1, it induces a positive impact on employment, if capital is not inelastic, which is reflected by the additional term in equation (7) compared to equation (5). Note that if capital is inelastic, and if there is no direct effect of competition on the productivity shock, firm entry has no effect on total employment.

At this point, in order to better understand local employment dynamics, it is clearly worth decomposing the local employment growth into two terms: First, an effect we call "internal growth", which is the growth of the size of existing firms, $\frac{dl_z}{l_z}$, where l_z is the employment per firm in region z, and second "external growth", due to the expansion of the number of firms, $\frac{dN_z}{N_z}$. In other words, we simply write:

$$\frac{dL_z}{L_z} = \frac{dl_z}{l_z} + \frac{dN_z}{N_z}, \tag{8}$$

which allows us to compute the impact of local externalities on average employment per firm, or firm size, $\frac{dl_z}{l_z}$, using equation (7):

$$\frac{dl_z}{l_z} = \frac{\varepsilon(\sigma-1)}{\varepsilon\sigma(1-\alpha)+\alpha\nu(\sigma-1)+\varepsilon(\alpha+\nu)+\nu+\sigma}\left((1+\nu)\frac{dA_z}{A_z} + \frac{\nu}{\sigma N_z - 1}\frac{dN_z}{N_z}\right) - \frac{dN_z}{N_z} \tag{9}$$

If the number of firms does not change, average employment per firm grows at the rate of total employment in the perfect competition setting, only through the direct impact of productivity on price. If the number of firms increases, employment per firm increases through both this effect and the indirect impact of competition on price as they appear in equation (7), but also simultaneously decreases through a direct competition effect, the last term in equation (9): the total production increase is split between a larger number of firms. Thus, the total effect of the productivity increase on firm size can be negative, if many firms simultaneously enter into the local market.

Next, we can separately study the impact of local externalities on firm creation, $\frac{dN_z}{N_z}$. Indeed, the previous discussion implicitly assumes an exogenous firm creation process. Now, local externalities may have an impact on the firm number, if this number is endogenous, as it is for instance the case if we assume that the observed situation corresponds to a long-run equilibrium. The firm number is set such as profits are zero and, following a productivity shock, it endogenously adjusts in order to keep this condition satisfied. By plugging the equilibrium price given by equation (6) in the profit definition and by next differentiating this equation, we obtain the adjustments of firm size and number of firms following a productivity shock in the long-run equilibrium, which are now both endogenous. They are given by:

$$\frac{dl_z}{l_z} = -\frac{(1+\nu)(\sigma-1)(\sigma N_z-1)}{\sigma(1+\varepsilon)((N_z-1)\nu+\sigma N_z-1)+\alpha(\sigma-1)(\nu-\varepsilon)(\sigma N_z-1)}\cdot\frac{dA_z}{A_z}, \tag{10}$$

$$\frac{dN_z}{N_z} = \frac{(1+\varepsilon)(1+\nu)(\sigma-1)(\sigma N_z-1)}{\sigma(1+\varepsilon)((N_z-1)\nu+\sigma N_z-1)+\alpha(\sigma-1)(\nu-\varepsilon)(\sigma N_z-1)}\cdot\frac{dA_z}{A_z}. \tag{11}$$

The total impact of the productivity shock on total employment can be recovered in the long run equilibrium, as:

$$\frac{dL_z}{L_z} = \frac{\varepsilon\left(1+\nu\right)\left(\sigma-1\right)\left(\sigma N_z-1\right)}{\sigma\left(1+\varepsilon\right)\left(\left(N_z-1\right)\nu+\sigma N_z-1\right)+\alpha\left(\sigma-1\right)\left(\nu-\varepsilon\right)\left(\sigma N_z-1\right)}\cdot\frac{dA_z}{A_z}. \tag{12}$$

Hence, all variables that have an impact on productivity have an impact both on "internal growth", the growth of the size of the firms that are already located in the region (equation 10) and on "external growth", the growth due to the creation of new firms (equation 11). However, the magnitude of these effects is different on both variables.

In the long-run, a positive productivity shock has a positive effect on the firm creation if the demand elasticity is sufficiently high, as previously, but a negative one on firm size, the direct competition effect mentioned above being dominant. Note, however, that it would be possible to consider less extreme cases, such as for instance a situation in which profit is non zero and firm creation is proportional to it. Weaker competition settings, as for instance price competition on differentiated goods would also reduce the direct competition effect. The algebra would be, however, more tedious. On the other hand, this would introduce some flexibility into the model. In any case, if the endogenous firm creation process is slow, equation (9) shows that a positive productivity effect may have a positive impact on firm size.

Thus, since the productivity shock may itself depend on the competition degree ("Porter" externalities), this imperfect competition model leads us to study the possibly contrasted impact of the local economic structure on average employment per firm and the number of firms, embodied in a VAR model, which we more precisely described below. Note that the simultaneous estimation of equations (10) and (11) allows us to identify more effects than the simple estimation of equation (5) under perfect competition, on which is implicitly based the above described literature, or even, under imperfect competition, of equation (12). We are able to distinguish the impact of the local economic structure on internal and external growth, respectively.

Note finally that the only candidate model able to sustain the kind of estimations performed in this literature necessarily implies that each region is a closed economy. Indeed, as soon as some trade is assumed between regions for instance, the equilibrium price does not depend anymore on the local productivity only, but also on the productivity of all trading partner regions. The derived specifications, as for instance in Combes and Lafourcade [2001], are in this case much more intricate and beyond the scope of this paper. Indeed, our purpose is to provide stylized facts on local growth dynamics and not to estimate a precise model of trade and technology diffusion for instance.

We now describe the variables that enter the VAR models and the data we use.

2.2 Data and variables studied

Data and endogenous variables This study is based on the 341 geographic units defined by the French National Institute of Statistics and Economic Studies (INSEE) and called *zones d'emploi* (EAs, "employment areas"). These EAs entirely and continuously cover the French territory, and thus include both urban and rural places. Their average area is 1570 km^2, which is fairly small (equivalent to a 40 $\times$ 40 kms square). The EA definition is based on the observation of workers' daily migrations. This makes them economically more homogenous than administrative units, which attenuates some contiguity effects. Importantly, this is consistent with the assumption that local growth only depends on local characteristics.

We use a dataset on plants ("Enquête Structure des Emplois", collected by INSEE), which includes all plants located in France that have more than 20 employees. It reports employment level of each plant between 1984 and 1993, the EA where the plant is located, and its industry. Only agriculture and non-market services are excluded: 36 sectors are considered that we can group into manufacturing, trade and services.

The local employment structure of an area z and sector s at time t is characterized by the pair $(L_{zst}/N_{zst}, N_{zst})$, where L_{zst} is the area z and sector s employment and N_{zst} is the number of plants located in area z and operating in sector s at time t. In order to study the dynamics of both variables, we adopt a logarithmic specification. This has the double advantage of normalizing the distribution of the variables and to make easier the interpretation of first-differences that correspond to growth rates.

Beginning with a rough description of the sample structure, table 1 reports the number of observations (i.e. the aggregate of plants with more than 20 employees in an area and a sector (z, s) at time t). Among those which are available at each period (there is at least one plant in a (z, s, t) cell) some started operating after the first period of observation only (1984).[1] Local areas and sectors where plants started operating after 1984 are scarce however except in 1985 when some areas of Provence were surveyed inadequately. Entries just below the diagonal reflect that problem. Most observations (z, s) are such that employment L_{zst} is positive at the first date ($t = 1984$) and the panel is therefore approximately balanced. We will neglect entries and attrition of areas and sectors into the panel in this empirical analysis. First, because the bulk of such movements comes from the survey problem in Provence mentioned above that we may presume to be exogenous to the size and number of plants (it was a coding error according to INSEE). Second, even if the endogeneity of other entering or exiting area and sector into the sample is obvious because entries and exits are commanded by a firm size becoming larger or smaller than 20 employees, the number of such cases is very small (Table1). Furthermore, when Tobit corrections are applied to simpler contexts, the effect is not dramtic (Combes, [2000]). Finally, we can always interpret our results conditional on areas and sectors being in the sample since in the absence of a structural model our results are purely descriptive.

Explanatory Variables Two groups of determinants of local growth make up the list of explanatory variables. First, Porter effects characterize the magnitude of competition between plants in the same sector; Second, Jacobs externalities describe the sectoral diversity of plants in the local market. The following indices describe sectoral diversity and local competition:

1. The local dispersion of employment between plants in the same sector as measured by the opposite of the logarithm of the Herfindahl index of within-sector and within-area concentration. We interpret this variable as indicating the intensity of local competition within sectors (Encaoua and Jacquemin, 1980) :

$$lcom_{zst} = -\log \left[\sum_{i \in (z,s,t)} \left(\frac{\ell_{it}}{L_{zst}} \right)^2 \right],$$

   where ℓ_{it} is employment in the ith plant at period t and where we denote $\{i \in (z, s, t)\}$ the set of all plants i operating in area z and sector s at period t. Note that if employment is concentrated in a single plant, this variable is equal to zero,

[1] The table reports the number of observations (z, s, t) for any possible pair (t, τ_{zst}) where $\tau_{zst} = t - \min\{t | L_{zst} > 0\} + 1 \in \{1, ..., t\}$.

the lowest degree of competition. It is equal to the logarithm of the number of plants if the distribution of employment is uniform among plants, the highest degree of competition.

2. A indicator of total absence of competition within a sector and area:

$$\begin{aligned} c_{zst} &= 1 \text{ if } N_{zst} = 1, \\ &= 0 \text{ if not} \end{aligned}$$

where N_{zst} is the number of plants. Variable c_{zst} is equal to 1 (no competition) in 25% of cases (z, s, t) in manufacturing, 16% in trading activities and 18,5% in services.[2]

These two variables vary across area z, sector s and date t . In contrast, the last three determinants are specific to area z and date t only:

3. The logarithm of the number of sectors in which at least one plant (employing more than 20 workers) is operating in area z at date t :

$$ls_{zt} = \log(S_{zt}),$$

This index is the first local indicator of sectoral diversity.

4. The opposite of the Herfindahl index of local concentration between sectors:

$$ld_{zt} = -\log\left[\sum_{s=1}^{S}\left(\frac{L_{zst}}{L_{zt}}\right)^2\right],$$

where L_{zt} is total employment in area z that is also a local index of sectoral diversity. This variable is equal to zero if local employment is concentrated into a single sector, the lowest possible diversity, and it is equal to the logarithm of the number of sectors, S_{zt} if the distribution of local employment is uniform across sectors, the highest degree of diversity.

5. The logarithm of total employment in area z at date t :

$$lL_{zt} = \log\left[\sum_{s=1}^{S} L_{zst}\right].$$

[2] Our specification is thus partly based on a non-linear VAR since this variable depends on the second dependent variable N_{zst}.

This last variable, frequently used in the literature, captures another kind of urbanization externalities not linked to the sectoral composition but simply to the size of the local area.

Such a choice of variables is justified by our brief survey of the literature presented in introduction and by the theoretical models described above. It is worth mentioning that the usual index of specialization which is the ratio of employment in area z and sector s and total employment in this area is not retained here. The coefficient of the logarithm of this variable cannot be identified because the employment level in logarithms is a linear combination of average employment per plant, $\log L_{zst}$, and of the logarithm of employment within-area z, lL_{zt} (Combes, [1999]).

Table 2 provides descriptive statistics of all variables. In particular note that in more than 20% of cases, labor employed by all plants with more than 20 employees in a sector and area is employed by a single plant, (c_{zst}).

In order to get rid of macro and sectoral specific shocks and concentrate on spatial effects, we demean all variables with respect to their mean in the cell (s,t), that is to say all areas z where plants of sector s are operating at date t. We thus consider variables:

$$\mathbf{y}_{zst} \equiv \begin{pmatrix} y^1_{zst} \\ y^2_{zst} \end{pmatrix} = \begin{pmatrix} \log\left(\frac{L_{zst}}{N_{zst}}\right) \\ \log N_{zst} \end{pmatrix} - \frac{1}{\#\{z \in (s,t)\}} \sum_{z\in(s,t)} \begin{pmatrix} \log\left(\frac{L_{zst}}{N_{zst}}\right) \\ \log N_{zst} \end{pmatrix}$$

$$\mathbf{x}_{zst} = \begin{pmatrix} lcom_{zst} \\ c_{zst} \\ ld_{zt} \\ ls_{zt} \\ lL_{zt} \end{pmatrix} - \frac{1}{\#\{z \in (s,t)\}} \sum_{z\in(s,t)} \begin{pmatrix} lcom_{zst} \\ c_{zst} \\ ld_{zt} \\ ls_{zt} \\ lL_{zt} \end{pmatrix},$$

denoting $\#\{\cdot\}$ the number of elements of the set $\{\cdot\}$. An analysis of variance using periods (1984-1993), sectors (36 positions) and their interactions shows that these factors "explain" around one fourth of the total variance of variables $\log(L_{zst}/N_{zst})$ and $\log N_{zst}$.[3] In what follows all variables are assumed to be demeaned with respect to the period and sector averages as shown in the previous formulas.

[3] 25% of the variance of the logarithm of average employment per plant, $\log(L_{zst}/N_{zst})$, and 23% of the variance of the logarithm of the number of plants, $\log N_{zst}$.

year/obs.	1	2	3	4	5	6	7	8	9	10
1984	7786									
1985	719	7603								
1986	148	719	7474							
1987	123	160	732	7369						
1988	86	112	158	732	7261					
1989	81	76	116	161	725	7133				
1990	88	96	74	116	176	733	7045			
1991	68	75	88	75	110	179	721	6971		
1992	61	64	78	82	79	105	170	700	6909	
1993	72	55	70	80	84	88	110	182	684	6826

Note : Entries in the table are read as: In 1984, the sample is composed by 7786 pairs (z, s) of local areas and sectors; In 1985, 719 pairs (z, s) entered the sample and were not there in 1985 while 7603 pairs (z, s) are active and were in the sample in 1984 etc.

Table 1 : Sample stocks, creation and destruction

	Average	Standard error	Min	Max
y^1_{zst}	4.18	.76	2.99	10.12
y^2_{zst}	1.49	1.16	0	7.54
$lcom_{zst}$	1.16	.95	0	6.33
c_{zst}	.21	.41	0	1
ld_{zt}	2.37	.42	.34	3.12
lL_{zt}	9.51	1.08	6.51	13.59
ls_{zt}	3.22	.24	1.79	3.58

Notes : (a) There are 82853 cells (z, s, t) in which employment L_{zst} is strictly positive.
(b) *Variables definition:* y^1_{zst}: log(plants' average employment); y^2_{zst}: log(Number of plants); $lcom_{zst}$: log(Index of local competition within sectors); c_{zst} : Index of monopoly power at the local and sectoral level; ld_{zt} : log(Index of local diversity between sectors); lL_{zt} : log(Total employment in the area); ls_{zt} : log(Number of sectors with at least a plant with more than 20 employees in the area).

Table 2 : Descriptive statistics

3 Covariance analysis

3.1 Cross-section Effects and Serial Dependence

As every variable varies in three dimensions z, s and t and as we demeaned variables with respect to sector and period effects, we now proceed by a descriptive analysis of the covariance structure of each variable setting forth their dependence on area and sector effects and the interactions of those with time. For any component, say X_{zst}, of the vector of endogenous variables $\mathbf{y}_{zst}$ or of determinants $\mathbf{x}_{zst}$, we analyze its cross-section and dynamic characteristics by writing:

$$X_{zst} = u_{zs} + \delta_t v_{zs} + \varepsilon_{zst}, \quad \varepsilon_{zst} \sim MA(q), \tag{13}$$

where random shocks u_{zs} and ε_{zst} are uncorrelated and where ε_{zst} is a moving average of an *a priori* unknown order equal to q. This representation, though by no means the most general, is well suited to summarize cross-section correlations (that is between pairs (z, s) through random variables such as u_{zs} and v_{zs}) and how these cross-section correlations vary with time (through parameters δ_t), as well as the serial dependence of each history specific to a given pair (z, s) through the random shock ε_{zst} (see Hsiao, 1986).

The different components of model (13) are estimated by minimizing the distance between the unrestricted variance-covariance matrix of X_{zst} across time, which entries are $E(X_{zst}X_{zst'})$, and the variance-covariance matrix restricted by different specification of equation (13) (Abowd and Card, 1989).[4] Results are reported in table 3. The first five columns report estimates of the variance of the area and sector effect u_{zs} and of the variance of the specific shock ε_{zst} as well as its first three serial dependence coefficients if the following constrained specification :

$$X_{zst} = u_{zs} + \varepsilon_{zst}, \quad \varepsilon_{zst} \sim MA(3), \tag{14}$$

is verified ($\delta_t = 0$). In other columns we report results of various specification tests. Using statistics W, specification (14) against a unrestricted alternative can be tested. Using T_1, we test that the fourth-order autocorrelation is equal to zero, this is to say specification (14) against :

$$X_{zst} = u_{zs} + \varepsilon_{zst}, \quad \varepsilon_{zst} \sim MA(4). \tag{15}$$

[4] The weighting matrix in the minimum distance procedure is the optimal weighting matrix computed from the sample. Small sample biases are neglected (see Altonji and Segal, 1996).

Last, using statistics T_2, we test that cross-section correlations are stable, this is to say specification (14) against the alternative:

$$X_{zst} = u_{zs} + \delta_t v_{zs} + \varepsilon_{zst}, \quad \varepsilon_{zst} \sim MA(3). \tag{16}$$

First, specification (14) is always rejected against an unrestricted alternative (column W). According to columns T_1 and T_2, it mainly stems from the instability of cross-section correlations and not from dynamics of higher order. The codependence between series in various area and sector (z, s) might not be stable across time. The hypothesis that the fourth-order autocorrelation is equal to zero is however rejected for three series out of 7 and in particular those which consist in aggregates at the geographical level.

The respective variances of area and sector effects u_{zs} and idiosyncratic shocks ε_{zst} differ by an order of magnitude. The variance of the former is between 2 and 350 times larger than the variance of the latter. Variability is therefore much larger in the spatial and sectoral dimension than in the time dimension. It is particularly true in the case of local aggregates such as (in logarithms) total employment and the number of active sectors in an area. It can be noted however that the time dimension is the poorest (10) among the three dimensions (sectors, 36, areas, 341).

This decomposition can be repeated for growth rates, i.e. the first differences of the series. After differencing the model (13) becomes:

$$\Delta X_{zst} = (\Delta\delta_t) v_{zs} + \Delta\varepsilon_{zst}, \quad \varepsilon_{zst} \sim MA(q), \tag{17}$$

If coefficients δ_t are a linear function of time the difference $\Delta\delta_t$ is constant. The estimation of an error component structure such as model (14) for first differenced series (which is not reported here) leads however to reject such a case. Nevertheless, the absence of area and sector effects is rejected for the series in first-differences (see table 4) because correlations between the dynamics of the series for each pair (z, s) vary with time and because $\Delta\delta_t$ is not constant (except for the first series y^1_{zst} where all $\Delta\delta_t$ are equal to zero).

Concluding, these results suggest that a specification such that:

$$X_{zst} = \alpha X_{zs,t-1} + e_{zs} + \eta_{zst}. \tag{18}$$

might be adapted. Effectively, by expanding the series we get:

$$X_{zst} = \alpha^t X_{zs0} + \frac{1-\alpha^t}{1-\alpha} e_{zs} + \eta_{zst} + \alpha\eta_{zst-1} + \alpha^2\eta_{zs,t-2} + ... + \alpha^{t-1}\eta_{zs1}.$$

	σ^2_u	σ^2_ε	ρ_1	ρ_2	ρ_3	T_1	T_2	W
y^1_{zst}	0.28 (30.9)	0.035 (28.6)	0.48 (41.1)	0.26 (24.0)	0.10 (14.6)	1.96 (0.16)	136.7 ($<10^{-5}$)	557.06 ($<10^{-5}$)
y^2_{zst}	0.85 (37.3)	0.046 (41.2)	0.51 (72.9)	0.28 (35.1)	0.11 (18.3)	7.92 (0.005)	55.7 ($<10^{-5}$)	872.06 ($<10^{-5}$)
$lcom_{zst}$	0.50 (35.5)	0.041 (40.6)	0.52 (68.3)	0.28 (36.0)	0.12 (18.8)	.40 (0.53)	429.38 ($<10^{-5}$)	941.86 ($<10^{-5}$)
c_{zst}	0.07 (39.0)	0.031 (29.1)	0.46 (42.5)	0.23 (20.9)	0.10 (11.4)	1.86 (0.17)	136.7 ($<10^{-5}$)	347.4 ($<10^{-5}$)
ld_{zt}	0.087 (25.6)	0.0025 (29.3)	0.45 (42.0)	0.21 (22.4)	0.10 (13.9)	32.6 ($<10^{-5}$)	404.9 ($<10^{-5}$)	1890.7 ($<10^{-5}$)
lL_{zt}	0.73 (34.0)	0.0024 (34.0)	0.47 (50.0)	0.25 (28.9)	0.14 (22.0)	4.94 (0.03)	278.4 ($<10^{-5}$)	1679.7 ($<10^{-5}$)
ls_{zt}	0.033 (34.5)	0.0012 (37.9)	0.52 (76.0)	0.31 (42.9)	0.13 (24.0)	23.0 ($<10^{-5}$)	427.0 ($<10^{-5}$)	1364.1 ($<10^{-5}$)

Notes : a. Each series is decomposed into (*) $X_{zst} = u_{zs} + \varepsilon_{zst}$ where u_{zs} and ε_{zst} are uncorrelated. σ^2_u is the variance of $u_{zs}, \sigma^2_\varepsilon$ is the variance of ε_{zst}, ρ_i are autocorrelations of order 1,2 and 3 of ε_{zst}. Student statistics are reported between brackets.

b. Column W reports the test statistics of specification (*). If (*) is true, W is distributed as a chi-square with 51 degrees of freedom. Statistics T_1 is used to test that the fourth-order autocorrelation is equal to zero. Under the null, it is distributed as a chi-square with one degree of freedom. Statistics T_2 is used to test that parameters δ_t in the specification (**) $X_{zst} = u_{zs} + \delta_t v_{zs} + \varepsilon_{zst}$ (u_{zs}, v_{zs}, ε_{zst} uncorrelated) are equal to zero. Under the null, it is distributed as a chi-square with nine degrees of freedom. p-values are given between brackets.

c. The data are balanced for each series.

Table 3 : Univariate analysis of each series in levels

Terms such as $\delta_t v_{zs}$ in the previous models could be compatible with the geometric effect of initial conditions $(\alpha^t(X_{zs0} - e_{zs}/(1-\alpha))$, and the presence of an area and sector effect, $e_{zs}/(1-\alpha)$. The smoothly decreasing and positive autocorrelations of shocks ε_{zst} (ρ_1, ρ_2 and ρ_3 in table 3) are also compatible with the autocorrelation structure induced by such a specification of the series.

3.2 Contemporaneous Correlations between Variables

Table 5 reports correlations between dependent variables, $\mathbf{y}_{zst}$, and determinants, $\mathbf{x}_{zst}$. First, the larger average employment per plant (y^1_{zst}) is, the larger the number of plants (y^2_{zst}), the more likely a monopoly situation (c_{zst}) and the larger, the local competition within sectors ($lcom_{zst}$), the diversity between sectors (ld_{zst}) and the number of active sectors (ls_{zt}) are. Moreover, the larger the number of plants is, the stronger the competition between plants within a sector ($lcom_{zst}$), the larger the number of active sectors(ls_{zt}), the larger the local size (lL_{zt}) and the local diversity (ld_{zt}) are. These correlations seem to reflect mainly the contrast between small and large markets.

To abstract from size effects, we report in table 6 correlations between growth rates. As is often the case with panel data, correlations between growth rates are generally weaker than those between the variables in level. Some correlations are however quite significant. For instance, the correlations between, on the one hand, the dependent variables – plants' average employment and the number of plants – and local diversity on the other hand remain positive, while the correlation between average employment and local competition within sectors becomes negative.

4 Multivariate models

The previous section suggested to use a vector autoregressive specification such as:

$$\mathbf{y}_{zst} = A_0(L)\mathbf{y}_{zs,t-1} + B_0(L)\mathbf{x}_{zst} + \widetilde{\varepsilon}_{zst} \tag{19}$$

where $A_0(L)$ and $B_0(L)$ are matrix polynomials in the lag operator L and where $\widetilde{\varepsilon}_{zst}$ is a vector of random shocks on average employment per plant and on the number of plants. As shown above, dependent variables are correlated and the variance-covariance matrix of $\widetilde{\varepsilon}_{zst}$ is not supposed to be a diagonal matrix.

	T_1	T_2	W
Δy^1_{zst}	0.74 (0.39)	12.4 (0.13)	81.44 (2.10^{-4})
Δy^2_{zst}	0.01 (0.92)	27.1 (6.10^{-4})	202.92 ($<10^{-5}$)
$\Delta lcom_{zst}$	0.62 (0.43)	33.6 ($<10^{-5}$)	175.02 ($<10^{-5}$)

Notes : a. Each series ΔX_{zst} is supposed to be autocorrelated of order 3. Area and sector effects are not allowed for since their presence is always rejected.

b. Statistics W is used to test the hypothesis that $\Delta X_{zst} = \varepsilon_{zst},\ \varepsilon_{zst} \sim MA(3)$. It is distributed as a chi-square with 42 degrees of freedom under the null hypothesis. Statistics T_1 is used to test that the fourth-order autocorrelation is equal to zero. Under the null, it is distributed as a chi-square with one degree of freedom. Statistics T_2 is used to test that parameters δ_t in the model $\Delta X_{zst} = \delta_t v_{zs} + \varepsilon_{zst}$ (u_{zs}, ε_{zst} uncorrelated) are equal to zero. Under the null, it is distributed as a chi-square with eight degrees of freedom. p-values are given between brackets.

c. The data are balanced for each series.

Table 4 : Univariate analysis of first differences

(Obs 82853)	y^1_{zst}	y^2_{zst}	$lcom_{zst}$	c_{zst}	ld_{zt}	lL_{zt}	ls_{zt}
y^1_{zst}	1.000						
y^2_{zst}	0.278	1.000					
$lcom_{zst}$	0.121	0.947	1.000				
c_{zst}	-0.218	-0.608	-0.569	1.000			
ld_{zt}	0.100	0.351	0.335	-0.222	1.0000		
lL_{zt}	0.205	0.717	0.668	-0.352	0.358	1.000	
ls_{zt}	0.167	0.595	0.563	-0.330	0.594	0.840	1.000

Table 5 : Raw correlations (in levels)

It is always possible to rewrite system (19) using one of its recursive forms (for instance Gouriéroux and Monfort, 1999):

$$y^1_{zst} = A_{11}(L)y^1_{zs,t-1} + A_{12}(L)y^2_{zst} + B_1(L)\mathbf{x}_{zst} + \eta^1_{zst} \quad (20)$$

$$y^2_{zst} = A_{21}(L)y^1_{zs,t-1} + A_{22}(L)y^2_{zs,t-1} + B_2(L)\mathbf{x}_{zst} + \eta^2_{zst} \quad (21)$$

where random shocks η^1_{zst} and η^2_{zst} are now uncorrelated and where $A_{ij}(L)$ and $B_i(L)$ are scalar polynomials in the lag operator. We chose this recursive form to emphasize that average employment per plant should be varying at higher frequencies than the series recording the number of plants. It is justified by the theoretical argument that employment decisions are taken conditional on the entry decisions of plants decided beforehand. This assumption makes possible a structural interpretation of equations (20) and (21).

As shocks are uncorrelated, we can estimate the two equations separately.

4.1 Average Employment per Plant

Two modeling frameworks are worth exploring empirically. One model is "static" in the sense that polynomials $A_{ij}(L)$ and $B_i(L)$ are constant and A_{ii} are supposed to be equal to zero. Second, in the so called dynamic model, these polynomials are supposed to be of higher order and in our empirical analysis, we will show that it is very likely that they are of order 1.

4.1.1 Static Models

Given the previous discussion, we used the following specification:

$$\begin{aligned} y^1_{zst} &= \alpha y^2_{zst} + \mathbf{x}'_{zst}b + u_{zs} + \varepsilon_{zst} \\ &\equiv \widetilde{\mathbf{x}}'_{zst}b + u_{zs} + \varepsilon_{zst} \end{aligned} \quad (22)$$

where u_{zs} stands for an area and sector effect.

In the case where covariates are exogenous – x_{zst} and ε_{zst} are uncorrelated– and are uncorrelated with area and sector effects, u_{zs}, a simple and natural estimation method is OLS. Results are reported in the first column of table 7. The coefficient of determination (R^2) is quite large (27.4%). As is well known, OLS estimates are biased if explanatory variables $\widetilde{\mathbf{x}}_{zst}$ are correlated with area and sector effects u_{zs}. It is why we report in the second column within-estimates which are robust to the former specification error under the assumption that variables $\widetilde{\mathbf{x}}_{zst}$ are strongly exogenous – x_{zst} and $\varepsilon_{zst'}$ are uncorrelated at any dates t and t'. Taking first differences and estimating by OLS the differenced series is another method to eliminate area and sector effects which results are reported in the third column. The last two procedures give very similar results.

Nevertheless, serial dependence was shown to be significant in the previous section. The persistence in the series cannot be explained by area and sector effects only. It could also be the case that explanatory variables are not strictly exogenous but weakly exogenous only – $\widetilde{\mathbf{x}}_{zst}$ and $\varepsilon_{zst'}$ are uncorrelated at all dates t less or equal to t' – or quasi-weakly exogenous – $\widetilde{\mathbf{x}}_{zst}$ and $\varepsilon_{zst'}$ are uncorrelated at all dates t less than t'. It is the case when past random shocks on the dependent variable only affect the future and/or present of explanatory variables. The difference between the two weak exogeneity assumptions stems from the assumption of a zero or non-zero contemporaneous correlation between the dependent variable and the explanatory variables at date t.

When explanatory variables are weakly exogenous, first-differencing the model eliminates area and sector effects, u_{zs}, while the serial dependence structure remains simple (in contrast with a within-type transformation). Write the model as:

$$\Delta y^1_{zst} = \Delta \widetilde{\mathbf{x}}'_{zst} b + \Delta \varepsilon_{zst}.$$

When variables are quasi-weakly exogenous, the lagged explanatory variables at orders 2, 3, etc can be used as instruments in this equation (Hausman and Taylor, 1981) since variables dated after $t-1$ are correlated with $\varepsilon_{zs,t-1}$ while those dated before $t-2$ are not. 2SLS estimation results are reported in column 5 (2SLS, D/L$_{-2}$). When variables are weakly exogenous in the usual sense, lagged variables at orders 1, 2, etc are valid instruments. 2SLS estimation results are reported in column 6 (2SLS, D/L$_{-1}$).

Alternatively, one might consider the initial equation in levels:

$$y^1_{zst} = \widetilde{\mathbf{x}}'_{zst} b + u_{zs} + \varepsilon_{zst},$$

and use as instruments the first differences $\Delta\widetilde{\mathbf{x}}_{zst}$, $\Delta\widetilde{\mathbf{x}}_{zst-1}$,..., if $\widetilde{\mathbf{x}}_{zst}$ is weakly exogenous or $\Delta\widetilde{\mathbf{x}}_{zs,t-1}$, $\Delta\widetilde{\mathbf{x}}_{zst-2}$, etc (i.e. omitting from the list $\Delta\widetilde{\mathbf{x}}_{zst}$) if variables are quasi-weakly exogenous only.

This estimation method of the model in level when the instruments are in first differences however is consistent if explanatory variables $\widetilde{\mathbf{x}}_{zst}$ are stationary only (see Blundell and

Bond, 1998). To see that, suppose:

$$\widetilde{\mathbf{x}}_{zst} = \rho \widetilde{\mathbf{x}}_{zs,t-1} + v_{zs} + \eta_{zst},$$

where η_{zst} is white noise. Iterating until date 0, we get:

$$\widetilde{\mathbf{x}}_{zst} = \rho^t \widetilde{\mathbf{x}}_{zs,0} + \frac{1-\rho^t}{1-\rho} v_{zs} + \tilde{\eta}_{zst},$$

where:

$$\tilde{\eta}_{zst} = \eta_{zst} + \rho \eta_{zst-1} + ... + \rho^{t-1} \eta_{zs1}$$

is a MA(1) process. Reshuffling and taking first differences, we obtain:

$$\Delta \widetilde{\mathbf{x}}_{zst} = (\rho^t - \rho^{t-1})(\widetilde{\mathbf{x}}_{zs,0} - \frac{1}{1-\rho} v_{zs}) + \Delta \tilde{\eta}_{zst}$$

The first term says that the process is in equilibrium if $\widetilde{\mathbf{x}}_{zs,0} = \frac{1}{1-\rho} v_{zs}$. If it is not, $\Delta \widetilde{\mathbf{x}}_{zst}$ include "non stationary" area and sector effects which might be correlated with the area and sector effect u_{zs} in the equation of interest (y^1_{zst}). It makes the first differences $\Delta \widetilde{\mathbf{x}}_{zst}$ invalid instruments (see Blundell and Bond, 1998). With this caution in mind, we report in table 7, column 4 (2SLS, L/D$_{-1}$) the two stage least squares estimates of the model in level using first differenced variables as instruments.

Given the relative merits of these estimation methods and specification statistics reported in the bottom part of Table 7, our preferred results are in column 6. Namely, the Sargan statistic is as large in column 6 as in column 5 and lower than in column 4. Generally speaking, OLS results strongly contrast with all other results. It is sufficient to control area and sector effects by the within or first differenced OLS estimation methods (columns 2 and 3) to bridge the gap with our preferred results (column 6). At a lesser degree, note also that instrumenting levels by first-differences (column 4) differ from results of instrumenting first-differences by the variables in levels (columns 5 and 6), which might point out that processes on the RHS of the equation of interest are not stationary. The hypothesis that contemporaneous correlation between the dependent and explanatory variables is absent, which can be evaluated by contrasting columns 5 and 6, and is not rejected. Instruments might be too weak however as shown by the imprecision of estimates in column 5.

Finally, specification diagnostics tell us that autocorrelation is significant up to the order 3 at least. It is why we are now looking for dynamic specifications that would agree with such results of the static model.

4.1.2 Dynamic Models

The most straightforward way to derive a dynamic model from a static equation like (22) is to assume that random shocks ε_{zst} follow an autoregressive process of order 1:

$$\varepsilon_{zst} = \rho\varepsilon_{zs,t-1} + (1-\rho)\eta_{zst},$$

where η_{zst} is stationary and is possibly autocorrelated. When $\rho < 1$ the process ε_{zst} is stationary. From equation (22) evaluated at periods t and $t-1$, we can derive that:

$$y^1_{zst} - \rho y^1_{zs,t-1} = \widetilde{\mathbf{x}}'_{zst}b + u_{zs} + \varepsilon_{zst} - \rho(\widetilde{\mathbf{x}}'_{zs,t-1}b + u_{zs} + \varepsilon_{zs,t-1}),$$

or equivalently:

$$y^1_{zst} = \rho y^1_{zs,t-1} + \widetilde{\mathbf{x}}'_{zst}b - \rho\widetilde{\mathbf{x}}'_{zs,t-1}b + (1-\rho)\left(u_{zs} + \eta_{zst}\right). \tag{23}$$

This expression is a particular case of the following linear model:

$$y^1_{zst} = \rho y^1_{zs,t-1} + \widetilde{\mathbf{x}}'_{zst}b - \widetilde{\mathbf{x}}'_{zs,t-1}b_1 + (1-\rho)\left(u_{zs} + \eta_{zst}\right), \tag{24}$$

when $b_1 = \rho b$. Equation (23) is thus the constrained dynamic equation while equation (24) describes the unconstrained model.

In such an autoregressive panel data model, $y^1_{zs,t-1}$ depends on the area and sector effect, u_{zs}, if y^1_{zst} does. Moreover, given results of the previous section, variables $\widetilde{\mathbf{x}}_{zst}$ are likely to be correlated with the fixed effect u_{zs}. It leads us to estimate equation (24) by instrumental variable methods as in the previous section.

To report on the strength of our instruments (Altonji and Segal, 1996), table 8 reports results of instrumental regressions that prove that instruments that we use are significant determinants of RHS variables in the equation of interest. First-differences of all variables are regressed by OLS on their lags of order 1, 2 and 3. We do not use higher-order lags in order to avoid superfluous moment conditions (Ziliak, 1997). All lagged variables are significant at least once in this table.

Variables are supposed to be weakly exogenous that is to say, shocks in the equation of interest are not correlated with the past and present of explanatory variables. We use the two estimation methods that we already presented. The equation is either estimated in first differences using instrument in levels (lagged once, twice or three times), or estimated in level using lagged first differences as instruments. Estimation results are reported in the first two columns of table 9.

The dynamic information from the series of interest itself remains to be used. If the random term, η_{zst}, in (24) is not autocorrelated, variable $y^1_{zs,t-2}$ is a valid instrument. Variable $y^1_{zs,t-1}$ is not since it is correlated with $\Delta\eta_{zst}$. If the autocorrelation of order 1 in (24) is not equal to zero, variable $y^1_{zs,t-2}$ loses its validity as an instrument. Longer lags are needed and it is only from $y^1_{zs,t-3}$ backwards that instruments are valid. As estimates show that the order of the autocorrelation of the series Δy^1_{zst} is at least equal to 2 – and therefore the order of autocorrelation in the series y^1_{zst} at least equal to 1 – we use $y^1_{zs,t-3}$ or longer lags as instruments.

Results of the various estimations of the unconstrained equation (24) are quite similar and the value of the Sargan statistic associated to the instrumentation of differences by levels (column 2) does not lead to reject overidentifying restrictions. The estimate of the autoregressive coefficient is very precise[5]. Note also the alternating signs of the coefficients of every explanatory variable and its lag which agrees well with the constrained specification (23).

It is why we estimate the constrained model (i.e. under the constraint $b_1 = \rho b$). As this model is not linear, it is estimated by two stage non linear least squares (2NSLS) in first difference.[6] As in the unconstrained equation, the instruments are variables $y^1_{zs,t-3}$ and $\widetilde{\mathbf{x}}_{zs,t-j}$ for $j = 0, 1, 2$. Results are reported in the last column of table 9. Estimates are very precise even though standard errors of estimates should be corrected for biases due to the bilinear structure of the estimation method as well as for the presence of serial and spatial dependence[7]. It is unlikely however that this correction, even if it usually tends to make standard errors larger, would change the very significant results of this estimation.

[5]In very few estimations that we performed, did we find that higher-order lags of the dependent variables were significant. A first-order VAR process seems to be sufficient to descrive these processes along with MA(1) random disturbances (see below).

[6]Note that the model is bilinear. Let z_{zst} a vector of instruments. Parameters ρ and b can then be estimated by using until convergence the following algorithm. Given a pair (ρ_n, b_n) obtained previously, (ρ_{n+1}, b_{n+1}) is estimated by regressing Δy_{zst} on variables $\Delta y_{zs,t-1}$ and $\Delta x_{zst} - \rho_n \Delta x_{zs,t-1}$ by 2SLS (instruments z_{zst}).

[7]In the experiments that we ran, corrections for bilinearity and sectoral or serial dependence do not seem to matter. Spatial dependence matters more and makes Student statistics decrease by a maximum factor of 30%.

Finally, estimated coefficients of explanatory variables in this model are very similar to the estimates in the static model which were reported in table 8. Namely, the dynamic model is coherent with previous results and in particular the significance of specific area and sector effects in the static model (22). Equation (23) is equivalent to:

$$y_{zst}^{1} = \widetilde{\mathbf{x}}_{zst}' b + u_{zs} + \rho^{t-1}(y_{zs1} - \widetilde{\mathbf{x}}_{zs1}' b - u_{zs}) + (1-\rho)(\eta_{zst} + \rho\eta_{zs,t-1} + ... + \rho^{t-2}\eta_{zs,2}),$$

in which the term $\rho^{t-1}(y_{zs1} - \widetilde{\mathbf{x}}_{zs1}' b)$ is an area and sector effect interacted with time due to the persistence of the initial conditions.

Finally, it is informative to analyze residuals of the estimated equation. In table 10, we report estimates of the variances of u_{zs} and of η_{zst}, as well as the first autocorrelation of η_{zst} and test statistics related to the hypothesis of a zero second order autocorrelation. The variance of the area and sector effects is smaller (20%) than in the univariate analysis reported in table 3. Random shocks, η_{zst}, are well described as a moving average of order 1 which autocorrelation is equal to -0.140. A negative sign might reflect errors of measure.[8] Moreover we report an estimate of the variance of the "long-term" error, ε_{zst}, in the original series when the the "short-term" error, η_{zst}, is assumed to be a MA(1) process. It is significantly larger that the estimated variance reported in table 3 when covariates are omitted.

We finally compute the contribution to the variance of the original series y_{zst}^{1} of the long-term target around which the series fluctuate, that is to say:

$$y_{zst}^{1*} = \widetilde{\mathbf{x}}_{zst}' b + u_{zs},$$

since equation (23) can be written as:

$$\begin{aligned} y_{zst}^{1} - y_{zst}^{1*} &= \frac{(1-\rho)\eta_{zst}}{1-\rho L} \\ &= \varepsilon_{zst}, \end{aligned}$$

where ε_{zst} is a stationary noise.

Nevertheless, in order to compute (predict) y_{zst}^{1*}, area and sector effects should first be estimated. When T is sufficiently large, averaging residuals yields such an estimate.

[8] We expect measurement errors in the data in particular stemming from the restriction of the sample to plants with less than 20 employees. Namely, employment in an area and sector is reduced by a significant amount whenever a plant reduces the number of workers below 20.

Denote:

$$\widehat{v}_{zst} = \frac{y^1_{zst} - \widehat{\rho} y^1_{zs,t-1} - \widetilde{\mathbf{x}}'_{zst}\widehat{b} + \rho \widetilde{\mathbf{x}}'_{zs,t-1}\widehat{b}}{1-\rho},$$

and:

$$\widehat{u}_{zs} = \frac{1}{T}\sum_{t=1}^{T} \widehat{v}_{zst}.$$

Results of the analysis of variance are reported in table 11. The variance of the long-term target is equal to 85% of the total variance. The contribution of the variance of the area and sector fixed effect in the variance of the target is large (87%) while the variance of what is determined by explanatory variables contribute to it moderately (16%). These components do not sum to one as explanatory variables and area and sector effects are significantly and negatively correlated (-0.04). Average employment per plant is therefore hardly affected by the structural explanatory variables, $\widetilde{\mathbf{x}}_{zst} = (y^2_{zst}, \mathbf{x}_{zst})$.

4.2 Determinants and Dynamics of the Number of Plants

In this section, we replicate the previous methodology to analyze the series of the number of plants in an area and sector. We start by presenting results of a static specification and then turn to results of the constrained and unconstrained dynamic models.

The static model is written as:

$$y^2_{zst} = \breve{\mathbf{x}}'_{zst} b + u_{zs} + \varepsilon_{zst}, \tag{25}$$

which differs from model (22) by the dependent variable : y^2_{zst} instead of y^1_{zst}, and inclusion of the lag of average employment per plant, $y^1_{zs,t-1}$, among the explanatory variables. Denote $\breve{\mathbf{x}}_{zst} = (y^1_{zs,t-1}, \mathbf{x}_{zst})$.

Estimated coefficients are reported in table 12. At a lesser degree that for average employment, area and sector effects are nevertheless significant. OLS estimates also differ from all other estimates. The divergence between signs across different columns is less noticeable than for average employment. Moreover, whereas the Sargan statistic of the estimation reported in column 4 indicates that overidentifying restrictions are not rejected, it is not the case of estimates reported in columns 5 and 6 – estimations in first differences. Differences are small however between estimates.

The two expressions for the dynamic model when it is constrained or not are:

$$y^2_{zst} = \rho y^2_{zs,t-1} + \breve{\mathbf{x}}'_{zst} b - \rho \breve{\mathbf{x}}'_{zs,t-1} b + (1-\rho)(u_{zs} + \eta_{zst}) \tag{26}$$

and:

$$y^2_{zst} = \rho y^2_{zs,t-1} + \breve{\mathbf{x}}'_{zst}b - \breve{\mathbf{x}}'_{zs,t-1}b_1 + (1-\rho)\left(u_{zs} + \eta_{zst}\right) \tag{27}$$

Estimation results are reported in table 13. The estimation of the unconstrained dynamic model (27) yields similar results whatever the estimation method is (in levels or in first differences). The signs of the coefficients of each variable and its lag are alternating again which confers some credibility to the constrained specification (26). Estimates in the pseudo-differenced equation are very precise. Sargan statistics indicate that overidentifying restrictions cannot be rejected at a reasonable level of significance. As for average employment, the order of autocorrelation is equal to 2 in first differences which corresponds to a moving average of order 1 when the dependent variable is in level.[9] Estimates in the dynamic model do not differ much from those in the static model. Specification diagnostics are better however in the dynamic version.

Finally, we can analyze residuals as in the previous section (tables 14 and 15). Autocorrelation estimates confirm results of table 13. Residuals η_{zst} are a moving average of order 1 and the coefficient of autocorrelation is equal to -0.123, which might reflect measurement errors as before. The variance of the area and sector effect is much smaller (1/10) than in the original series analyzed in table 3. The variance of η_{zst} is also much smaller. The model is thus better suited for explaining (the logarithm of) the number of plants than average employment per plant. It is confirmed by what we report in table 15. The variance of the long-term target is equal to 74% of the variance of the original series and the long-term variance is mainly composed of the variance of what is determined by explanatory variables (96%). Area and sector effects contribute very little to this variance (0.4%) and the correlation between explanatory variables and area and sector effects is very significant (0.26). The number of plants is therefore well explained by the model.

4.3 Interpretations

In this section we put into perspective the estimation results of the dynamic models and results that can be obtained from a disaggregated analysis by sectors – manufacturing, trade, and services – reported in tables 16 and 17.

[9] In a similar way than in the previous section, standard errors of coefficients should be corrected fo the bilinear nature of the estimation method and the presence of serial and spatial dependence.

Let us first note the persistence of shocks as measured by the autoregressive coefficient, ρ. Estimates of this coefficient for both series of average employment and number of plants lie between .75 and .81 for the former variable and between .50 and .73 for the latter. When the dependent variable is average employment, there is little difference in persistence between sectors (table 16). By contrast, persistence in the number of plants is more variable across sectors (table 17). Trade and services differ from manufacturing by a weak persistence in their creation/destruction of plants and therefore in external growth. Internal growth – average employment per plant – is much more persistent, which has an important policy implication. Economic policies would be more efficient when targeted on the number of plants locally than those trying to influence the growth of existing plants, especially regarding trade and services.

Moreover, the effect of explanatory variables on both dependent variables is most often similar across sectors (tables 16 and 17) even if some small differences underlined below may be observed. The significance of estimates also slightly differ across sectors but it might only reflect small sampling errors in the samples concerning trade and services.

Let us start by the impact on local growth of the global size of the local area (lL_{zt}). We find that in larger areas, cities as opposed to more rural areas for instance, both internal and external growth is stronger. It is consistent with the ongoing increase in urban concentration observed in the US by Black and Henderson [1998] even if these authors also underline recent examples of small but rapidly growing cities. Combes [2000] also concludes for France that growth is more important in large cities as regards service sectors but the reverse happens in manufacturing. Do not forget however that we control for the short run dynamics and that mean reversion is indeed observed (controling for area and sector effects). For instance the lower the sectoral employment per firm, the stronger its growth. Contrary to previous studies, we are able to distinguished this short-run dynamic effects from the impact of the local economic structure conditional on the presence of area and sector effects.

Hence, the data exhibit global agglomeration economies. Larger areas where both technological spillovers are supposed to be stronger and where final and intermediate good markets are larger have larger plant size as well as stronger plant creation. This last point is in particular consistent with the idea of "nursery" cities developed by Duranton and Puga

[2001]. Cities, where ideas and knowledge are concentrated, would be the most favorable places for creating and innovating at the first stage of the product life cycle, activity moving next towards less dense areas at later stages. This appears to be even more valid in France as regards service activities, which again makes sense if one think that these products are more innovation intensive and frequently renewed.

The global size of the local economy is sometimes considered as part of the so called urbanization economies. Nevertheless, this latter term has recently tended to describe the impact of the local sectoral diversity (ld_{zt}) on local growth. As underlined previously, the existing literature simultaneously identifies localization economies, that is the effect of the own sector specialization, but only thanks to a non log-linear specification. Besides, contradictory results are obtained on the US by GKSS and HKT even if both the methodology and the period of observation slightly differ: the latter find localization economies but not urbanization ones except in the high-tech activities, while in the former only urbanization economies are significant (on average on all sectors), specialization playing a negative rôle on local growth. Combes [2000] also shows that the effect of sectoral diversity may depend on the sector in France. The new approach we propose here allows to further consider the impact of the local sectoral composition on local growth. Since the effect of the standard specialization variable cannot be identified from the short-run employment dynamics, we include the number of active sectors (ls_{zt}) as an extra explanatory variable, next to the diversity index. Both variables are systematically significant, for all sectors. Diversity has a positive effect as well on average employment as on the creation of plants. By contrast, the number of operating sectors in an area (ls_{zt}) has a negative effect in both cases.

As a consequence, the message regarding the rôle of the sectoral composition is clearer. Internal and external growth are maximized in areas where the number of operating sectors is small but where diversity is large. That is to say, the most favorable local sectoral structure would consist in a small number of sectors but of roughly the same size: For a given total local employment, areas having such a sectoral structure are characterized by larger plant sizes and larger numbers of plants. In terms of agglomeration forces, it would be consistent with the idea that sectors need different inputs in similar quantity, even if the number of these inputs is not necessary large, and that technological externalities may be cross sectoral but do not extend to all sectors. Spillovers would be maximized inside fairly small but balanced sub-groups of sectors, those being not numerous but of similar size.

Ceteris paribus, the effect of the number of plants (y^2_{zst}) on the average plant size (y^1_{zst}) is positive. In other terms, employment in an area and sector grows more quickly than the number of plants. Some caution should be exercised when interpreting these results since creation and destruction of employment in small plants should also be taken into account (Davis, Haltiwanger and Schuh, 1996). They are not here because plants with more than 20 employees only are selected into the sample. Nevertheless, the effect of the lagged average employment (y^1_{zst}) on the number of plants (y^2_{zst}) is small but negative. Second, local competition between plants within sectors ($lcom_{zst}$) has a strong and negative effect on average employment and has a strong and positive effect on the number of plants. The more concentrated the plants are, the more employment is growing internally, within plants, but the smaller is the plant creation. The effect of the variable that denotes a monopoly situation (c_{zst}) goes in the reverse direction.[10] In other words, competition seems to have non-linear effects on the growth of areas and sectors.

Even if more complex, these results about the effect of competition shed new light on what is found in the literature and have also some important policy implications. In GKSS, competition is proxied by the (inverse) average size of plant, which is difficult to interpret and can be hardly compared to our approach. In Combes [2000] only one competition variable, the number of local plants, is considered. It has a quasi systematic negative effect, except in a few service sectors. Again, the inclusion of different competition variables here, and the fact that they are all significant (except the monopoly situation in services), allows a more precise verdict. Internal growth is maximized when the number of local plants is large, when they are definitely not in a situation of local monopoly and when, simultaneously, the average size of plants is uneven. One can think about a situation in which some large leader firms impulse the dynamics of a large number of smaller plants. The size of the first ones would induce benefits due to economies of scale, while the other ones could for instance gain from lower transport costs to large markets or from a better matching with their partners. It is also consistent with the idea of large plants doing research and development, which benefits to all other plants, a structure that would maximize technological spillovers and knowledge diffusion. The counterpart would be that, once controlled by the mean reversion

[10] This variable has obviously been omitted from the equation explaining the number of plants.

effect (plant creation is stronger in areas where the number of plants is low), the existence of plants of even size is more favorable to the creation of new plants.

5 Conclusion

We analyze yearly data extracted from an employment survey of plants to study the impact of the local economic structure on local growth between 1984 and 1993 in France. We first show that the persistence of the dependent variables is fairly important in the short run, even more as regards the average employment per plant than the number of plants. The period under study may be too short to expect strong effects of local characteristics. The dynamics of the first variable is fairly stable and only partly determined by exogenous factors. By contrast, the number of operating plants in a given area and sector seems to be less persistent and better determined by exogenous factors.

Larger areas benefit from more plant creation simultaneously with larger average plant size. Whereas the number of locally active sectors does not need to be large, sectors of comparable size favor both internal and external growth. Last, plants appear to be larger in areas where they are more numerous, where they are definitely not in a situation of local monopoly and where they are of uneven size. On the other hand, the number of plants grows faster in places where plants are less numerous and of even size. Thus, large areas having a small number of even size sectors and where are located large leader firms impulsing growth to smaller and numerous plants benefit from larger growth.

These results can be reinterpreted in the light of recent works in economic geography. The positive effect of the area total size can be due to either economies of scale gains or to strong/high quality technological spillovers. An interpretation of the sectoral composition effect would be that technological spillovers can be cross-sectoral but do not extend to all sectors, and similarly for intermediate inputs that are not necessary numerous but equally important. Last, as regards the impact of local competition, large leaders, either benefiting from economies of scale or having research and development units of efficient size, would impulse growth to smaller and numerous plants surrounding them and benefiting for instance from technological spillovers or from large markets and improved matching with their partners. All of these clearly shed new light on which local economic structure is the most favorable to local growth. Even if one has not to forget the persistence of both variables, plant size in particular, which might limit the extent to which economic policies may be efficient, an optimal structure of local areas is characterized.

Our analysis also throws some light in the debate about the development of weakly diversified regions within the European Union, by decomposing total employment in an area and sector into average employment per plant and into the number of plants. Regions where employment grows faster are not only regions which are weakly diversified in manufacturing and service activities, even if the active sectors have to be of similar size, but also those where average employment per plant is strongly diversified as if some large leaders determine the dynamics of other smaller plants (through subcontracting or not). Aeronautics in the region of Toulouse is such an example.

Replication of studies such as ours would make possible a precise characterization of the different forms of local development that are undertaken in each of the countries of the European Union and to a factual analysis of the efficiency of creating employment according to these references. Besides, we are not able to state which kind of agglomeration externalities, technological or market-based, are more important for local growth, a question on which more research efforts should certainly be put. Another line of research would also consist in evaluating the spatial extent to which the local structure acts on local growth. We assume here that it is restricted to the local area itself, but Desmet and Fafchamps [2001] propose a methodology that could be mixed to ours to evaluate the distance at which agglomeration forces work.

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(Obs 72780)	y^1_{zst}	y^2_{zst}	$lcom_{zst}$	c_{zst}	ld_{zt}	lL_{zt}	ls_{zt}
y^1_{zst}	1.000						
y^2_{zst}	-0.095	1.000					
$lcom_{zst}$	-0.264	0.828	1.000				
c_{zst}	0.032	-0.677	-0.563	1.000			
ld_{zt}	0.026	0.083	0.069	-0.047	1.0000		
lL_{zt}	0.081	0.213	0.155	-0.082	-0.069	1.000	
ls_{zt}	0.004	0.088	0.077	-0.039	0.250	0.387	1.000

Table 6 : Raw correlations (in first differences)

y^1_{zst}	OLS (Level)	Within	OLS (Diff)	2SLS (L/D$_{-1}$)	2SLS (D/L$_{-2}$)	2SLS (D/L$_{-1}$)
y^2_{zst}	1.00	.257	.283	.302	.138	.327
	(148.5)	(36.9)	(43.7)	(4.9)	(1.9)	(14.7)
$lcom_{zst}$	-1.116	-.544	-.566	-.360	-.469	-.634
	(-148.2)	(-85.0)	(-94.1)	(5.1)	(-9.4)	(-34.2)
c_{zst}	-.109	-.066	-.077	.071	-.074	-.085
	(-16.2)	(-11.9)	(-15.7)	(1.5)	(1.4)	(-5.4)
ld_{zs}	.0031	.148	.137	-.540	.096	.143
	(0.51)	(16.3)	(15.1)	(-2.5)	(1.2)	(4.8)
lL_{zt}	-.016	.311	.277	.052	.173	.226
	(-3.8)	(31.8)	(30.4)	(0.4)	(1.3)	(6.5)
ls_{zt}	.052	-.203	-.183	.550	.041	-.277
	(2.7)	(-10.6)	(-10.5)	(3.0)	(0.2)	(-4.5)
R^2	27.4%	11.8%	13.2%			-
Sargan	-			$<10^{-5}$	0.030	0.038
AC(1)	.906 $(<10^{-4})$	.954 $(<10^{-4})$	$-.217$ $(<10^{-4})$	.939 $(<10^{-4})$	$-.206$ $(<10^{-4})$	$-.218$ $(<10^{-4})$
AC(2)	.852 $(<10^{-4})$	.931 $(<10^{-4})$	$-.025$ $(<10^{-4})$	.904 $(<10^{-4})$	$-.029$ $(<10^{-4})$	$-.033$ $(<10^{-4})$
AC(3)	.806 $(<10^{-4})$	.912 $(<10^{-4})$	$-.018$ (10^{-4})	.873 $(<10^{-4})$	$-.035$ $(<10^{-4})$	$-.025$ $(<10^{-4})$
Obs	82846	82846	72773	46099	46099	54657

Notes : a. "Level" and "Differences" refer to variables in levels, X_{zst}, or in first differences, ΔX_{zst}. 2SLS estimations are such that: i. For L/D$_{-1}$, variables are in levels and the set of instruments comprises all variables in first differences lagged once, twice and three times. ii. For D/L$_{-2}$, variables are in first differences and the set of instruments comprises all variables in levels lagged twice, three and four times. iii. For D/L$_{-1}$, variables are in first differences and the set of instruments comprises all variables in levels lagged once, twice and three times.

b. "Sargan" is the Sargan or J-test of overidentifying restrictions. p-values only are reported. AC(k) is the estimated value of the autocorrelation of order k. p-values associated to the test that these autocorrelations are equal to zero are reported below the estimates between brackets.

c. Standard errors are not corrected for spatial or serial dependence.

Table 7: Average employment per plant, y^1_{zst}

(Obs 54642)	Δy^1_{zst}	Δy^2_{zst}	$\Delta lcom_{zst}$	Δc_{zst}	Δld_{zs}	ΔlL_{zt}	Δls_{zs}
$y^1_{zs,t-1}$	−.270 (−58.6)	−	−	−	−	−	−
$y^1_{zs,t-2}$	.150 (27.3)	.024 (−4.0)	−	−.014 (−2.7)	.004 (1.8)	−	−
$y^1_{zs,t-3}$	.058 (13.4)	.011 (2.3)	−	−	−.003 (−1.9)	−.003 (1.7)	−
$y^2_{zs,t-1}$	−.040 (−5.1)	−.262 (−30.9)	.078 (9.6)	−.042 (−5.8)	−	.006 (2.7)	−
$y^2_{zs,t-2}$	.018 (2.0)	.130 (12.9)	−.018 (1.9)	.021 (2.5)	−	−	−
$y^2_{zs,t-3}$	.038 (5.0)	.093 (11.1)	−	.015 (2.1)	−	−.007 (−2.2)	−
$lcom_{zs,t-1}$	.062 (8.2)	−	−.339 (−42.9)	−	−	−	−
$lcom_{zs,t-2}$	−.030 (−3.4)	.017 (1.7)	.170 (18.1)	−	−	−	−
$lcom_{zs,t-3}$	−.039 (−5.2)	−	.068 (8.7)	−	−	−	−
$c_{zs,t-1}$	−	.080 (12.0)	.069 (10.8)	−.415 (−73.2)	−	.005 (2.3)	−
$c_{zs,t-2}$	−	.016 (2.0)	.013 (1.8)	.139 (21.0)	−	−	−
$c_{zs,t-3}$	−.012 (−2.1)	−	−	.112 (20.0)	−	−.006 (−2.9)	−
$ld_{z,t-1}$	−	−	−	−	−.321 (−70.4)	−.017 (−4.4)	.007 (2.9)
$ld_{z,t-2}$	−	−	−	−	.186 (34.2)	−	.011 (4.0)
$ld_{z,t-3}$	−	.024 (2.1)	.028 (2.5)	−	.077 (17.1)	.035 (8.9)	−.009 (−3.8)
$l_{z,t-1}$	−	−.024 (−1.8)	−.026 (2.0)	.023 (2.0)	−.025 (−4.9)	−.340 (−75.3)	−.006 (−2.4)
$l_{z,t-2}$	−	.076 (5.0)	.045 (3.1)	−.041 (−3.1)	−	.259 (50.5)	.013 (4.3)
$l_{z,t-3}$	−	−.031 (−2.7)	−	−	.022 (5.0)	.081 (21.2)	.006 (−2.7)
$ls_{z,t-1}$	.086 (3.9)	−	−	−	.141 (15.7)	−	−.317 (−68.0)
$ls_{z,t-2}$	−.060 (−2.3)	−	.052 (1.9)	−	−.048 (−4.5)	.046 (4.9)	.200 (36.3)
$ls_{z,t-3}$	−	−	−.048 (−2.2)	−	−.024 (−2.7)	−.065 (−8.6)	.055 (12.3)
R^2	0.089	0.098	0.100	0.148	0.107	0.114	0.100

Notes : OLS estimates of first-differences of variables of interest on lagged variables.

Table 8 : Instrumental regressions

Variable	y^1_{zst}	y^1_{zst}	y^1_{zst}
Method	In levels	In differences	In pseudo-differences
Instruments	$\Delta y_{zs,t-2}$ $(\Delta\widetilde{\mathbf{x}}_{zs,t-j})_{j=0,1,2}$	$y_{zs,t-3}$ $(\widetilde{\mathbf{x}}_{zs,t-j})_{j=0,1,2}$	$y_{zs,t-3}$ $(\widetilde{\mathbf{x}}_{zs,t-j})_{j=0,1,2}$
y^2_{zst}	.248 (20.6)	.281 (4.9)	.287 (20.1)
$lcom_{zst}$	$-.505$ (-38.3)	$-.497$ (-11.9)	$-.576$ (26.7)
c_{zst}	$-.053$ (-6.4)	$-.002$ (-0.1)	$-.063$ (8.5)
ld_{zt}	.013 (-0.2)	.166 (2.4)	.136 (9.8)
lL_{zt}	.274 (13.9)	.257 (1.6)	.268 (15.3)
ls_{zt}	$-.126$ (-3.2)	$-.093$ (0.5)	$-.231$ (8.7)
$y^1_{zs,t-1}$	.851 (30.7)	.878 (16.3)	.809 (20.1)
$y^2_{zs,t-1}$	$-.249$ (25.1)	$-.257$ (11.5)	
$lcom_{zs,t-1}$	.504 (30.0)	.529 (16.3)	
$c_{zs,t-1}$	.068 (8.2)	.072 (4.9)	
$ld_{z,t-1}$	$-.156$ (-7.1)	$-.109$ (-4.4)	
$l_{z,t-1}$	$-.233$ (-11.1)	$-.237$ (-4.2)	
$ls_{z,t-1}$	.221 (7.5)	.239 (4.1)	
Sargan	.025	.839	.521
$AC(1)$	0.061 $(<10^{-5})$	-0.579 $(<10^{-5})$	-0.576 $(<10^{-5})$
$AC(2)$	0.194 $(<10^{-5})$	0.084 $(<10^{-5})$	0.082 $(<10^{-5})$
$AC(3)$	0.194 $(<10^{-5})$	-0.003 (0.57)	-0.004 (0.53)
Obs	54664	54664	54664

Notes : a. Estimation by 2SLS. In column "in levels", dependent variables in levels are regressed on explanatory variables using first differences as instruments; in column "in differences", dependent variables are in first differences and variables in levels are used as instruments. Pseudo-differences are build as $\Delta_\rho X_{zst} = X_{zst} - \rho X_{zs,t-1}$ where ρ is the coefficient of $y^1_{zs,t-1}$. We use the bilinear method explained in the text and we report results in column "in pseudo-differences".

b."Sargan" reports p-values associated to the Sargan statistic. AC(k) is the estimated autocorrelation coefficient of order k. p-values associated to the test that these coefficients are equal to zero are reported below the estimates and within brackets.

c. The estimation of standard errors are not corrected for biases due to the bilinear nature of the estimation method nor for biases due to serial and spatial dependence.

Table 9 : The dynamics of average employment per plant, y^1_{zst}

σ_u^2	σ_η^2	σ_ε^2	ρ_1	T	W
0.239 (26.9)	0.853 (34.6)	0.110	-0.140 (-12.8)	0.01 (0.92)	71.72 (0.028)

Notes : a. σ_u^2 is the variance of the area and sector effect, σ_η^2 is the variance of the residual effect, ρ_1 its autocorrelation coefficient of order 1, T is the test statistic corresponding to a zero second order autocorrelation. W tests the validity of this representation of the series. We denote σ_ε^2 the variance of $\varepsilon_{zst} = y_{zst} - \widetilde{\mathbf{x}}_{zst} + u_{zs}$. It is deduced from $\hat{\sigma}_\eta^2, \hat{\rho}_1$ and $\hat{\rho}$ using the expression:

$$\sigma_\varepsilon^2 = V\left(\frac{1-\rho}{1-\rho L}\eta_{zst}\right) = \frac{1-\rho}{1+\rho}(1+2\rho\rho_1)\sigma_\eta^2.$$

b. Between brackets, Student statistics for coefficients and p-values for test statistics.

Table 10 : Analysis of variance of the residuals

	$\frac{Vy_{zst}^{1*}}{Vy_{zst}}$	$\frac{V(\widetilde{\mathbf{x}}'_{zst}\hat{b})}{Vy_{zst}^*}$	$\frac{V(u_{zs})}{Vy_{zst}^*}$	$Corr(\widetilde{\mathbf{x}}'_{zst}\hat{b}, u_{zs})$
y_{zst}^1	.852	.161	.871	-0.042

Notes : The long-term target is denoted $y_{zst}^{1*} = \widetilde{\mathbf{x}}'_{zst}\hat{b} + u_{zs}$ where coefficient $\hat{b}$ is taken from column 3 of table 9.

Table 11 : Factor contributions to the variability of average employment

y^2_{zst}	OLS (Level)	"Within"	OLS (Diff.)	2SLS (L/D$_{-1}$)	2SLS (D/L$_{-2}$)	2SLS (D/L$_{-1}$)
$y^1_{zs,t-1}$	.222	.033	-.040	-.012	-.114	-.012
	(143.1)	(14.2)	(-16.8)	(-0.5)	(-3.2)	(-1.5)
$lcom_{zst}$	1.04	.853	.850	.937	.697	.815
	(620.7)	(363.0)	(356.9)	(55.3)	(13.1)	(72.5)
ld_{zs}	.071	.117	.103	.217	.024	.076
	(22.2)	(19.6)	(16.2)	(2.8)	(0.4)	(3.4)
lL_{zt}	.161	.263	.244	.202	.225	.233
	(76.3)	(35.9)	(33.3)	(3.9)	(2.1)	(8.4)
ls_{zt}	-.247	-.111	-.097	-.196	-.205	-.162
	(-24.9)	(-8.9)	(-7.8)	(-1.8)	(-1.4)	(-3.5)
R^2	92.9%	68.8%	67.7%			-
Sargan	-			0.80	0.002	5.10^{-5}
AC(1)	.825 ($<10^{-4}$)	.974 ($<10^{-4}$)	$-.253$ ($<10^{-4}$)	.908 ($<10^{-4}$)	$-.215$ ($<10^{-4}$)	$-.244$ ($<10^{-4}$)
AC(2)	.766 ($<10^{-4}$)	.962 ($<10^{-4}$)	$-.045$ ($<10^{-4}$)	.860 ($<10^{-4}$)	$-.079$ ($<10^{-4}$)	$-.058$ ($<10^{-4}$)
AC(3)	.705 ($<10^{-4}$)	.951 ($<10^{-4}$)	$-.034$ (10^{-4})	.818 ($<10^{-4}$)	$-.044$ ($<10^{-4}$)	$-.038$ ($<10^{-4}$)
Obs	72780	72780	63523	37826	37826	46099

Notes : a. "Level" and "Differences" refer to variables in levels, X_{zst}, or in first differences, ΔX_{zst}. 2SLS estimations are such that: i. For L/D$_{-1}$, variables are in levels and the set of instruments comprises all variables in first differences lagged once, twice and three times. ii. For D/L$_{-2}$, variables are in first differences and the set of instruments comprises all variables in levels lagged twice, three and four times. iii. For D/L$_{-1}$, variables are in first differences and the set of instruments comprises all variables in levels lagged once, twice and three times.

b. "Sargan" is the Sargan or J-test of overidentifying restrictions. p-values only are reported. AC(k) is the estimated value of the autocorrelation of order k. p-values associated to the test that these autocorrelations are equal to zero are reported below the estimates between brackets.

c. Standard errors are not corrected for spatial or serial dependence.

Table 12: Number of plants, y^2_{zst}

Variable	y^2_{zst}	y^2_{zst}	y^2_{zst}
Method	In level	In differences	In pseudo-differences
Instruments	$\Delta y^2_{zs,t-2}$ $(\Delta \mathbf{x}_{zs,t-j})_{j=0,1,2}$	$y^2_{zs,t-3}$ $(\mathbf{x}_{zs,t-j})_{j=0,1,2}$	$y^2_{zs,t-3}$ $(\mathbf{x}_{zs,t-j})_{j=0,1,2}$
$y^1_{zs,t-1}$	$-.047$ (-7.2)	$-.041$ (-1.7)	$-.042$ (-10.1)
$lcom_{zst}$	.848 (168.2)	.818 (32.1)	.831 (37.1)
ld_{zt}	.099 (2.9)	.082 (1.5)	.096 (9.3)
lL_{zt}	.246 (20.5)	.191 (1.9)	.243 (18.5)
ls_{zt}	$-.110$ (-3.4)	$-.107$ (-0.8)	$-.108$ (-5.3)
$y^2_{zs,t-1}$	.787 (34.5)	.829 (15.6)	.710 (27.4)
$y^1_{zs,t-2}$	.023 (4.6)	.036 (5.1)	–
$lcom_{zs,t-1}$	$-.661$ (-32.7)	$-.692$ (-16.1)	–
$ld_{z,t-1}$	$-.067$ (-4.7)	$-.086$ (-4.5)	–
$l_{z,t-1}$	$-.189$ (-11.4)	$-.219$ (-6.4)	–
$ls_{z,t-1}$	.061 (2.9)	.092 (2.4)	–
Sargan	.065	.30	.122
$AC(1)$	0.075 $(<10^{-5})$	-0.571 $(<10^{-5})$	-0.561 $(<10^{-5})$
$AC(2)$	0.204 $(<10^{-5})$	0.062 $(<10^{-5})$	0.058 $(<10^{-5})$
$AC(3)$	0.203 $(<10^{-5})$	-0.001 (0.91)	-0.003 (0.71)
Obs	46099	54664	54664

Notes : a. Estimation by 2SLS. In column ”in levels”, dependent variables in levels are regressed on explanatory variables using first differences as instruments; in column ”in differences”, dependent variables are in first differences and variables in levels are used as instruments. Pseudo-differences are build as $\Delta_\rho X_{zst} = X_{zst} - \rho X_{zs,t-1}$ where ρ is the coefficient of $y^1_{zs,t-1}$. We use the bilinear method explained in the text and we report results in column ”in pseudo-differences”.

b.”Sargan” reports p-values associated to the Sargan statistic. AC(k) is the estimated autocorrelation coefficient of order k. p-values associated to the test that these coefficients are equal to zero are reported below the estimates and within brackets.

c. The estimation of standard errors are not corrected for biases due to the bilinear nature of the estimation method nor for biases due to serial and spatial dependence.

Table 13 : Dynamics of the number of plants, y^2_{zst}

σ_u^2	σ_η^2	σ_ε^2	ρ_1	T	W
0.090 (33.4)	0.173 (36.0)	0.027	−0.123 (−11.3)	0.90 (0.34)	74.78 (4.10^{-5})

Notes : a. σ_u^2 is the variance of the area and sector effect, σ_η^2 is the variance of the residual effect, ρ_1 its autocorrelation coefficient of order 1, T is the test statistic corresponding to a zero second order autocorrelation. W tests the validity of this representation of the series. We denote σ_ε^2 the variance of $\varepsilon_{zst} = y_{zst} - \widetilde{\mathbf{x}}_{zst} + u_{zs}$. It is deduced from $\hat{\sigma}_\eta^2, \hat{\rho}_1$ and $\hat{\rho}$ using the expression:

$$\sigma_\varepsilon^2 = V\left(\frac{1-\rho}{1-\rho L}\eta_{zst}\right) = \frac{1-\rho}{1+\rho}(1+2\rho\rho_1)\sigma_\eta^2.$$

b. Between brackets, Student statistics for coefficients and p-values for test statistics.

Table 14 : Analysis of variance of the residuals

	$\frac{Vy^{2*}_{zst}}{Vy_{zst}}$	$\frac{V(\mathbf{x}'_{zst}\hat{b})}{Vy^*_{zst}}$	$\frac{V(u_{zs})}{Vy^*_{zst}}$	$Corr(\mathbf{x}'_{zst}\hat{b}, u_{zs})$
y^2_{zst}	.744	.965	0.004	0.263

Notes : The long-term target is denoted $y^{1*}_{zst} = \widetilde{\mathbf{x}}'_{zst}\hat{b} + u_{zs}$ where coefficient $\hat{b}$ is taken from column 3 of table 13.

Table 15 : Factor contributions to the variability of the number of plants

Dependent variable	$y^1_{zs,t}$		
Estimation method	Pseudo-differences		
Instruments	$\begin{pmatrix} y^1_{zs,t-3} \\ (\widetilde{\mathbf{x}}_{zs,t-j})_{j=0,1,2} \end{pmatrix}$		
	Manufacturing	Trade	Services
$y^1_{zs,t-1}$	.786	.754	.748
	(16.2)	(8.5)	(9.3)
y^2_{zst}	.195	.316	.457
	(12.6)	(10.2)	(11.8)
$lcom_{zst}$	-.593	-.539	-.613
	(-21.1)	(-11.5)	(-13.0)
c_{zst}	-.107	-.067	-.001
	(-9.7)	(5.0)	(-0.1)
ld_{zt}	.151	.125	.097
	(7.9)	.(5.0)	(3.2)
lL_{zt}	.333	.257	.121
	(12.9)	(8.0)	(3.9)
ls_{zt}	-.231	-.210	-.250
	(6.4)	(-4.6)	(-4.1)
Sargan test (p-value)	0.064	0.824	0.057
$AC(1)$.	-0.567	-0.559	-0.598
	($<10^{-5}$)	($<10^{-5}$)	($<10^{-5}$)
$AC(2)$	0.083	0.051	0.091
	($<10^{-5}$)	($<10^{-5}$)	($<10^{-5}$)
$AC(3)$	-0.067	0.0291	-0.012
	(0.37)	(0.03)	(0.35)
Observations	39932	10270	11462

Table 16 : The dynamics of average employment, y^1_{zst}, by sectors

Dependent variable	$y^2_{zs,t}$		
Estimation method	Pseudo-differences		
Instruments	$y^2_{zs,t-3}$ (d) $(\mathbf{x}_{zs,t-j})_{j=0,1,2}$		
	Manufacturing	Trade	Services
$y^2_{zs,t-1}$	.727	.561	.505
	(16.1)	(9.4)	(6.6)
$y^1_{zs,t-1}$	-.036	-.051	-.032
	(-5.3)	(-3.3)	(2.1)
$lcom_{zst}$	.952	.678	.330
	(5.8)	(4.4)	(1.9)
ld_{zt}	.066	.183	.183
	(2.8)	(3.4)	(3.1)
lL_{zt}	.180	.289	.445
	(3.7)	(4.0)	(5.2)
ls_{zt}	-.076	-.067	-.191
	(-3.1)	(-1.3)	(-2.5)
Sargan test (p-value)	.90	.56	.26
$AC(1)$.	-0.557	-0.532	-0.523
	($<10^{-5}$)	($<10^{-5}$)	($<10^{-5}$)
$AC(2)$	0.047	0.032	0.037
	($<10^{-5}$)	(0.02)	(0.004)
$AC(3)$	0.005	0.029	-0.013
	(0.58)	(0.06)	(0.36)
Observations	27749	8706	9644

Notes : a. In that case, instruments do not comprise $lcomzs_{-1}$ and $lcomzs_{-2}$. Their validity is rejected.

Table 17 : The dynamics of the number of plants, y^2_{zst}, by sector