Spatial concentration and plant-level productivity in France

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Abstract

This paper analyzes empirically the effect of spatial agglomeration of activities on plant-level productivity, using French firm and plant-level data from 1996 to 2004. We exploit short-run variations of variables by making use of GMM estimation. This allows us to control for endogeneity biases that the estimation of agglomeration economies typically encounters. This means that our paper focuses on a subset of agglomeration economies, the short-run ones. Our results show that French plants benefit from localization economies, but we find very little –if any– evidence of urbanization economies. We also show that those localization benefits are relatively well internalized by firms in their location choice: we find very little difference between the geography that would maximize productivity gains in the short-run and the geography actually observed.

Keywords: Clusters, Localization economies, Spatial concentration, Productivity
JEL: C23, R10, R11, R12, R15

1. Introduction

Aside from its academic interest, the analysis of agglomeration economies has potentially important policy implications. Since the 1980's, agglomeration economies have been used to justify cluster policies by national and local governments in Germany, Brazil, Japan, Southern Korea, Spanish Basque country or more recently in France. Some of those policies are very costly. For example, 1.5 billions euros have been devoted to the "Competitiveness clusters" policy by the French government from 2005 to 2008, and again for the 2009-2011 period. Two separate questions deserve attention. First, how large are the gains from agglomeration? In particular, how much does the productivity of a firm increase when other firms from the same sector or from another sector decide to locate nearby? Second, how much do firms internalize these gains when deciding where to locate? The answer to the first question should help understand how much economic gains can be expected from clusters. The answer to the second question should help understand whether there is a strong case for public intervention in favor of industrial clusters.[1]

Rosenthal and Strange (2004) survey this literature, and report that the elasticity of productivity with respect to the size of the city or to the size of the industry generally lies between 3% and 8%. This survey and other recent work on the literature by Combes et al. (2010) for instance also emphasize that until recently, estimates of agglomeration externalities suffered from serious endogeneity problems. From a technical point of view, the estimation of geographical externalities is subject to two main sources of endogeneity: unobserved heterogeneity and simultaneity bias.

Ciccone and Hall (1996) are the first to address directly and carefully these endogeneity issues. They study the impact of county employment density on American states' labor productivity. The authors insist that if there are unmeasured and/or unobserved differences in the determinants of productivity across states, and if these determinants are correlated with counties employment density within states, the measure of the returns to density by simple OLS may be spurious. They take the example of climate or transportation infrastructures which will both enhance workers' productivity and the attractiveness of the place. They consequently resort to an instrumental variables approach. Also controlling for the average level of education within the state or the county, the authors find that a doubling of local employment density increases labor productivity by 5% to 6%.

Ciccone and Hall's article represents an important step in the empirical approach of agglomeration externalities. Nevertheless, their work relies on an aggregate measure of labor productivity. In the present paper, the use of firms and plants panel data allows a careful treatment of endogeneity issues and a measurement of agglomeration externalities which is very close to the micro theories. As far as we know, Henderson (2003) was the first paper to use plant-level data for such an analysis and is the closest to the present paper. His data is available at five years intervals from 1972 to 1992. He estimates a plant level production function for two broad sectors,

[1]See Duranton et al. (2010) for more detail about this.

machinery industries and high-tech industries, and measures the elasticity of TFP to the number of other plants of the same industry in the county. Using industry-time and plant-location fixed effects, he finds a positive and significant elasticity of 8% in the high-tech industry only.[2] He does not find evidence of gains arising from agglomeration of firms belonging to different industries . The use of fixed effects accounts for a large part of unobserved heterogeneity. Henderson also addresses the question of simultaneity bias by adding location-time fixed effects.

Our paper goes further than Henderson (2003) in several directions. We use French firms and plants panel data, for all manufacturing sectors, with yearly observations from 1996 to 2004. Our sample is therefore larger and more complete than Henderson's one which allows us to deal with simultaneity bias and instrumentation more directly. We adopt a two-step estimation strategy. We first estimate plant-level production functions for each 2-digit industry. Using those coefficients, we then compute individual productivities and estimate agglomeration economies through a GMM specification, decomposing carefully the agglomeration effects into own industry (localization) / other industries (urbanization) externalities, as well as diversity and competition effects. We also discuss spatial selection of firms. In this paper, we find that the gains from clustering do exist: our benchmark regression shows that a 10% increase of employment in neighboring plants of the same industry increases a plant's productivity by around 0.55%. As stated above, these estimates are based on yearly variations in TFP and are therefore *best interpreted as short-run gains from agglomeration*, which has important implications in particular for the source of the effects we are estimating. Since our paper focuses on agglomeration economies that take place over a short period of time, we believe that we capture externalities on the labor and input markets, rather than technological spillovers or human capital externalities that should take more time to realize.

The second consequence has to do with urbanization economies, which take probably even longer to implement. That we do not find evidence of urbanization economies should probably be interpreted as the fact that they are better captured by cross-sectional analysis than by the short-term analysis we conduct here. Another way to understand our method is that it

[2]In regressions not reported here but available upon request, we also ran the analysis separately for low-tech and medium low-tech industries on the one hand, and high-tech and medium high-tech industries on the other hand. Agglomeration economies are significant for low-tech and medium low-tech industries only. However, instruments do not pass the validity tests for high-tech and medium high-tech industries.

tries to purge productivity from any firm-level component that is constant over time to deal with endogeneity. But doing so, it also purges the analysis from a large part of the long-term agglomeration economies "capitalized" in this fixed firm-level component. Consequently, we consider our paper to complement existing research that relies more heavily on cross-sectional variations and which thus captures longer-term agglomeration gains.

Finally, using a non linear specification, we can estimate the geography that maximizes short-run productivity gains from clustering and compare it to the observed geography. A disturbing feature of the existing empirical literature is that one would be tempted to conclude from the results usually obtained that more agglomeration is always better because it increases the productivity of plants. This does not look very plausible as congestion costs must necessarily appear and dominate at a certain level of agglomeration. If this was not so, one should also conclude that the observed geography (where all plants of the same sector are not located in the same region) is vastly suboptimal. Another important contribution of this paper is that we find the relation between productivity gains and agglomeration to be bell-shaped. Previous papers have failed to exhibit such a non-linear relationship because they were mostly based on long-run analysis; the presence of "sub-optimal" observations in the data, necessary to estimate a bell-shaped curve, is indeed more plausible in the short-run. When using a non-linear specification, we are able to estimate the peak agglomeration that maximizes the productivity gains.[3] We find that a plant that would move (with its time-invariant idiosyncratic characteristics and for a given level of employment and capital) from a location with no other workers to a location with 1150 employees in the same sector (the peak of the observed distribution in France) would gain 53.8% in TFP. However, going to an "over-crowded" area (with more than 9000 employees) would eliminate these TFP gains. Hence, geography matters a lot for French plants and they are aware of it: French plants seem to take into account the TFP gains in their location choice. Indeed, when we compare the geography that maximizes productivity gains and the observed geography, we find very little difference between the two. From this point of view, our paper suggests that the short term gains of cluster policies which aim is to increase the size of clusters, should be very modest.

The remainder of the paper is as follows. Section 2 details our empirical

[3] Au and Henderson (2006) analyze this question for Chinese cities and also find a bell-shaped curve.

strategy, section 3 then proceeds to a description of the data used, while section 4 presents basic results and section 5 goes further in the comprehension of short-run agglomeration economies and assesses in particular the existence of non-linearities.

2. Estimating agglomeration externalities: empirical strategy

2.1. The model

Agglomeration economies are generally assumed to improve total factor productivity (TFP) of plants through localization economies (externalities on inputs markets, on labor markets or knowledge externalities, following the classification proposed by Marshall (1890)) and urbanization economies (cross fertilizations of different industries on a given territory, as emphasized by Jane Jacobs). When plant-level data is available, this suggests a natural empirical strategy, based on the estimation of a Cobb-Douglas production function:[4]

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} \tag{1}$$

where Y_{it} is value-added of plant i at time t, A_{it} is TFP, K_{it} the capital stock and L_{it} the labor-force (in terms of employees) of plant i at time t. We then assume that TFP of plant i depends on a plant-level component, U_{it}, but also on its immediate environment in terms of localization and urbanization economies:

$$A_{it} = \left(\mathrm{LOC}_{it}^{sz}\right)^{\delta} \left(\mathrm{URB}_{it}^{sz}\right)^{\gamma} U_{it}, \tag{2}$$

where LOC_{it}^{sz} is a measure of localization economies and URB_{it}^{sz} is a measure of urbanization economies for plant i, which belongs to sector s and area z, at time t. Log-linearizing expressions (1) and (2), one obtains:

$$y_{it} = \alpha k_{it} + \beta l_{it} + a_{it}, \tag{3}$$

[4] Combes et al. (2008a) (among many others) estimate agglomeration economies using wages as a dependent variable. An advantage of using wages for the evaluation of agglomeration economies is that wages are measured more precisely than TFP. The measurement of TFP involves a variety of estimation procedures, which all have their own issues or implementation problems. On the other hand, we do not know precisely how agglomeration gains are distributed among production factors. If the gains are not distributed in proportion to the share of each factor in value-added, using wages could bias the estimation of agglomeration effects on productivity. Therefore, we stick to the more direct method using TFP as a dependent variable here (see chapter 11 of Combes et al. (2008b) for the theoretical relationship between the two methods).

and

$$a_{it} = \delta \text{loc}_{it}^{sz} + \gamma \text{urb}_{it}^{sz} + u_{it}, \tag{4}$$

where lower-case letters denotes the log of upper-case variables in equations (1) and (2).

Our strategy consists first in estimating equation (3) at the 2-digit industry level, used to calculate a_{it}. We then estimate equation (4). The model can be estimated by simple Ordinary Least Squares (OLS) regressions if all the independent variables are observable and at least weakly exogenous, but this hypothesis is rarely valid. Consequently, several estimation issues arise that we now detail.

2.2. Estimation issues

Two main issues arise when estimating production functions and agglomeration economies: unobserved heterogeneity and simultaneity. Several estimation procedures of production functions have been developed since the mid-1990's in order to cope with these issues. We follow Levinsohn and Petrin (2003)'s approach. We obtain standard estimates for inputs elasticities, ranging approximately from 0.6 to 0.85 for labor and from 0.07 to 0.35 for capital. Most of the results presented in this paper are robust when using an OLS estimate for TFP. In the following, we detail successively unobserved heterogeneity and simultaneity issues for the estimation of agglomeration economies and we propose methods to solve them.

2.2.1. Unobserved heterogeneity

Some characteristics, unobserved by the econometrician, can be related to both plant-level TFP and some of the explanatory variables. In this case, u_{it} is correlated with the independent variables; consequently, the OLS estimates of the coefficients are potentially biased, since the endogenous variables will partly capture the effect of unobserved characteristics. This issue is better known as the "unobserved heterogeneity" problem. In our specification, loc_{it}^{sz} and urb_{it}^{sz} are both likely to be correlated with u_{it}: Local climate, transportation infrastructures, natural resources or public services to plants can in many ways increase the TFP of a plant. In the same time, a region richly endowed with those environmental elements will be more attractive for firms. There is a positive correlation between unobserved (or unmeasured) plant's environmental variables and localization and/or urbanization indices which potentially biases the estimation of δ and γ.

The first estimations of agglomeration economies were often based on aggregate and cross-sectional data (as Shefer (1973) or Sveikauskas (1975) for example) that could not take into account the potential biases just mentioned. The use of plant-level panel data enables us to address directly these questions.

If we consider plants that do not change industry or region across time, the plant-level environmental unobserved characteristics can be appropriately dealt with using plants' fixed effects, which will take into account all plants' specific characteristics that are invariant across time, whether or not those characteristics are observable. This amounts to assuming that $u_{it} = \phi_i + \epsilon_{it}$:

$$a_{it} = \delta \text{loc}_{it}^{sz} + \gamma \text{urb}_{it}^{sz} + \phi_i + \epsilon_{it}, \tag{5}$$

where the remaining error term ϵ_{it} is now assumed to have the required properties, and in particular not to be correlated with explanatory variables.

Combes et al. (2007) and Combes et al. (2008a) have shown the spatial sorting of workers to be important. That spatial sorting must be reflected in firms' TFP but we do not have information about the skills mix within firms. If skills composition of firms' workforce does not change over the period, firm-level fixed effect will also take into account the heterogeneous quality of labor among firms.

Using a panel of firms over several years, one can use standard fixed effects techniques, which involve the introduction of a set of firm dummies, or equivalently mean-differencing expression (5). Alternatively, one can "eliminate" ϕ_i using a time differencing approach. The estimated equation is in this case:

$$\Delta a_{it} = \delta \Delta \text{loc}_{it}^{sz} + \gamma \Delta \text{urb}_{it}^{sz} + \Delta \epsilon_{it}. \tag{6}$$

However, unobserved heterogeneity is not the only source of endogeneity affecting agglomeration effects estimation.

2.2.2. Simultaneity bias

Estimating agglomeration economies raises simultaneity issues: as a consequence of the negative (or positive) economic shock in the region or in the industry, other firms may close (open) or lay off (hire) employees. ϵ_{it}, loc_{it}^{sz} and urb_{it}^{sz} are possibly correlated and the estimations of δ and γ may be spurious.

To address the simultaneity issue, we adopt a GMM approach. The method follows Bond (2002): we start by first-differencing each variable, as in (6) to address the unobserved heterogeneity issue. We then instrument first-differenced independent variables by their level at time $t-2$, following a GMM procedure. The economic rationale to use lagged levels as instruments is convergence: for each variable, we expect first differences to be negatively correlated to the past level of variables. The underlying econometric assumption is that the idiosyncratic shock at time $t-2$ is orthogonal to $\Delta\epsilon_{it}$, which makes the instruments exogenous.

At this stage, several remarks are in order about the type of agglomeration economies that one can capture with a GMM estimation.

2.3. What can we learn about agglomeration economies from GMM?

Glaeser and Mare (2001), followed by Combes et al. (2008a) among others estimate the impact of agglomeration on wages exploiting workers who move as a source of variation; such a strategy is hard to replicate for plants since those are less mobile.[5] We focus our analysis on plants that do not change area nor sector over the time-period under study and we exploit short-run variations of agglomeration variables by resorting to fixed effects or first-differences estimations. This is very different from exploiting cross-sectional variations like in Combes et al. (2007) or Barbesol and Briant (2008). Indeed, estimation strategies based on cross-sectional variations capture the impact of agglomeration economies accumulated during all the years that precede the year of observation of data. Such analyses consequently address the issue of the impact of spatial agglomeration in the long run. On the contrary, our estimation strategy, based on yearly variations in the data, will capture short-run effects of spatial agglomeration. Our focus is thus different from previous papers and some of our results, such as the absence of urbanization economies and the non-linearity of localization economies, may be specific to this short-run approach. Consequently, they should not be seen as conflicting with previous results obtained in the literature but as complementary. This focus on the short-run raises some important conceptual and theoretical issues about agglomeration economies:

1. *The type of agglomeration economies*: The literature has distinguished intra-industry (localization) from inter-industry (urbanization) agglomeration economies. It seems reasonable to expect urbanization economies to take place over a longer time period, and therefore be captured by the fixed firm-level component that we difference out with our methodology. Failure to find important short-run urbanization economies does not mean that they do not exist in the longer run.

[5] In fact, it is even hard from a statistical point of view to systematically detect movements of producing units inside France. The identification number of each producing unit is supposed to be location-dependent and should therefore change when the unit is re-located.

2. *The channels of agglomeration economies*: we think that our strategy may hardly capture technological/knowledge spillovers, since a long time is probably needed for new ideas to circulate and be implemented in neighboring firms.[6] Nevertheless, knowledge spillovers are only one of the sources of agglomeration economies, and according to Rosenthal and Strange (2001) and Ellison et al. (2010), they would not be the main one. Agglomeration economies on the labor and inputs' markets are more direct externalities and their impact could thus be more rapidly detected. The opening of new plants or the growth of existing plants in a given sector-area could make it profitable for public authorities to propose specific trainings that could improve workers' efficiency. It could also become profitable for some transport companies to serve the firms in the area which would decrease the production costs there. We believe that we capture that kind of externalities by using short-term variations.
3. *Local infrastructures and the bell-shaped curve*: previous studies found a monotonic effect of agglomeration economies. This is to some extent puzzling since theory in economic geography and urban economics suggests that besides positive agglomeration externalities, congestion effects exist and could, all else equal, offset agglomeration economies above a certain threshold. In this respect, it might be argued that short-run variations are the relevant focus point to detect non-linear agglomeration economies, since rational profit-maximizing firms should all be located in optimal places in the long-run. Moreover, it is possible that gains from agglomeration are bell-shaped in the short-run but less so in the longer run. Indeed, in the medium-run or in the long-run, public authorities should provide the necessary local public services and infrastructure to avoid congestion effects. The estimation of agglomeration effects in the long-run could thus consist in the estimation of an envelop curve corresponding to the increasing segments of successive bell-shaped curves. This would explain why papers based on cross-sectional variations usually find a linear effect of agglomeration, unable to capture short-run non linearities.

Finally, from an empirical point of view, we show in section 4.1 that even though plant-level TFP is largely explained by time invariant elements, the within dimension is not negligible and is highly correlated with département-industry-year fixed effects. Consequently, the investigation of short-run ag-

[6]The same is probably true for human capital externalities.

glomeration economies is worth scientific scrutiny. We do not provide in this paper a complete theoretical framework to deal with the temporal scope of agglomeration economies and the provision of local infrastructures, but it could be a fruitful direction for future theoretical research.

3. Data and variables

We present in this section the data we use, the way we build our sample and some issues about the construction of our variables.

3.1. The French annual business surveys: data and selection issues

We use French annual business surveys[7] data, provided by the French Ministry of Industry. We have information at the firm and at the plant level. The data set covers all the firms with more than 20 employees, or some smaller firms with sales higher than 5 millions euros, and all the plants of those firms over the 1996-2004 period.

At the firm level, we have all balance-sheet data (production, value-added, employment, capital, exports, aggregate wages etc.) and information about the firm's location, industry classification and structure (number of plants, etc.). At the plant level, data are less exhaustive; they mainly contain plant location, plant industry classification, number of employees and information about the firm the plant belongs to. Capital and value-added data are available at the firm level only, which is a problem for multi-plant firms. However, estimating agglomeration economies for multi-plant firms is also a problem since the definition of the relevant geographic environment for a firm that would have a plant in Paris and another one in Marseille is not straightforward. To cope with these issues, we decide to run our analysis at the plant-level, allocating firm-level value-added and capital among plants according to their respective share in firm's total employment. We are aware that this strategy is not without raising concerns. This is why we show in section 5.3 that the main result of the paper, the one on the bell-shaped curve, holds for different samples that are not subject to this capital and value-added allocation rule.

Annual business surveys cover firms larger than 20 employees. There is consequently a selection of firms in our sample according to their size. Theoretical work (Melitz and Ottaviano, 2008; Baldwin and Okubo, 2006) has shown that there might be spatial selection of firms, the most productive

[7] Called in French "Enquêtes annuelles d'entreprises".

ones being predominantly located in denser areas. Yet, we know that bigger firms are more productive. The incompleteness of our sample could consequently be a problem. In this respect, note first that we run the analysis at the plant-level which allows us to consider entities smaller than 20 employees (i.e., plants smaller than 20 employees belonging to firms bigger than 20 employees), which does not solve entirely the problem of representativeness of our sample, but hopefully reduces it.[8] Moreover, if the unobserved efficiency parameter is fixed over time, it is adequately taken into account by a plant-level fixed effect or by first-differences. Note that since we keep in the sample plants that do not change industry nor area over the period, this strategy also controls for the quality of local infrastructure and public services. Nevertheless, it is true that we base our estimation on a large time-span (9 years): the quality of local transport infrastructure and public services might change over the period. If these changes are correlated with changes in agglomeration variables, estimation will be spurious in spite of plant-level fixed effects. The resort to first-differences has here a great advantage: it allows us to control for all characteristics that do not change at the plant level over two consecutive years, and not only over the entire period. In that sense, first differences are less restrictive in terms of fixed characteristics that are taken into account. There still remains a problem for the years in which changes occur. This is why we instrument first-differenced variables by their level in $(t-2)$. Given reported tests, we are confident that our estimation strategy deals adequately with this spatial selection issue.

3.2. The variables

Firm value added, employees and capital (measured at the beginning of the year) are directly available in the annual business surveys. The creation of agglomeration variables is more elaborate. First of all, the geographical and the sectoral level of aggregation could have an impact on our measure of agglomeration economies[9]. This is why we decided to focus on two geographical entities, the départements, which are administrative entities (there are 100 départements in France, of which 4 are overseas départements) and the employment areas, which are economic entities defined on the basis of workers' commuting (there are 348 employment areas in metropolitan France).

[8]We focus on plants bigger than 10 employees, since the estimation of production functions is made difficult by the small sample of very small firms. Plants between 10 and 20 employees represent 10% of the sample.

[9]For more details about the impact of spatial zoning on economic geography estimations, see Briant et al. (2010)

From a sectoral point of view, we consider the French sectoral classification (Naf) at both the three and two-digit levels. Consequently, we create our agglomeration variables at four levels: département/Naf 3-digit, employment area/Naf 3-digit, département/Naf 2-digit and employment area/Naf 2-digit. The definition of our variables follows:

- *localization economies:* to deal with intra-industry externalities, we compute, for each plant, the number of other employees working in the same industry and in the same area. Concretely, we use the annual business surveys at the plant level and calculate the number of workers by year, industry and area. For plant i, in industry s, area z and time t, we then define our localization economies variable as:

$$\text{loc}_{it}^{sz} = \ln(\text{employees}_t^{sz} - \text{employees}_{it}^{sz} + 1).$$

- *urbanization economies:* we use two variables to capture urbanization economies. The first one is the number of workers in other industries on the territory z where plant i is located.[10] Using the same notation, we have:

$$\text{urb}_t^{sz} = \ln(\text{employees}_t^{z} - \text{employees}_t^{sz} + 1).$$

  We also add an industrial diversity index

$$\text{div}_t^{sz} = \ln\left(\frac{1}{H_t^{sz}}\right),$$

  faced by plants of industry s, territory z and time t, with H_t^{sz} defined as follows:

$$H_t^{sz} = \sum_{s' \neq s} \left(\frac{\text{employees}_t^{s'z}}{\text{employees}_t^{z} - \text{employees}_t^{sz}}\right)^2.$$

We introduce a last variable to control for local strength of competitive pressure. The use of such a variable aims to test Michael Porter's idea about competition and agglomeration: competition whips up innovation so that more intense competition within clusters improves firms' performance

[10] From the point of view of the plant, the variables l_{it}, loc_{it}^{sz} and urb_t^{sz} operate an exhaustive tripartition of local employment in manufacturing.

(Porter, 1998). We therefore use an Herfindahl index of employment concentration inside industry s and area z:

$$\text{Herf}_t^{sz} = \sum_{j \in S_t^z} \left(\frac{\text{employees}_{jt}^{sz}}{\text{employees}_t^{sz}} \right)^2$$

where S_t^z is the set of firms belonging to industry s on territory z at time t[11]. The variable

$$\text{comp}_t^{sz} = \ln \left(\frac{1}{\text{Herf}_t^{sz}} \right)$$

measures the degree of competition a plant of sector s faces on territory z at time t. This gives us the relation we want to bring to data:

$$a_{it} = \delta \text{loc}_{it}^{sz} + \gamma \text{urb}_{it}^{sz} + \mu \text{div}_t^{sz} + \lambda \text{comp}_t^{sz} + \phi_i + \epsilon_{it}. \tag{7}$$

3.3. Construction of the sample

We create 4 samples, crossing the two territorial and the two sectoral levels mentioned in the previous section, and proceed to several "cleaning" procedures. From a geographical point of view, we drop all plants located in Corsica and in overseas départements. Consequently, our sample covers the 94 and the 341 continental French départements and employment areas respectively. Industry-wise, we keep in the sample plants that belong to manufacturing sectors only. Plants in the food-processing sector have been dropped, since the information related to those plants come from a different survey, not entirely compatible with the rest of manufacturing. The sample we use in our estimations spans over nineteen 2-digit and eighty-eight 3-digit industrial sectors.[12]

For each sample, we drop all plants that changed geographical unit or industrial sector during the period.[13] Indeed, we do not know if such information reflects true relocation or errors in reporting. Our effects are consequently not identified on "movers" but, for a given plant, on the growth of agglomeration variables across time. We also make simple error checks;

[11] We assume that plants from the same firm are not direct competitors. We construct Herf_t^{sz} from plant-level data, so that $\text{employees}_{jt}^{sz}$ is really the number of employees working in plants of firm j on territory z at time t.

[12] In the French 2-digit classification, manufacturing sectors correspond to sector 17 (textile) to sector 36 (miscellaneous), sector 23 (refining) excluded.

[13] At the Départements/Naf 3-digit level, they represent around 5% of the observations

among other things, we drop all observations for which value-added, employment or capital are missing, negative or null. We deflate value-added data by an industry-level price index and capital data by a national investment price index.

Finally we clean up our sample from large outliers, dropping the 1% extreme values for the following variables: capital intensity, yearly mean capital intensity growth rate, yearly capital growth rate, yearly employment growth rate.

3.4. Summary statistics

In this section, we present summary statistics for the Département/Naf 3-digit sample, on which we will focus most of our empirical analysis.

Table 1 shows how our sample exhibits temporal attrition. This is due to the fact that during the recent period, manufacturing industry has been losing, in France as in other industrial countries, many firms and employees.

Table 1: Temporal composition of the sample Département/Naf 3-digit

Year	Observations	Percent	Cum. Percent
1996	25469	11.77	11.77
1997	24458	11.31	23.08
1998	24287	11.23	34.31
1999	24093	11.14	45.45
2000	23993	11.09	56.54
2001	23973	11.08	67.62
2002	23709	10.96	78.58
2003	23504	10.86	89.44
2004	22854	10.56	100.00
Total	216340	100.00	

Table 2 shows the usual descriptive statistics of our variables. First note that most variables exhibit strong variability, as shown by the large values of standard-deviations respective to their mean.

The minimum value for the localization economies variable (in terms of employees and of plants) is zero: some plants are the sole representative of their industry in their département. For those firms, there are consequently no localization economies.[14]

[14] Since $\text{loc}_{it}^{sz} = \ln(\text{employees}_t^{sz} - \text{employees}_{it}^{sz} + 1)$, $\text{loc}_{it}^{sz} = 0$ when $\text{employees}_t^{sz} - \text{employees}_{it}^{sz} = 0$.

Table 2: Summary statistics Département/Naf 3-digit

Variable	Mean	Std. Dev.	Min	Max
Value added	5104.56	18357.77	1.43	1440578
Firm's employment	93.41	256.86	11	19385
Firm's capital	6554.73	39285.63	10.85	4283886
# employees, other plants, same industry-area	1762.04	3205.69	0	24475
# other plants, same industry-area	33.48	76.01	0	874
# other employees, other industries-same area	44337.15	30867.67	357	135657
# other plants, other industries-same area	665.30	509.11	12	2873

Note: Number of observations: 216340 in all rows. Value-added and capital are expressed in thousands of real euros

Note that the minimum value of plants' number of employees is 11; we focus on plants bigger than 10 employees because the estimation of production functions for smaller plants is difficult due to more measurement errors and less observations for such plants.

Table 12 in the Appendix displays between and within variations of log variables for the sample used in the GMM estimation. Even if between variations account for a large part of heterogeneity, within standard-deviation is not negligible (above 10% for all variables except the urbanization economies one). Hence, our identification strategy based on short run variations appears valid (except maybe, as stated earlier, for urbanization economies).

4. How large are agglomeration economies ?

As analyzed in subsection 2.2, estimates of agglomeration economies suffer from two main biases, unobserved heterogeneity and simultaneity. We address those two problems through a fixed effects approach first (for unobserved heterogeneity), and then through a GMM approach. Before presenting empirical results, we perform a variance decomposition analysis in order to assess the extent to which agglomeration economies can explain short-run variations of plant-level productivity.

4.1. Variance decomposition analysis

Variance decomposition is a useful exercise since it allows us to assess how much of plant-level TFP observed variations we can hope to explain by exploiting short-run variations. We first regress plant-level TFP, obtained through the estimation of Levinsohn and Petrin (2003) production functions at the 2-digit level, on year dummies and plant fixed effects. Not surprisingly, as shown in table 3, plant fixed effects capture most of plant-level TFP variations. We then regress in table 4 the plant fixed effects on the average number of employees in the other plants from the same industry-département (localization economies) and in the plants from the other industries of the département (urbanization economies). Table 4 shows that both localization and urbanization economies explain significantly the time-invariant element of plant-level TFP, with coefficients that are close to those obtained by Combes et al. (2008a) or Barbesol and Briant (2008), even though data and methodologies differ. However, table 3 shows that the time-varying dimension contained in the residuals, even though much less important, is not null and is positively correlated with plant-level TFP. In addition, if we regress plant-level TFP net of plant fixed effects (the plant residual) on département-industry-year dummies, we can see in the bottom part of table 3 that the standard-deviation of département-industry-year fixed effects is equal to half of the standard-deviation of plant-level time-varying TFP. These département-industry-year fixed are moreover highly correlated with time-varying component of plant-level TFP.

To sum up, plant-level TFP is largely explained by time invariant elements, among which average localization and urbanization economies over the period. However, the variance decomposition shows that the within dimension is not negligible and that it is highly correlated with département-industry-year fixed effects. In the investigation of the effect of agglomeration economies on plant-level TFP, the time dimension is important.

Table 3: Summary statistics Variance decomposition of TFP (Levinsohn-Petrin)

	Std. Dev	Corr. with plant TFP
Plant TFP	0.600	1.000
Plant fixed effect	0.559	0.935
Plant residual (TFP - fixed effect)	0.210	0.350
	Std. Dev	Corr. with plant residual (TFP - fixed effect)
Plant residual (TFP - fixed effect)	0.210	1.000
Département-Industry-Year fixed effects	0.101	0.482

4.2. Measuring agglomeration economies taking into account unobserved heterogeneity

We now turn to actual regressions. As stated in section 2, all explanatory variables in our regressions are potentially correlated with omitted time-invariant variables. To capture these, we add plant fixed effects to the simple

Table 4: Local determinants of plant fixed effects, Département/Naf 3-digit

Dep Var:	Plant fixed effect
Average ln (# employees, other plants, same industry-area+1)	0.016^a
	(0.004)
Average ln(# employees, other industries, same area)	0.038^a
	(0.005)
Industry fixed effects	yes
N	46855
R^2	0.526

Note: Standard errors in parentheses. ^{a}, ^{b} and ^{c} respectively denoting significance at the 1%, 5% and 10% levels. Standard errors are corrected to take into account autocorrelation at the industry-département level.

OLS regression. To capture shocks which affect all firms of the sample in a given year, we also use year fixed effects. Results are presented in table 5.

Table 5: Fixed effects approach, Département/Naf 3-digit

Dep Var:	ln Levinsohn-Petrin TFP			
Model :	(1)	(2)	(3)	(4)
ln (# employees, other plants, same industry-area+1)	0.024^a	0.008^a	0.037^a	0.007^a
	(0.002)	(0.002)	(0.002)	(0.002)
ln(# employees, other industries, same area)	0.054^a	0.017	0.066^a	0.018
	(0.004)	(0.019)	(0.004)	(0.020)
competition			-0.038^a	0.008^c
			(0.004)	(0.005)
sectoral diversity			-0.072^a	0.003
			(0.007)	(0.011)
Time fixed effect	yes	yes	yes	yes
Plant fixed effects	no	yes	no	yes
N	216340	216340	216340	216340
# plants	46855	46855	46855	46855
R^2	0.028	0.018	0.032	0.018

Note: Standard errors in parentheses. ^{a}, ^{b} and ^{c} respectively denoting significance at the 1%, 5% and 10% levels. Standard errors are corrected to take into account individual autocorrelation.

The first two regressions concentrate on localization and urbanization economies. According to the simple OLS regression of column (1), increasing by 10% the number of other workers of the same industry-area, keeping the size of the other sectors in the area constant, increases the TFP of a plant by 0.24%. Considering the other variable, increasing the size of the other sectors in the area by 10%, increases the TFP of a plant, all else equal, by 0.54%. Those results would indicate a domination of urbanization economies at the firm level. The estimation of agglomeration economies must however deal with the spatial selection of plants. Column (2) controls for this issue by integrating plant fixed effects. Doing so, we exploit the variance over time of different variables. Since we focus on plants that do not change industry or area over the period, these fixed effects also control for differences in terms of local endowments or industrial specificities that are fixed over time. Localization economies are now the only ones to be significant, with a small, but highly significant coefficient. Controlling for local competition and sectoral diversity does not affect the results. Competition appears to have a positive impact on plant-level TFP in the short-run, but the coefficient is only weakly significant. However, controlling for plant fixed effects does not solve potential simultaneity issues. We now refine our first results with an instrumental variables approach.

4.3. Measuring agglomeration economies taking into account both unobserved heterogeneity and simultaneity

In order to correct the simultaneity bias, we resort, as explained above, to a GMM approach. Such a method reduces drastically the size of the sample, since an observation is included if and only if, for the same plant, the two preceding observations are also available. Consequently, the first two years of the sample, 1996 and 1997, are dropped and only plants that survive long enough are considered. This may be an issue if agglomeration affects firm survival. Three cases must be distinguished:

- *Plants in agglomerated areas have higher survival rates due to better unobserved characteristics*: this should not be a problem, since plant-level characteristics that are fixed over time are purged by first-differences.

- *Agglomeration has a positive effect on survival rate through a productivity channel*: in that case, not controlling for exit could lead to underestimating agglomeration economies. However, our estimation strategy still captures the evolution of productivity for years preceding the exit, and thus measures part of the effect for disappearing firms.

- *Agglomeration has a negative effect on survival rate through a competition effect*: not taking this into account could lead to an overestimation

> of agglomeration economies. However, Combes et al. (2009) show that this is not the case for French firms: differences in terms of productivity between areas are mainly explained by local externalities and not by selection. Consistently with this result, in unreported regressions, we estimate a logit and we show that conditioning on firm-level size, productivity, wages, industry fixed effects and area fixed effects, local variables (size of the industry, size of other industries, competition and diversity) have a less important impact on plant-level survival than internal variables, either in terms of statistical significance or in terms of marginal effect.

We thus conclude that survival bias is unlikely to be a major issue for our estimation.

Regressions (1) and (3) of table 6 are OLS on first-differenced variables. In regressions (2) and (4), we instrument first-differenced variables by levels in $t-2$ and use the GMM option. Standard errors are clustered at the area-industry-year level. Indeed, Moulton (1990) showed that when not doing so, regressing individual variables on aggregate variables could induce a downward bias in the standard-errors. First-stage regressions are presented in an online Appendix. For all variables, the first difference is negatively and significantly affected by the level in $t-2$. Since Cragg-Donald and Stock and Yogo tests are not strictly valid in the presence of heteroskedasticity, we refer to the often used "rule of thumb" to test for the presence of weak instruments: For each first-stage regression, the F-statistic is at least equal to 10 so that there is no evidence of weak instruments problem. We also present the Kleinbergen-Paap weak-identification test, that is valid in the presence of heteroskedasticity. In all cases (except at the Département-Naf 2-digit level, see below), the test is passed.

Our results show that there are positive and significant localization economies in the short-run: for a plant, all other things being equal, a 10% increase from one year to the other in the number of workers of the industry in the rest of the employment area increases the value added produced by that firm by around 0.5-0.6%. The number of employees in the other sectors of the area, competition and sectoral diversity have no significant impact. Moreover, our specification is robust to the Sargan-Hansen test of joint validity of instruments. The economic rationale which underlies our empirical strategy is therefore not invalidated. Again, these effects are based on yearly variations and should thus be interpreted as short-run effects.

We note that the estimated coefficient on localization variable is larger compared to the fixed effects estimation and very close to the estimates in the existing literature (see Rosenthal and Strange (2004)). While we expected a positive correlation between shocks and the agglomeration variables loc_{it}^{sz} and urb_{it}^{sz}, this suggests that the correlation was rather negative. A first explanation is the presence of measurement errors in the agglomeration variables, which would cause a downward bias in the fixed effects estimates. A second explanation is linked to an argument made by Cingano and Schivardi (2004). They suggest that there is a possible negative impact of an increase of productivity on employment. Indeed, if demand is sufficiently inelastic, a positive productivity shock may negatively affect employment. The macroeconomic literature (see Gali (1999) for example) corroborates the idea that in the short-run, a positive technology shock reduces employment. Our instrumentation strategy may enable us to correct for this problem which was biasing downwards our non-instrumented regressions.

To sum up, for French firms and in the short-run, no evidence of Jacobs' urbanization economies is detected: ceteris paribus, sectoral diversity and the scale of activities in other sectors have no significant effect on firms' TFP. When exploiting annual variations of the data, the only source of agglomeration economies are localization externalities, with a positive and significant coefficient indicating that a 10% increase of employment in neighboring firms of the same industry increases a firm productivity by around 0.5-0.6%.

The results in the literature regarding the strength of localization vs urbanization economies are mixed. Henderson (2003) or Rosenthal and Strange (2003) show the domination of localization economies on US data, while Combes et al. (2007) or Barbesol and Briant (2008) show the reverse on French data. Our results can therefore be seen as complementing the conclusions reached by the two papers on French firm-level data. Recall that we measure the impact of agglomeration economies on short-run variations of plant-level TFP, while these two papers focus on cross-sectional, and thus long-run variations. One interpretation,which can help reconcile conflicting results in the literature, is that the nature of agglomeration economies varies with time.

4.4. Marginal effects and explanatory power of localization economies

In this subsection, we analyze the impact of the choice of classification on the intensity of localization economies; we then study the explanatory power of localization economies.

Table 6: Instrumental variables approach, Département/Naf 3-digit

Dep Var:	Δ ln Levinsohn-Petrin TFP			
Model :	(1)	(2)	(3)	(4)
Δ ln(# employees, other plants, same industry-area+1)	-0.002	0.059^b	-0.002	0.055^c
	(0.002)	(0.028)	(0.002)	(0.029)
Δ ln(# employees, other industries, same area)	-0.005	-0.060	0.003	-0.005
	(0.021)	(0.149)	(0.022)	(0.206)
Δ ln (sectoral diversity)			0.013	-0.056
			(0.012)	(0.130)
Δ ln (competition)			0.002	0.057
			(0.005)	(0.047)
N	126794	126794	126794	126794
# plants	29514	29514	29514	29514
R^2	0.003	0.0006	0.003	0.0004
Kleinbergen-Paap test		60.581		15.158
Hansen overidentification test p-value		0.402		0.130

Note: Standard errors in parentheses. ^{a}, ^{b} and ^{c} respectively denoting significance at the 1%, 5% and 10% levels. (1) and (3) simple OLS, (2) and (4) are GMM, with standard-errors clustered at the area-industry-year level. For columns (2) and (4), R^2 are computed as the squared correlation between the predicted and actual values of the dependent variable.

4.4.1. *Different intensities for localization economies or Modifiable Areal Unit Problem?*

We reproduce the same analysis for the other three levels of sectoral and geographical aggregation. The results of GMM regressions are presented in tables 15 and 16 in the appendix. Localization economies are significant in all cases except at the Employment area/Naf 3-digit industry when competition and diversity are accounted for. The coefficient at the Département/Naf 2-digit level is strikingly high. The Kleinbergen-Paap and Sargan-Hansen statistics show that GMM perform poorly at this level of aggregation making those results unreliable. Since diversity and competition are never significant, we always ignore these variables in the following.

As we can see in table 7, the impact of a doubling of the localization economies variable on productivity varies according to the aggregation level.[15] They are in particular much smaller at the Employment area/Naf 3-digit level. Two explanations are possible: localization economies really vary according to the spatial and the industrial level of aggregation, or the different intensities are only due to statistical noise (this problem is also known as Modifiable Areal Unit Problem (MAUP), see Briant et al. (2010)). At this stage, we cannot distinguish between those two effects.

Table 7: Results across aggregation levels

Dép./Naf 3-digit	EA/Naf 3-digit	Dép./Naf 2-digit	EA/Naf 2-digit
4.17%	1.96%	n.a.	3.89%

Note: Each column gives the percentage increase in productivity following a doubling of the localization economies for each sample.

4.4.2. *Explanatory power of localization economies*

The explanatory power of a variable depends both on the value of the coefficient attached to it and on its variability. If a variable has a very low variance, its explanatory power will be small, even if it has a large coefficient. The explanatory power of an independent variable is strong if, all other things being equal, a standard-deviation of that variable implies a large variation of the dependent variable.[16] We consequently calculated the

[15] If $\ln y = \alpha \ln x$, y increases in percentage by $(2^\alpha - 1) \times 100$ when x is doubled.

[16] If $\ln y = \alpha \ln x$, we define the explanatory power of x as $[\exp(\alpha \ln(1 + \frac{\sigma_x}{\overline{x}})) - 1] \times 100 = [(1 + \frac{\sigma_x}{\overline{x}})^\alpha - 1] \times 100$, where σ_x and $\overline{x}$ are the standard deviation and the mean of x

explanatory power of localization economies. The results are presented in table 8. The explanatory power of localization economies variables appears small but non negligible.

Table 8: Explanatory power of localization economies

	Naf 3-digit		Naf 2-digit	
	Dep.	Emp. Area	Dep.	Emp. Area
# employees, other plants, same industry-area	6.29%	3.70%	n.a.	5.99%

Note: The table reads as follows: for a plant, all other things being equal, a standard-deviation with respect to the mean of the number of employees in the other plants from the same industry-area generates, at the Département/Naf 3-digit level, an increase of plant-level productivity by 6.29%.

5. Robustness checks and further issues

5.1. Who generates externalities: plants or employees?

Theory offers several possible channels for localization economies. A notable alternative is whether externalities transit through firms or workers. For a firm, is it the same to have in the neighborhood one firm of the industry with a hundred employees or ten firms, each of them employing ten workers ? The question is important for policy makers interested in clusters; according to the answer, an extensive or an intensive development strategy will be preferable.

Henderson (2003) finds that plants generate externalities, but not workers. If we consider each plant as a source of knowledge, this result is the sign, according to Henderson, that information spillovers are more important than labor market externalities.

Our results are quite different. For a plant i from sector s in area z at time t, we decompose the number of employees in its own industry-area into two components: the number of plants in sector s and area z at time t and the average size of those plants. Keeping the *number of plants* constant, an increase of the *average size* of plants generates an increase of the *total*

respectively.

number of employees in the sector. We present in table 9 the results of GMM estimations.

When the number of own industry plants and their average size are both taken into account, the latter is the only one to be significant. Interestingly enough, coefficients on the average size variable are very close to those on the localization economies variable in our first specification.

To sum up, the case of French firms indicates that in the short-run, there are no specific externalities we can attribute to plants *per se* but that there are positive and significant externalities linked to the number of employees in surrounding plants. The number of employees in the other plants is a better indicator of the size of the industry a plant faces on its territory than the number of plants. This points to an interpretation under which localization economies are, for a plant, due to the "thickness" of the industry around it. Our results are interesting for policy-makers; they suggest that boosting externalities within clusters involves the promotion of internal growth of existing plants or the attraction of big plants on the territory rather than multiplying the number of small plants. Moreover, our results support those of Rosenthal and Strange (2001), who find, on American data, that labor pooling and input-output linkages are -in this order- the two main determinants of industries co-agglomeration.

5.2. Do small plants benefit more from localization economies than the others?

The impact of localization economies may be heterogeneous across plants. Specifically, small plants may be more dependent on their local environment, and thus more sensitive to agglomeration economies. To test this idea, we split the samples at each level of aggregation according to the size of plants with respect to the average in the sample. As emphasized in table 10, we find that localization economies are stronger for plants that are smaller than the average plant in the sample. This confirms the intuition that smaller plants benefit more from localization economies than the others.[17]

5.3. Is there enough clustering?

Our results show that plant productivity increases with clustering. Does this imply that more clustering is always better and that public intervention to increase the size of clusters is justified? In theoretical models, clustering

[17] In related work, Henderson (2003) and Rosenthal and Strange (2003, 2010) also find that small firms benefit more and generate more agglomeration economies.

Table 9: Instrumental variables approach/Employees, plants and agglomeration economies

Dep Var:	Δ ln Levinsohn-Petrin TFP		
Model :	Dép./Naf 3-digit	EA/Naf 3-digit	EA/Naf 2-digit
Δ ln (Average size of other plants, same industry-area+1)	0.060^b	0.027	0.049^b
	(0.024)	(0.020)	(0.022)
Δ ln(# other plants, same industry-area+1)	-0.035	0.030	-0.074
	(0.117)	(0.083)	(0.138)
Δ ln(# employees, other industries, same area)	0.029	-0.233	-0.265
	(0.174)	(0.162)	(0.234)
N	126794	126786	129521
# plants	29514	29512	30078
R^2	0.0006	0.0005	0.0006
Kleinbergen-Paap test	8.333	19.831	4.462
Hansen overidentification test p-value	0.893	0.681	0.184

Note: Standard errors in parentheses. ^{a}, ^{b} and ^{c} respectively denoting significance at the 1%, 5% and 10% levels. All regressions are GMM, with Moulton standard errors. R^2 are computed as the squared correlation between the predicted and actual values of the dependent variable.

Table 10: Size heterogeneity

	Dep Var: Δ ln Levinsohn-Petrin TFP					
Model :	Dép./Naf 3-digit ≤ Avg size	Dép./Naf 3-digit > Avg size	EA/Naf 3-digit ≤ Avg size	EA/Naf 3-digit > Avg size	EA/Naf 2-digit ≤ Avg size	EA/Naf 2-digit > Avg size
Δ ln(# employees, other plants, same industry-area+1)	0.050^c	0.042	0.033^b	0.003	0.050^c	0.035
	(0.029)	(0.057)	(0.016)	(0.029)	(0.029)	(0.055)
Δ ln(# employees, other industries, same area)	0.036	-0.419	-0.126	-0.769^b	-0.119	-0.859^b
	(0.163)	(0.299)	(0.183)	(0.328)	(0.224)	(0.361)
N	94879	31915	94879	31907	96989	32532
# plants	22835	6679	22835	6677	23287	6791
R^2	0.0007	0.001	0.0004	0.0004	0.0007	0.0003
Kleinbergen-Paap test	47.120	20.514	57.332	46.104	19.772	21.503
Hansen overidentification test p-value	0.493	0.025	0.489	0.151	0.669	0.147

Note: Standard errors in parentheses. ^{a}, ^{b} and ^{c} respectively denoting significance at the 1%, 5% and 10% levels. All regressions are GMM, with Moulton standard errors. R^2 are computed as the squared correlation between the predicted and actual values of the dependent variable.

has the characteristic of an externality: plants benefit from the fact that other plants in the same sector decide to choose to locate nearby. These plants do not internalize the productivity benefit they bring to other plants through this location choice. This suggests that the market equilibrium may be characterized by suboptimal clustering that would translate into suboptimal productivity. This is the basic argument (although not always put in these terms) that many proponents of cluster policies (such as Michael Porter) put forward to defend public policies that help foster larger clusters.

However, besides cluster benefits, other externalities, such as congestion effects may also exist. These congestion effects could affect the utility of agents (through increased traffic, pollution etc...) which we cannot measure, but could also impact negatively local growth[18] and the productivity of firms. Combes and Duranton (2006) also show that firms, when they cluster in the same local labour market, face a trade-off between the benefits of labour pooling (i.e., access to workers whose knowledge helps reduce costs) and the costs of labour poaching (i.e., loss of some key workers due to competition between plants that would have a negative impact on the productivity). The existence of such a trade-off means that the productivity-cluster relationship may not be linear. This suggests that the effect we measured is the average *net effect* of localization economies and congestion effects.

To test the existence of such non-linear localization economies, we introduce in the former regression quadratic and cubic terms of the localization economies variable.[19] We retain a GMM estimation on first differenced variables and compute standard errors using Moulton's correction.

Results are presented in table 11. We run the regressions on the sample used so far, but also on single-plant firms only, since for those firms, the allocation rule of value-added and capital among plants of a given firm does not play any role. We further show the results when regressions are run at the firm level, and not at the plant level, firm-level localization economies variable being calculated as the log of a weighted average or as the weighted average of the log of plant-level localization economies variable. In all cases, table 11 shows statistical significance for all three terms of localization economies (the Sargan-Hansen test being slightly low at the plant-level).

[18] Hymel (2009) shows for example that traffic congestion reduces employment growth in US metropolitan areas.

[19] The theory does not tell us much on the exact form of the relation. We show the specification with quadratic and cubic terms because it produces the best fit.

Table 11: Bell-shaped curve Département-Naf 3-digit

Dep Var:	Δ ln Levinsohn-Petrin TFP			
	(1)	(2)	(3)	(4)
Model :	Plants	Single plant firms	Firms	Firms
Δ ln(# employees, other firms, same industry-area+1)	-0.256^a	-0.298^a	-0.227^a	-0.223^a
	(0.088)	(0.114)	(0.080)	(0.078)
Δ ln(# employees, other firms, same industry-area+1)^2	0.086^b	0.113^b	0.076^a	0.074^b
	(0.034)	(0.044)	(0.029)	(0.029)
Δ ln(# employees, other firms, same industry-area+1)^3	-0.006^c	-0.009^b	-0.005^b	-0.005^c
	(0.003)	(0.004)	(0.003)	(0.002)
Δ ln(# employees, other industries, same area)	-0.046	0.144	-0.051	-0.044
	(0.184)	(0.238)	(0.145)	(0.149)
N	126794	63675	95077	95077
# plants	29514	15221	20479	20479
R^2	0.0005	0.0002	0.0005	0.0004
Kleinbergen-Paap test	7.829	6.832	12.329	14.443
Hansen overidentification test p-value	0.047	0.692	0.311	0.366

Note: Standard errors in parentheses. ^{a}, ^{b} and ^{c} respectively denoting significance at the 1%, 5% and 10% levels. All regressions are GMM, with Moulton standard errors. Column (1) presents regressions with TFP calculated at the plant-level, column (2) with TFP computed at the firm-level for single plant firms only. Column (3) presents results at the firm-level, agglomeration at the firm-level being calculated as the log of the weighted average of plant-level environment, using plant-shares in firm-level employment as weights. Column (4) presents results at the firm-level, agglomeration at the firm-level being calculated as the the weighted average of the log of plant-level environment, using plant-shares in firm-level employment as weights. R^2 are computed as the squared correlation between the predicted and actual values of the dependent variable.

We present the results for single-plant firms and for plants in figures 1 and 2. The dark curve is the estimate of the TFP surplus gain for each level of the localization variable (computed with the estimated coefficients). The net effect of localization economies has the same form in both cases: an inverted U-shape pattern. The net TFP surplus due to localization economies is however negative for small values of the localization variable.

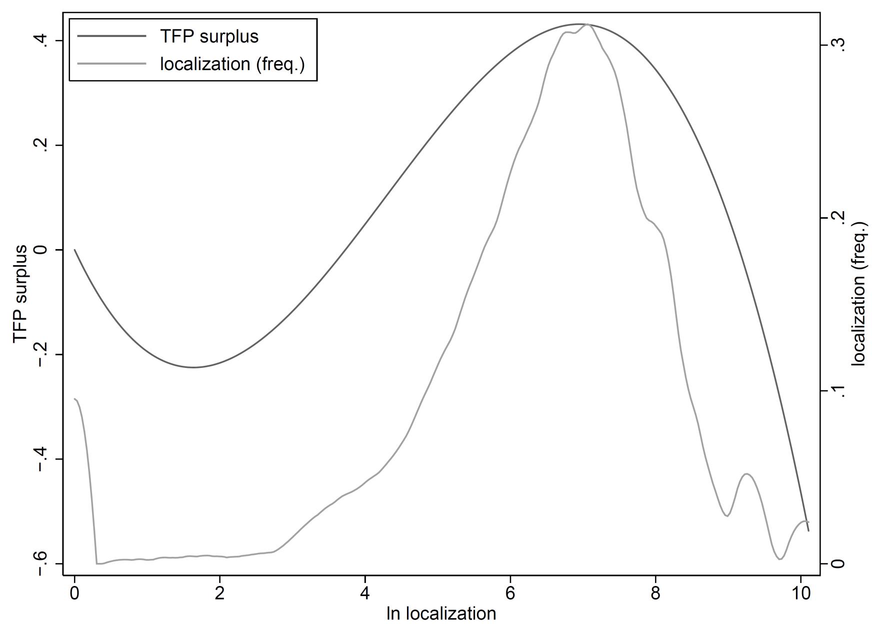

Figure 1: Localization economies for single-plant firms- Département/Naf 3-digit

We now proceed to a quantitative analysis on single-plant firms, since it is for those firms that our estimation is less noisy. At the département/Naf 3-digit level, the threshold for which the gains from clusters become positive is around 40-45 employees. Remember this does not include the workers of the plant/firm itself. The second threshold for which the negative effect of clusters dominates the positive effect is around 9500 employees. This confirms the existence of non linear effects of localization on productivity and suggests that clustering benefits and congestion effects vary in relative strength depending on the size of the cluster. One possible way to rationalize what we find is the following. At low levels of clustering, and therefore with a small number of plants, the labor poaching argument of Combes and

Duranton (2006) where strategic interactions of firms are key, may be at play and may dominate the other effects. When the cluster is large enough, localization effects dominate. However, when pushed too far, clustering generates congestion effects that dominate localization effects.

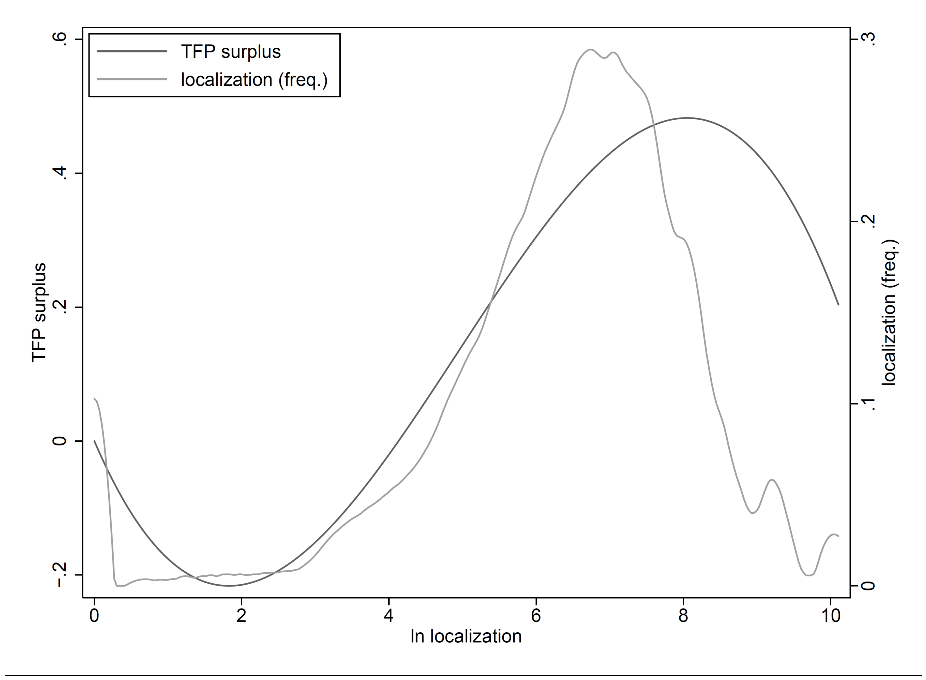

Figure 2: Localization economies for plants- Département/Naf 3-digit

The peak, at which the marginal congestion effects of increasing the number of workers in the same département and the same sector start to dominate the localization effects, is estimated at more or less 1000 employees.

On the same graph we plot with the grey curve the actual distribution of the localization economies variable for French plants present in the sample. The peak of the distribution is obtained for plants located in départements that have around 1150 employees in the same sector (again excluding the workers of the plant itself). The productivity gain for a plant that would go from the observed peak to the estimated peak is very small, only 0.001%. This does not mean however that all plants are located optimally. If it were the case, we would not be able to estimate the bell-shaped curve. For example, a plant corresponding to the first decile in terms of localization economies variable (76 employees) that would move to the estimated peak would experience a productivity gain of around 37.9%. This gain would be around 10.5% for plants at the first quartile, 0.005% for the median plant, 2.2% for a plant at the third quartile and 12.8% for a plant at the last decile of the distribution of the localization economies variable.

Consequently, the comparison of the two curves suggests that French single-plant firms do internalize to a large extent the short-run productivity gains of clustering when making location choices. Another way to see this is that very few plants locate in areas for which the TFP surplus that comes from localization is negative (6.3% of the observations in our sample). Note that these results are average results and that they are obtained assuming that all sectors are equally sensitive to localization economies. A more disaggregated analysis is here impossible because of the insufficient number of observations for some sectors. The results are less striking for the whole set of firms but still comparable (see figure 2). This result is qualitatively robust for different levels of sectoral and geographic aggregation and for OLS TFP index.

Our estimation enables us to perform the following thought experiment. Think of a single-plant firm (with its time invariant idiosyncratic characteristics and for a given level of employment and capital) that has to choose its location among many départements. Strictly speaking, this firm should be small enough so that its location choice does not matter for other firms. Relocating from a département with no other workers in its own sector to a département with 1150 employees in its own sector (the peak of the observed distribution), generates an estimated large TFP gain of 53.8%. The same gain would be obtained when a firm relocates from an over-crowded area (with 9500 employees in the same sector) to the observed peak of the distribution. This suggests that clusters are a natural implication of firms maximizing profits[20], but that larger clusters are not always better, at least in the short-run, keeping local infrastructures and all the other local determinants of productivity constant. Hence, one should not conclude from our study that geography does not matter for firms. It matters a lot and firms are aware of it.

6. Conclusion

We have shown that, once taking into account several possible sources of bias, agglomeration externalities in France take the form of localization

[20] This is consistent with the results of Crozet et al. (2004) who find that a very important determinant of location choice in France for multinational firms is the localization variable.

economies in the short-run. This does not mean that urbanization economies are not important but our results suggest that they may be more a long-run phenomenon. A question remains unanswered: who benefits from these short-run productivity gains linked to localization economies? Workers, capital owners or land owners? According to Combes et al. (2008a), the elasticity of wages to employment's area specialization, on French data, is around 2.1%. Even though the methodology, data and classifications are not strictly comparable, the returns of localization economies would be inferior for wages than those estimated for TFP in our paper, which range between 5 and 10%. This suggests that workers do not capture fully the gains from localization economies. We also tried to analyze the effect of localization externalities on profits but did not find any conclusive result. This suggests that a large part of the surplus is captured by the immobile factor, namely land[21], which would be consistent with theory. At this point however, this hypothesis, while plausible, would need further investigation.

Our results have several interesting policy implications in a context in which cluster policies are popular among governments and local authorities. First, the starting point of those who favor cluster policies is right: clusters bring productivity gains in the short run. However, our results suggest that those gains are well internalized in the location decisions of firms. Consequently, the gains we can expect from more policy-induced clustering are, at least in the short-run, relatively small. The comparison between an estimated geographical distribution of plants that would maximize productivity and the one that is actually observed suggests no large gap, at least in the French case. It points neither to a situation where geography is too concentrated/specialized nor to a geography that needs more clustering. This result is "only" about productivity and is not about welfare which agglomeration could affect through other channels than through productivity. However, our results suggest that even though the starting point of cluster policy advocates is right, the next step of the argument –advocating for costly public intervention in favor of clusters– is not supported by the French evidence. In a related paper, Martin et al. (2009), using the same dataset as in this paper, we find no evidence that a French cluster policy, the "Systèmes Productifs Locaux", had any effect on firms' productivity.

[21] This is indeed what Arzaghi and Henderson (2008) find in their study of clusters in advertising in New York city. In different contexts, Gautier et al. (2009) and Pope (2008) show clearly that land and housing prices are very responsive to shocks affecting the desirability of a given place.

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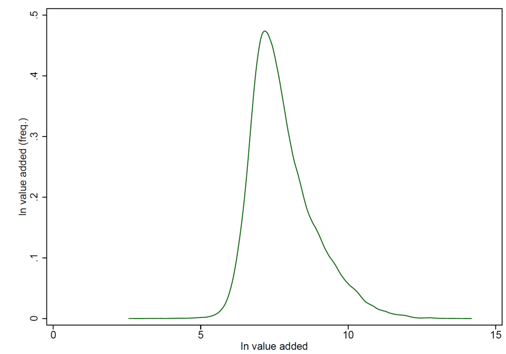
APPENDIX

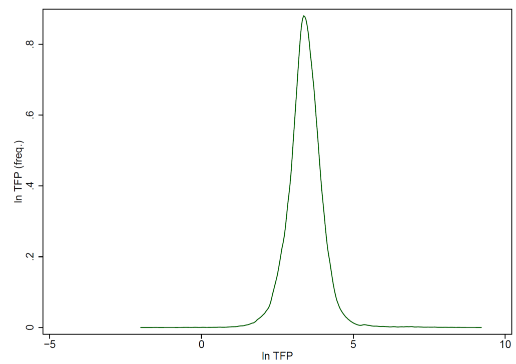
Table 12: Between/Within heterogeneity

		Mean	Std Deviation
ln (value added)	Overall	7.79	1.09
	Between		1.09
	Within		0.23
ln (employees)	Overall	4.01	0.93
	Between		0.93
	Within		0.14
ln (capital)	Overall	7.51	1.51
	Between		1.54
	Within		0.22
ln (Levinsohn-Petrin TFP)	Overall	3.41	0.59
	Between		1.54
	Within		0.22
ln (# employees, other plants, same industry-area+1)	Overall	6.32	1.90
	Between		0.60
	Within		0.19
ln (# employees, other industries, same area+1)	Overall	10.43	0.76
	Between		0.75
	Within		0.04

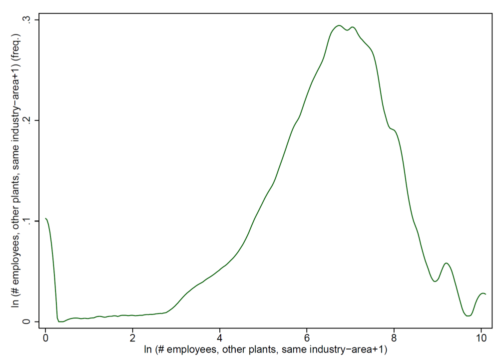
Note: Number of observations: 126794 in all rows. All variables are in logarithm and the sample is the one used for GMM regressions at the Département/Naf 3-digit level.



(a)



(b)



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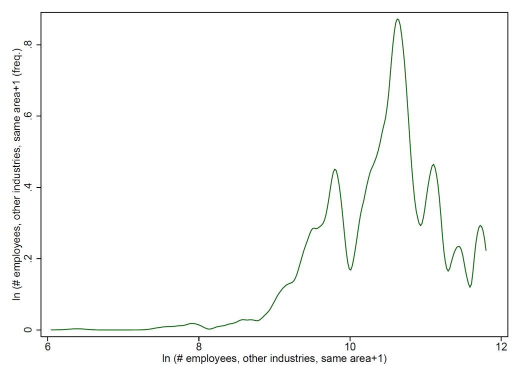

(d)

Figure 3: Distribution of variables-Département/Naf 3-digit level-GMM sample

Table 13: First stage regressions-online appendix

Dep Var:	Δ ln (# employees, other firms, same industry-area+1)	Δ ln(# employees, other industries, same area)
ln (# employees, other firms, same industry-area+1)$_{t-2}$	-0.029^a	0.000
	(0.002)	(0.000)
ln(# employees, other industries, same area)$_{t-2}$	-0.005^b	-0.008^a
	(0.002)	(0.001)
ln(# other firms, same industry-area+1)$_{t-2}$	0.032^a	0.001
	(0.003)	(0.001)
N	126794	126794
# plants	29514	29514
R^2	0.01	0.223
F-Stat	69.72	123.53

.5 Note: Standard errors in parentheses ^{a}, ^{b} and ^{c} respectively denoting significance at the 1%, 5% and 10% levels. Standard errors are corrected to take into account correlation of errors at the area-industry-year level.

Table 14: First stage regressions-online appendix

Dep Var:	Δ ln (# employees, other firms, same industry-area+1)	Δ ln(# employees, other industries, same area)	Δ ln sectoral diversity	Δ ln competition
ln (# employees, other firms, same industry-area+1)$_{t-2}$	-0.032^a	0.000	0.003^a	-0.004^a
	(0.002)	(0.000)	(0.000)	(0.001)
ln(# employees, other industries, same area)$_{t-2}$	-0.008^a	-0.007^a	-0.002^c	-0.003
	(0.003)	(0.001)	(0.001)	(0.002)
ln(# other firms, same industry-area+1)$_{t-2}$	0.052^a	0.000	-0.013^a	0.031^a
	(0.005)	(0.001)	(0.002)	(0.004)
ln sectoral diversity$_{t-2}$	0.006	-0.002^a	-0.017^a	0.006^c
	(0.004)	(0.001)	(0.002)	(0.003)
ln competition$_{t-2}$	-0.020^a	0.000	0.007^a	-0.044^a
	(0.004)	(0.001)	(0.001)	(0.004)
N	126794	126794	126794	126794
# plants	29514	29514	29514	29514
R^2	0.01	0.224	0.052	0.018
F-stat	42.88	85.40	70.30	37.26

Note: Standard errors in parentheses ^{a}, ^{b} and ^{c} respectively denoting significance at the 1%, 5% and 10% levels. Standard errors are corrected to take into account correlation of errors at the area-industry-year level.

Table 15: Instrumental variables approach

Dep Var:	Δ ln Levinsohn-Petrin TFP			
	Dép./Naf 3-digit	EA/Naf 3-digit	Dép./Naf 2-digit	EA/Naf 2-digit
Δ ln(# employees, other firms, same industry-area+1)	0.059^{b}	0.028^{c}	0.283^{b}	0.055^{b}
	(0.028)	(0.015)	(0.126)	(0.027)
Δ ln(# employees, other industries, same area)	-0.060	-0.245	-0.303	-0.294
	(0.149)	(0.168)	(0.255)	(0.209)
N	126794	126786	129529	129521
# plants	29514	29512	30080	30078
R^2	0.0006	0.0005	0.0003	0.0005
Kleinbergen-Paap test	60.581	71.007	7.996	28.680
Hansen overidentification test p-value	0.402	0.679	0.083	0.192

Note: Standard errors in parentheses. ^{a}, ^{b} and ^{c} respectively denoting significance at the 1%, 5% and 10% levels. All regressions are GMM, with Moulton standard errors. R^2 are computed as the squared correlation between the predicted and actual values of the dependent variable.

Table 16: Instrumental variables approach

Dep Var:	Δ ln Levinsohn-Petrin TFP			
	Dép./Naf 3-digit	EA/Naf 3-digit	Dép./Naf 2-digit	EA/Naf 2-digit
Δ ln(# employees, other firms, same industry-area+1)	0.055^{c}	0.020	0.219^{c}	0.055^{b}
	(0.029)	(0.017)	(0.116)	(0.027)
Δ ln(# employees, other industries, same area)	-0.005	-0.136	0.031	-0.202
	(0.206)	(0.252)	(0.339)	(0.247)
Δ ln (sectoral diversity)	-0.056	-0.077	-0.495^{c}	-0.079
	(0.130)	(0.130)	(0.299)	(0.145)
Δ ln (competition)	0.057	0.064	0.004	0.004
	(0.047)	(0.052)	(0.061)	(0.056)
N	126794	126786	129529	129521
R^2	0.0004	0.0004	0.0003	0.0006
Kleinbergen-Paap test	15.158	9.313	2.401	5.828
# plants	29514	29512	30080	30078
Hansen overidentification test p-value	0.130	0.223	0.306	0.127

Note: Standard errors in parentheses. ^{a}, ^{b} and ^{c} respectively denoting significance at the 1%, 5% and 10% levels. All regressions are GMM, with Moulton standard errors. R^2 are computed as the squared correlation between the predicted and actual values of the dependent variable.