Miren Lafourcade and Giordano Mion

Concentration, agglomeration and the size of plants

Article (Accepted version)
(Refereed)

Original citation:
Lafourcade, Miren and Mion, Giordano (2007) *Concentration, agglomeration and the size of plants. Regional science and urban economics*, 37 (1). pp. 46-68. ISSN 0166-0462
DOI: 10.1016/j.regsciurbeco.2006.04.004

Concentration, Agglomeration and the Size of Plants*

Miren Lafourcade[†] Giordano Mion[‡]

April 27, 2005

Abstract

This paper investigates whether the geographic distribution of manufacturing activities in Italy is likely to differ according to the scale of plants. We find strong evidence of a significant positive relationship between size and concentration, as in Kim (1995) or Holmes and Stevens (2002, 2004). However, we go one step further in examining how sensitive is this feature to the consideration of spatial dependence between geographic units. We show that, while large plants exhibit a clear tendency to cluster within narrow geographical units such as local labor systems, small establishments, by contrast, rather co-locate within wider areas in which a distance-based pattern emerges. These findings are consistent with plants of heterogeneous size engaging in different transport intensive activities.

JEL classification: C21, L11, R12, R30, R34.
Keywords: Concentration, Spatial Auto-Correlation, Size of Plants.

*The authors would like to thank Giuseppe De Arcangelis, Jérome Carreau, Bart Jourquin, Renato Santelia and Stefano Usai for their critical help in gathering data, and Antonio Ciccone, Thierry Mayer, Henry Overman, Frédéric Robert-Nicoud, Fabiano Schivardi, Eric Strobl, Stefano Usai and three anonymous referees for very helpful comments. Mion gratefully acknowledges financial support from the CEPR Research Network on "The Economic Geography of Europe: Measurement, Testing and Policy Simulations", funded by the European Commission under the Research Training Network Programme (Contract No: HPRN-CT-2000-00069). The usual disclaimer applies.

†Université d'Évry (IUT - Département GLT) and PSE (Paris-Jourdan Sciences Économiques), Unité Mixte de Recherche CNRS-EHESS-ENPC-ENS. PSE, 48 boulevard Jourdan, 75014 Paris, France. lafourca@enpc.fr. http://www.enpc.fr/ceras/lafourcade/.

‡Corresponding author. Universita di Bologna. Dipartimento di Scienze Economiche, Universita di Bologna, str. Maggiore 45, 40125 Bologna, Italy. mion@spbo.unibo.it. http://www.dse.unibo.it/mion/.

1 Introduction

Economists, geographers and historians share a considerable interest in analyzing the causes of regional specialization. Among the myriad of determinants which have been explored, particular attention was deserved to regional endowments or raw material intensity, comparative advantages, localized externalities, or, more recently, transport costs and market potential. In this paper, we focus on a particular aspect of this complex set of mechanisms, which remains quite unexplored: the size of plants. Our main contributions are to investigate whether the geographic distribution of manufacturing activities is related to their establishments' scope, and to seek for specific distance-based patterns that could arise from differences in the size of plants.

We address this question by examining Italian census data on manufacturing industries for different years, geographic and industrial scales. By extending the empirical focus on Europe, we thus hope to complement the seminal empirical studies of Kim (1995) and Holmes and Stevens (2002, 2004), which had both focused on North-American countries. Kim (1995) reports a positive correlation between concentration and both the average plant size per worker and the intensity of raw materials, across the U.S. manufacturing industries. Holmes and Stevens (2002) find strong support of the same phenomenon within industries: Plants located in areas where an industry concentrates are larger, on average, than outside such areas, especially for the manufacturing sector. In addition to Kim (1995), Holmes and Stevens (2002) emphasize that this positive relationship is robust to the control of the establishments' own effects on concentration.

In order to go further in examining the relation between plant size and distribution patterns, we extend the analytical framework to account for the spatial dependence of geographic units. Recent papers such as Arbia (2001a), Duranton and Overman (2004) or Marcon and Puech (2003) all point to significant differences in the patterns of concentration obtained from distance-based measures conveying the possible propagation of a spatial phenomenon in a continuous space. Accounting for spatial dependence is therefore important regarding economic policy, as it may alter the picture of economic density we draw from standard indexes of concentration. Since labor productivity is positively related to employment density, as shown by Ciccone and Hall (1996) or Ciccone (2002), examining how densely clustered are the establishments of an industry and how this is likely to depend upon their employment size, remains high on the police makers' agenda.

Although our approach builds on this recent revival of spatial dependence, we keep working with a discrete vision of space as formed by a number of spatial units (which can be more or less aggregated). This allows us to complement a standard concentration index with an indicator of spatial association (the Moran index) in order to account for possible spatial auto-correlation patterns. Spatial auto-correlation is a feature of spatial distribution that has received relatively less attention than concentration and that can be related to transport costs minimization, as supported by the New Economic Geography literature. Therefore, in the paper, we use the term "agglomeration" to refer to spatial auto-correlation patterns or, more intuitively, to distance-based clusters that possibly overlap the boundaries of the geographic units chosen to measure concentration.

We find strong evidence of a non-random positive relationship between size and concentration, as in Kim (1995) or Holmes and Stevens (2002). Going one step further in examining how sensitive is such a feature to the consideration of spatial dependence we find that, on average, small plants exhibit stronger agglomeration patterns. This result suggests that, while large plants would cluster within narrow geographical units such as local labor systems, small firms, by contrast, would rather co-locate within wider areas in which a distance-based pattern emerges. One interpretation of these findings is that the location choices of large Italian plants is less sensitive to domestic distances and translates into narrow scope dense clusters of activities mainly oriented towards either the local or the foreign markets. Conversely, small Italian establishments are possibly engaged in transport intensive activities requiring some proximity to domestic consumers' markets, which, in return, would make them more sensitive to national distances than larger establishments. Some exceptions arise, however, for most of the industries characterizing the so called "Italian Districts", where manufacturing activities appear to be extremely concentrated, but only weakly agglomerated, despite low plant scales.[1] We provide several checks showing that these results are robust to changes in the partition of space and plants, in the industry definition, in the measure of distance, and to the consideration of industry specific characteristics. Furthermore, as regards the time evolution of spatial distribution patterns, we find that concentration (agglomeration) has slightly decreased (increased) over the period 1981-1996, small plants being conducive to more dynamics.

The rest of the paper is organized as follows. Section 2 presents the analytical framework relating plant scale, industry concentration and industry agglomeration. Section 3 describes the data we use to investigate the geographic distribution of manufacturing activities in Italy and its dependence to plant size effects. Furthermore, it discusses briefly how we deal with some well known spatial issues such as the Modifiable Unit Area Problem (MAUP). Section 4 provides the results of a cross-section analysis performed for Italian Local Labor Systems and 3-digit manufacturing industries in 1996. Section 5 checks for the robustness of the results and explores long-run trends. Finally, Section 6 concludes and opens new lines of research.

[1] This comforts the pertinence of a definition of districts based on two 'implicit' criteria: A strong concentration of plants among which a consistent share of small establishments can be found (Sforzi, 1990), and a production mainly oriented towards foreign markets (Bagella, Becchetti and Sacchi, 1998).

2 Analytical Framework

Various indexes can be used to investigate the regional localization patterns of economic activities.[2] A large set of the indexes used by economists, which we refer to as the "concentration" family, splits space into a certain number of geographic units and seek for relative differences in the number of activities within each of these units, abstracting from their relative position in space. The second family of measures, which is generally preferred by geographers, tries to account for the spatial dependence of regions. We will group this second set of indexes under the "agglomeration" label. The patterns of regional specialization derived from these two families rarely concur unfortunately. As both types of indexes present pros and cons, we examine how plant size impacts regional specialization within an analytical framework combining the two families. This section presents our "bi-dimensional" framework.

2.1 Measuring concentration

Among the most popular measures of concentration are the location quotient (also known as the Hoover's coefficient of localization) and the Gini coefficient. However, such indexes are not directly appropriate to test for a possible correlation between plant size and concentration: In the case when, by chance, a location gets a very large plant, a positive correlation would emerge randomly, without testifying of a real link between concentration and plant size yet.

Although it is possible to adapt such indexes in order to control for random causality, as Holmes and Stevens (2002) do for the location quotient for instance, a more theory-grounded framework has been proposed by Ellison and Glaeser (1997) to purge concentration from the own plant size effect. The measure of concentration we use for Italy builds on their model of location choices.[3] Let us recall briefly the basics of the Ellison and Glaeser's (1997) model (henceforth EG).[4]

Let M (S) denote the number of spatial geographic units (sectors), $s_i^s = emp_i^s / \sum_{i=1}^{M} emp_i^s$ the location i share of employment in the manufacturing industry s, and $x_i = \sum_{s=1}^{S} emp_i^s / \sum_{i=1}^{M} \sum_{s=1}^{S} emp_i^s$ its share of total employment. Henceforth, we omit the industry superscript s, for notation convenience.

The EG approach consists in starting from the employment-based index G_{EG}, equal to $G_{EG} = \sum_{i=1}^{M} (s_i - x_i)^2$, and then in neutralizing for differences in the industrial structure by means of an

[2] The reader will find in Holmes and Stevens (2004), Combes and Overman (2004), and Fujita, Henderson and Mori (2004), exhaustive presentations of the indexes used in a large set of empirical studies regarding the North-American, European and Asian countries, respectively.

[3] Many previous empirical studies adopted the Ellison and Glaeser (1997) framework to study the geographic distribution of activities. See for instance Maurel and Sédillot (1999) for France, or Devereux, Griffith and Simpson (2004) for the UK.

[4] Our description of the EG model here builds on the simplified version proposed by Maurel and Sédillot (1999).

Herfindahl index of concentration. The EG index obtained derives from a rigorous probabilistic model of plant location yet. Let N denote the number of plants and $z_1, ..., z_j, ...z_N$, the shares of these plants in the total employment of an industry. The fraction of sectoral employment related to location i is therefore

$$s_i = \sum_{j=1}^{N} z_j \, u_{ji}, \tag{1}$$

where $u_{ji} = 1$ if the business unit j locates in area i, and 0 otherwise. The u_{ji} are non-independent Bernouilli variables such that $P(u_{ji} = 1) = x_i$, which means that a random process of plants' location choices will, on average, lead to a pattern of employment shares matching the aggregate one (x_i), as well assumed to be exogenous as the size of each plant (z_j). More precisely, the authors propose to model the interaction between the location decisions of any pair of plants j and k belonging to the same industry by

$$Corr(u_{ji}, u_{ki}) = \gamma \quad for \; j \neq k, \tag{2}$$

where γ is a parameter lying between -1 and 1 describing the strength of spillovers within the industry. In that case, the probability that business units j and k locate in the same area i is independent upon j and k:

$$p(i, i) = E[u_{ji} \, u_{ki}] = Cov(u_{ji}, u_{ki}) + E[u_{ji}] \, E[u_{ki}] = \gamma x_i (1 - x_i) + x_i^2. \tag{3}$$

The probability P that the two plants co-locate in *any* of the M locations is therefore a linear function of γ:

$$P = \sum_{i=1}^{M} p(i, i) = \gamma \left(1 - \sum_{i=1}^{M} x_i^2 \right) + \sum_{i=1}^{M} x_i^2, \tag{4}$$

By using data on the location of plants to estimate P, one can thus trace back the parameter γ.

One of the most appealing way to interpret this model is, as suggested by Ellison and Glaeser themselves, to think about plants as darts thrown in space. Imagine a two-stage process in which nature first chooses to weld some of the darts into clusters (representing groups of plants that are sufficiently interdependent that they will always locate together), and then each cluster is thrown randomly at the dartboard to choose a location. The importance of spillovers is then captured by the parameter γ, which can be viewed as the "fraction" of plants among which co-location occurs.

Ellison and Glaeser (1997) propose the following un-biased estimator of γ

$$\hat{\gamma}_{EG} = \frac{\frac{G_{EG}}{1 - \sum_{i=1}^{M} x_i^2} - H}{1 - H}, \tag{5}$$

where $H = \sum_{j=1}^{N} z_j^2$ is an Herfindahl index controlling simultaneously for industrial differences in both the number and size of plants.

2.2 Concentration and the size of plants

The EG index allows one to compare geographic concentration across industries because it is immune to biases arising from differences in their establishment structure. However, the EG location model neglects the possible occurrence of a correlation between plant size and concentration, as, within each industry, the probability $p(i, i)$ for two plants to co-locate is independent upon their size. In the same spirit as in Holmes and Stevens (2002), a simple argument can be used to test for a non random relation between concentration and the size of plants, however: In a world where the size of establishments would be independent on concentration patterns, all the variability in the geographic distribution of manufacturing activities should equally reflect differences in the number of plants.

By comparing the EG employment-based measure of concentration to its plant-based counterpart, whose properties have been studied by Maurel and Sédillot (1999), one can therefore exhibit possible discrepancies arising from differences in the scale of plants. As far as both the employment-based and plant-based estimators are equivalent under the null of a random link between concentration and size, but still different under the alternative, one can relate the differences arising under this alternative to the size of plants in each industry. The plant-based estimator proposed by Maurel and Sédillot (1999), henceforth labeled "un-weighted" (UW) because it treats all observations the same, is

$$\hat{\gamma}_{UW} = \frac{\frac{G_{UW}}{1-\sum\limits_{i=1}^{M} x_i^2} - \bar{H}}{1 - \bar{H}}, \tag{6}$$

where $G_{UW} = \sum_{i=1}^{M} \left(\frac{n_i}{N}\right)^2 - \sum_{i=1}^{M} x_i^2$ and $\frac{n_i}{N}$, the share of plants located in i. The Herfindahl $\bar{H} = 1/N$, which accounts for differences in the number of plants, is the counterpart of the one used in the employment-based EG index.

Maurel and Sédillot (1999) proved that this plant-based index of concentration is also an unbiased estimator of the spillover parameter γ. Furthermore, it is easy to show that $\hat{\gamma}_{UW}$ is more efficient than its employment-based counterpart $\hat{\gamma}_{EG}$.[5]

Significant data discrepancies between $\hat{\gamma}_{UW}$ and $\hat{\gamma}_{EG}$ testify of a non random relationship between plant size and location choices. Indeed, if one relaxes the assumption that the tendency for plants to concentrate would not depend upon the establishment scale, then the EG and UW estimates should depart significantly one from the other. The EG index would actually reflect the concentration of

[5]Like in the standard linear regressions framework, both a weighted and an un-weighted estimator are un-biased but, if there is no heteroscedasticity, the latter should have a smaller variance.

large plants, while the UW counterpart would be more illustrative of small plants (whose number is much larger).

We now turn to the issue of spatial auto-correlation and its link with the size of plants.

2.3 Measuring agglomeration

The picture we draw from a partition of space into isolated grids is likely to be altered by the consideration of spatial linkages between grids. Let us illustrate the role of spatial dependence with an example inspired from Arbia (2001b), in which we consider the distribution of 12 plants over the 9 locations embodied in the cells of a 3x3 grid.

Figure 1: Agglomeration or concentration?

3	3	
3	3	

a

	3	
3		3
	3	

b

In Figure 1, the uneven distribution of activities results in two different spatial configurations. One (case b) is *concentration*, which can be referred to as a concept of variability that is not sensitive to the permutation of observations in space. Indicators such as the location quotient, the Gini coefficient, or even the $\widehat{\gamma}_{EG}$ and $\widehat{\gamma}_{UW}$ estimators, actually measure spatial concentration because they give *a quantification of how much a phenomenon presents spatial variability with respect to some average*. However, they treat data without considering their relative position in space (i.e. they do not consider distances between spatial units), so that their value would be the same in both the cases a and b of Figure 1. By contrast, the other configuration (case a) reflects *agglomeration*[6] because it testifies of a certain degree of spatial dependence, which translates into the left corner distance-based cluster among observations. More precisely, there is spatial auto-correlation as long as, for each industry, knowing the location of plants in region i is 'linearly' informative about the location of the other plants of the same industry in neighboring regions.

In order to capture the spatial phenomenon of agglomeration, very accurate indexes have been developed. Among such indicators are the statistics proposed by Cliff and Ord (1981), Getis and Ord (1992), or Moran (1950), the latter being the one we actually use in this paper. Define first a

[6]The exact terminology used by Arbia (2001b) is actually "polarization". However, we prefer "agglomeration" because it is the term that is now widely used in the field of New Economic Geography (NEG) to actually reflect the location process arising from the interaction between transport costs (and so distance) and increasing returns to scale. For a comprehensive review of NEG theoretical frameworks, see Fujita, Krugman and Venables (1999) or Fujita and Thisse (2002).

$M \times M$ spatial weighting matrix W, as the matrix whose generic element w_{il} is the relative weight of location l for location i and $w_{ii} = 0$. w_{il} may either rely on simple contiguity criteria (for instance, a first-order contiguity matrix will give weight one to all contiguous locations and zero otherwise, including the own location), or be inversely related to the distance d_{il} between i and l (under various analytical forms such as $d_{il}^{-\tau}$ or $\exp^{-\tau d_{il}}$). The Moran's formula is then given by

$$I = \frac{M \sum\limits_{i=1}^{M} y_i \sum\limits_{l=1}^{M} w_{il} y_l}{S_0 \sum\limits_{i=1}^{M} y_i^2}, \tag{7}$$

where y_i is a measure of economic activity in location i and $S_0 = \sum_{i=1}^{M} \sum_{l=1}^{M} w_{il}$. As proposed by Anselin (1988), the weighting matrix can be row-standardize so that S_0 equals to M (each row is therefore divided by the sum of the row elements).

The most intuitive interpretation of the Moran's I is found in the regression context. If we actually regress the spatially weighted variable Wy on y (where y is the vector of y_i), then the slope coefficient of the regression is precisely given by I, which is the ratio of $cov(W_i y, y_i)$ over $var(y_i)$, where $W_i = (w_{i1}, ..., w_{il}, ..., w_{iM})$ is the i-related raw of the weighting matrix W. Therefore, the Moran's I is the correlation coefficient between y_i and its neighbors' counterparts that enables to detect departures from spatial randomness and to determine whether neighboring areas are more similar than would be expected under the null hypothesis.

The issues related to the measurement of agglomeration are to some extent similar to those related to concentration. As in the EG model with no spillovers, if plants were distributed according to a random scheme that reproduces, on average, the overall distribution of activities, then largest regions should receive more plants. A simple way to control for this location-size effect is to center the variable y using its mean, so that $y_i = s_i - x_i$ as in the EG model. Under this null, the mean Moran is $E[I] = -1/(M-1)$,[7] while under the alternative, it could be either positive or highly negative, depending on the sign of the existent spatial auto-correlation. We can therefore make a test of the absence of spatial dependence between geographic units by using the variance of I under the null.

2.4 Agglomeration and the size of plants

In order to be consistent with the concentration framework presented in Section 2.2, we investigate the role of plant size by comparing the Moran's I statistics computed for two different (zero mean) variables, based respectively on the employment and the number of plants: $y_i = s_i - x_i$ and $y_i =$

[7] See Cliff and Ord (1981) for further details.

$\left(\frac{n_i}{N}\right) - x_i$. We therefore obtain the two following measures of agglomeration:

$$I_W = \frac{(M/S_0)\sum_{i=1}^{M}(s_i - x_i)\sum_{l=1}^{M} w_{il}(s_l - x_l)}{\sum_{i=1}^{M}(s_i - x_i)^2} \quad \text{and} \quad I_{UW} = \frac{(M/S_0)\sum_{i=1}^{M}\left(\frac{n_i}{N} - x_i\right)\sum_{l=1}^{M} w_{il}\left(\frac{n_l}{N} - x_l\right)}{\sum_{i=1}^{M}\left(\frac{n_i}{N} - x_i\right)^2}, \tag{8}$$

For these two Moran indexes, we face an issue similar to that of the concentration framework. In order to perform comparisons between sectors, we have to consider that extreme agglomeration may occur because, in some industries, only a very small number of plants operate in comparison with the number of locations. For such industries, strong positive auto-correlation may thus testify of emptiness surrounded by emptiness. As the consideration of neighboring empty locations may lead to over-estimate the true number of industrial clusters, we will actually check whether the correlation identified between agglomeration and plant size is not triggered by industries with an extremely low numbers of plants.

A specific issue, to which concentration indexes are immune, and which is thus inherent to the Moran index, arises from its regression coefficient nature. As in all regression contexts, the presence of outliers in the sample may bias the Moran indicator towards an agglomeration tendency that is not representative of the majority of observations. In order to not over-estimate the degree of spatial auto-correlation, Anselin (1995) proposes an identification procedure based on a conditional randomization approach. For each location i, Anselin (1995) suggests first to compute a *local* Moran statistic, I_i, measuring the correlation between a particular y_i and its specific neighbors, and then to make a test of its local instability. Furthermore, as the Moran index corresponds to the sample average of the $I_i's$, he also suggests to use the sample variance of the $I_i's$ to identify the outliers on a two-sigma rule basis. The locations that emerge as extreme values with both tests are actually *spatial outliers* or, borrowing the terminology of Anselin (1995), "hot spots". The reason for this double check is the need to test for local instability when the null is not randomization, but some degree of spatial correlation. Under spatial correlation indeed, the presence of outliers is more likely to occur than under a random scheme. We will thus pay particular attention to identify and analyze these "hot spots", in order to be sure that the agglomeration indexes obtained are representative of the majority of industrial observations and provide a robust measure of the correlation found between agglomeration and plant size.

3 Data and methodological issues

We use data from the Italian Census of economic activities, which gives information on the location and employment of the universe of Italian plants. This data set is very detailed in its geographic coverage of manufacturing industries. The geographic scale of observation can be disaggregated up to the 8192 Italian commons and the industrial scale up to the 3-digit NACE nomenclature (revision 1) for the years 1981 and 1991, and to the 5-digit category counterpart for 1996.

Contrary to most of the previous empirical studies investigating the geographic distribution of activities (as Ellison and Glaeser, 1997, Maurel and Sédillot, 1999, or Holmes and Stevens, 2002 and 2004), there is no problem of withheld data in this sample, the only limitation being that, in some cases, the size of plants had to be recovered from the size-range groups to which data are allocated. Nonetheless, it is important to notice that, given the high level of data disaggregation, in roughly 90% of the cases, the size of plants was directly identified and not estimated. Moreover, information on the size of plants is not necessary to obtain $\hat{\gamma}_{UW}$ and I_{UW}, which are less demanding than $\hat{\gamma}_{EG}$ and I_W.

3.1 Partitioning space and industries

To apply both the concentration and agglomeration indexes, we have first to choose an adequate scale of industry aggregation and an appropriate geographic unit of analysis.

As recalled by Kim (1995), the definition of industry aggregation depends on the subjacent phenomena one is willing to understand through the geographic distribution of activities. Indeed, industrial spillovers and the incentives for plants to co-locate can either operate within a narrowly defined category of industries such as the 3-digit nomenclature of activities, or a more broadly defined category such as the 2-digit nomenclature. As regards the Italian census, the 3-digit category leads to study 103 different sub-activities within the manufacturing industry, whereas the 2-digit counterpart would divide the latter in only 23 sub-industries. In the case of Italy, the 3-digit category makes more salient the industries that gave birth to some well-known districts, such as 'Preparation and spinning of textile fibres' (3-digits NACE number 171), 'Textile weaving' (172), 'Tanning and dressing of leather' (191), 'Watches and Clocks' (335), 'Manufacturing of Musical instruments' (363), or 'Ceramic tiles and flags' (263). Although we will put the emphasis on the results obtained under the finest level of industrial disaggregation to account for the district phenomenon, we will also use the information provided by the sample of 2-digit activities to check for the robustness of the results to a change in the industry partition.

The second issue we have to tackle is the Modifiable Unit Area Problem (henceforth MAUP), which arises from partitioning space into an arbitrary number of geographic units. The problem, which is very well documented in Arbia (1989 and 2001b), concerns both the boundaries and the scale chosen. It can be illustrated as follows:

Figure 2: The MAUP problem

As apparent from Figure 2, one can see that, by enlarging the grid of squares of Figure 1 in an asymmetric way, we may alter the picture of both agglomeration and concentration. Figure 2 leads to the exactly reverse configuration than that observed in Figure 1: Case c, which is the counterpart of case a, now reflects pure concentration, whereas case d, which is the counterpart of case b, embodies agglomeration.

The first precaution we take to minimize the MAUP is to choose a partition of space that relies on real economic features. The partition we adopt is the one of Local Labor Systems (henceforth LLS). The LLS spatial nomenclature, which covers both urban and rural areas, divides the Italian territory into 784 geographic units. The average LLS spreads over 384 km^2, which is equivalent to splitting the U.S. continental territory into more than 25,000 units. Therefore, the LLS grid is not far from being equivalent to the U.S. partition into 41,313 zip-code units. The boundaries of LLS were defined in 1991 by the Italian Statistic Institute on the basis of minimum daily commuting patterns, so as to maximize the correspondence between the people living and working areas. The geographic scale of LLS is therefore much less arbitrary than a more standard partition based on simple administrative schemes.

Although the core of the paper will focus on LLS only (Section 4), we will be cautious in that the distribution patterns obtained for LLS do not hold only for this specific partition scheme. In section 5, we will thus check for the robustness of the results to the adoption of a more aggregated partition of space. We choose the NUTS3 scale of aggregation (Italian "provincie"), which splits the Italian territory in 95 geographic units. Checking for the robustness of the results to a thinner partition of space than LLS - which, as recalled, is already very disaggregated as it is almost equivalent to a partition of the U.S. space into zip-codes - would certainly warrant consideration. However, since disaggregating further the geographic scale would reduce computational practicality and lead to extremely heavy calculations,[8] we investigate the issue of considering wider geographic units only.

[8] A disaggregation into the 8192 municipalities, for instance, requires to treat 103 x 8192 = 843,716 industry-space

3.2 Partitioning the universe of plants

In order to explore the role of plant heterogeneity, we must partition the universe of establishments into at least two groups: Large and small. However, defining a clear frontier between the two is far from being trivial. As in Holmes and Stevens (2002), pragmatism leads us to adopt the simple strategy of cutting the sample of plants according to their number of employees. The choice of an employment threshold is obviously arbitrary, but knowing the features of Italian labor markets is helpful in reducing such arbitrariness. Regarding the employment legislation in Italy, two minimum cut-off values arise naturally.

A first threshold of 20 workers makes sense regarding both the fiscal and legal status of Italian firms. Indeed, Italian firms with less than 20 workers ("piccole imprese") benefit from specific incentives such as tax credits, or lower social contributions and loan interest rates. Furthermore, in order to have an employee board a firm must have at least 20 employees. Finally, this 20 employees cut-off, which has been also chosen by Holmes and Stevens (2002) for the U.S., offers an interesting comparison perspective, on top of being the only threshold that is compatible with the 1981 and 1991 older census data. Table 1 exhibits summary statistics for the two sub-samples obtained when partitioning the universe of Italian plants according to the more or less than 20 workers scheme. As apparent from Table 1, the threshold of 20 matches nearly the median plant, which actually comforts its judiciousness regarding a dichotomic partition scheme.

Table 1: Summary Statistics on the 20-workers partition of Italian plants.

	Sample of small plants	Sample of Large plants
Mean size	3.73	67.84
St. deviation	11.26	222.18
Coefficient of variation	3.02	3.27
Number of manuf. plants	549,747	41,363
% of manuf. plants	93.01	6.99
% of manuf. employment	42.20	57.80

However, a second minimum threshold of 15 workers is more pertinent as regards the Italian dismissing law.[9] Indeed, when a dismissal is judged illegal, a worker has the right to be reintegrated in the firm if the latter is larger than 15 employees, otherwise he is entitled to receive a monetary compensation. This distinction actually turns out to be crucial as regards labor costs because it favors smaller units. Furthermore, the 15 employees threshold is used by the Italian legislation with reference to many other labor and fiscal issues such as working overtime, disabled's hiring, training, or tax benefits.

observations, meaning that the calculation of indexes is not feasible under reasonable delays.

[9] See "Statuto dei Lavoratori" art. 18.

Although the first cut-off of 20 is preferable in terms of cross-studies and cross-time comparisons, the second one seems more reasonable from a legal point of view. We will concentrate first on the 20-workers partition scheme (Section 4) and then turn to robustness checks. As the distribution of employment is more detailed in 1996 than in 1981 and 1991, we will check in Section 5 whether the 1996 results are robust to the threshold chosen (15 *vs* 20) and the dichotomic partition scheme adopted (small/large *vs* small/medium/large plants).

3.3 Measures of distance and weighting matrix

In order to compute the Moran statistic, we need a spatial weighting matrix. Following Harris (1954) and the large strand of gravity estimations recently surveyed by Disdier and Head (2005), we use the inverse of bilateral distance to measure the spatial interdependence of LLS.[10] The only measure of distance available at the very disaggregated scale of LLS is the great-circle distance.[11] Section 4 will thus report the agglomeration indexes derived from the implementation of this linear-distance based matrix.

However, we have to be cautious in that the geographic scope of agglomeration is likely to depend upon *effective* rather than linear distance. For instance, if mountainous relief impedes one to access a location, as it might be the case in the Italian Alps, the firms may prefer to locate elsewhere. Likewise, the configuration of real transport networks may also affect the firms' location choices. In order to guarantee fast delivery and implement "just-in-time" practices for instance, plants may prefer to locate alongside highways, as illustrated for instance in Arbia (2001a) for the San Marino Republic. Unfortunately, an effective measure of distance is not available at the scale of Italian LLS, which is too thin. However, real distances can be computed at the more aggregated geographic scale of the 95 Italian provinces, and we will use them in Section 5 to check for the robustness of our results. The calculation of effective bilateral distances builds on an original GIS provided by Bart Jourquin, that we implement on the TRIPS transport modelization software. This association allows us to extract the distance related to the fastest itinerary connecting any pair of Italian provinces through the real road transport network in 1996.[12]

[10] In Lafourcade and Mion (2003), we also experiment first-order contiguity matrices, but as the results obtained are qualitatively similar, we do not report them.

[11] The great-circle distance is the shortest bilateral distance between the centroids of two geographic units, assuming they would be on a sphere without any physical or network constraint between them. The average great-circle distance between Italian LLS is 467 km.

[12] For more details on the methodology, see Combes and Lafourcade (2005).

4 Basic Results for Italy: LLS, 3-digit industries, 1996

To explore the impact of plant size on the geographic distribution of activities, Section 4.1 first compares the concentration and agglomeration indexes computed on both an employment and a number of plants basis. Section 4.2 seeks for the role of plant size heterogeneity in explaining the large discrepancies found within industries. Section 4.3 ends with a cross-industry comparison of the influence of plant size.

4.1 Discrepancies between the employment- and plant-based indexes of concentration and agglomeration

As apparent from Table 2, one can see that the correlation between the employment- and plant-based measures of both the concentration and the agglomeration measures is quite weak.

Table 2: Concentration and agglomeration indexes (784 LLS): All plants.

	Concentration		Agglomeration	
	$\hat{\gamma}_{EG}$	$\hat{\gamma}_{UW}$	I_W	I_{UW}
Average value	0.033	0.022	0.010	0.018
Average st. deviation	0.0115	0.0018	0.0025	0.0031
R^2	0.20		0.60	
R^2 ranks	0.54		0.67	
Number of manuf. plants	591,110		591,110	
Number of industries	103		103	
Number of spatial units	784		784	

See Appendix B for detailed results on the 103 3-digit industries.

As regards concentration, both the weighted and un-weighted indexes suggest that Italian manufacturing activities are strongly concentrated. Based on a two-sigma rule criterion,[13] $\hat{\gamma}_{EG}$ ($\hat{\gamma}_{UW}$) are significantly different from zero in 91% (97%) of the industries.[14] However, the average weighted estimator is 50% larger than its un-weighted counterpart and we estimate that around 60% (25%) of the industries exhibit a significant positive (negative) differential.[15] Such discrepancies are very large and suggest that concentration is significantly stronger for large establishments (that are over-weighted in the employment-based indexes) than for small ones. The difference in average standard

[13]The difference between the index and its expected value under the null of no spillovers (zero) has to be larger than twice its standard deviation for an industry to be concentrated.

[14]Ellison and Glaeser (1997) define the degree of concentration by classifying industries on a scale referring to both the mean and median $\hat{\gamma}$. They find that 25% of the U.S. manufacturing industries are highly concentrated, while 50% testify of slight concentration only. The Maurel and Sédillot (1999) and Devereux, Griffith and Simpson (2004) counterpart values are respectively, 27% (for France) and 16% (for the UK) of highly concentrated industries, against respectively 50% (for France) and 65% (for the UK) of slightly concentrated ones. Our results lead to the same concentration ranges for Italy.

[15]The variance of $\hat{\gamma}_{EG}$ and $\hat{\gamma}_{UW}$ is available only under the null of no spillover effect ($\gamma = 0$), so that it is not possible to properly test the differences between two positive values of the estimators. However, assuming normality, we can use the variances to perform a test based on twice the sum of the standard deviations.

errors is also important, with a magnitude so strong (up to 15 times) that this is suggestive of a strong un-accounted heterogeneity in the sample of plants. Furthermore, correlations between the weighted and un-weighted concentration indexes are very weak, for both the values and ranks.

As regards agglomeration, a two-sigma rule criterion[16] leads to the result that 66% (86%) of the industries exhibit a significant tendency to be agglomerated according to I_W (I_{UW}). Such features, which are reminiscent of the trends found by Usai and Paci (2002), testify of the crucial role played by spatial dependence in the location of manufacturing plants. As for discrepancies among the indexes, the average un-weighted Moran is 80% larger than its weighted counterpart, the difference being significantly positive (negative) for around 55% (5%) of the industries. This difference comforts the evidence of the sample heterogeneity already found for concentration indexes. Finally, one can notice that the correlations found between the weighted and un-weighted agglomeration indexes, despite being much larger than their concentration counterparts (for both values and ranks), are not as high as what would be expected from location choices that would not depend upon the size of plants.

Discrepancies between employment- and plant-based indexes of both concentration and agglomeration are therefore large. What is the source of such heterogeneity? Next section puts the emphasis on the role of plant size in explaining such differences.

4.2 Large *vs* small plants: Within-industry comparisons

Table 3 disentangles the calculation of concentration and agglomeration indexes between plants with less than and at least 20 employees.

Table 3: Concentration and agglomeration indexes (784 LLS): Small *vs* large plants

	Sample of small plants				Sample of large plants			
	Concentration		Agglomeration		Concentration		Agglomeration	
	$\hat{\gamma}_{EG}$	$\hat{\gamma}_{UW}$	I_W	I_{UW}	$\hat{\gamma}_{EG}$	$\hat{\gamma}_{UW}$	I_W	I_{UW}
Average value	0.024	0.022	0.016	0.018	0.036	0.033	0.007	0.009
Average st. deviation	0.0016	0.0010	0.0029	0.0032	0.0047	0.0020	0.0024	0.0025
R^2	0.90		0.89		0.81		0.70	
R^2 ranks	0.92		0.85		0.73		0.72	
Number of manuf. plants	549,747		549,747		41,363		41,363	

See Appendix B for detailed results on the 103 3-digit industries.

In both cases, the correlation between the weighted and the un-weighted indexes is now quite good, suggesting that, once controlled for the heterogeneity of plant size, the employment- and plant-based indicators become data consistent. This is particularly true for the sub-sample of small establishments for which this correlation amounts to as much as 0.90, for both the concentration and

[16] The difference between the Moran and its expected value under the null (-1/(M-1)) has to be larger than twice its standard deviation for an industry to be agglomerated.

agglomeration indexes. The relatively higher correlation found for small plants can be attributed to the larger homogeneity of the related sample. For the sample of large plants, the ratio between the smallest and the biggest business unit is around one hundred indeed, which is much higher than 19. Moreover, differences in the average indexes reduce drastically, in all cases. Finally, the evidence of a clear non-random relation between the geographic distribution of manufacturing activities and the size of plants is further supported by a strong reduction in the data variability when splitting the sample. For instance, while the un-weighted concentration estimator has a lower variance, coherently with the underlying EG model, the magnitude of the difference is now compatible with a simple efficiency problem rather than with a plant size heteroscedasticity issue.

Once it is recognized that the partition into small and large units gives coherent results independently on the particular index used, it seems reasonable to evaluate different concentration and agglomeration patterns based on different plant sizes. Comparing the samples of large and small plants, it is straightforward to see that plant-based concentration indexes are around 50% larger for large than for small establishments. More precisely, with a two-sigma rule on $\hat{\gamma}_{UW}$, we find that, in 60% of the industries, large plants are significantly more concentrated than small ones. The converse is true only in 26% of the industries. Holmes and Stevens (2002) find comparable results for the U.S.: The EG index for plants belonging to the fourth quartile (268 employees on average) is found to be twice larger than its first quartile counterpart (25 employees on average). Our results therefore support the non-random positive relationship between size and concentration already found by Holmes and Stevens (2002) for the U.S. or by Barrios, Bertinelli and Strobl (2003) for Ireland.

However, as one can also notice, small plants exhibit stronger agglomeration patterns than large establishments, on average. The mean I is actually 2-3 times larger when computed for the sample of small plants than for its counterpart. Moreover, applying a two-sigma rule on I_{UW} reveals that small plants are significantly more (less) spatially correlated than large ones in 52% (9%) of industries. Small plants thus seem to be more sensitive to distance-based patterns. Furthermore, although the evidence of agglomeration weakens when we exclude the spatial outliers identified with the methodology of Anselin (1995), the result that the distribution of smaller firms is characterized by a higher spatial correlation still holds. This feature, which is thus robust to the exclusion of “hot spots”, suggests that, while large plants would locate within narrow geographical units such as local labor systems, small firms, by contrast, would rather distribute into wider distance-based clusters.

Measures of concentration and agglomeration therefore strongly depend upon differences in the size of plants within industries. In Section 4.3, we provide cross-industry comparisons based on extreme patterns of concentration and agglomeration in order to highlight the following question: Relying on plant size characterization of concentration and agglomeration, what could be the underlying mechanisms governing the spatial distribution of activities? This issue is likely to be an important topic as regards the design of regional development policies.

4.3 Large *vs* small plants: Between-industry comparisons

Tables 4 and 5, derived from the detailed 3-digit LLS results presented in Tables 13, 14, and 15 in Appendix B, report the ten manufacturing industries displaying the largest and lowest indexes of concentration and agglomeration. As the distinction between the un-weighted and weighted indexes is no longer an issue once corrected for the heterogeneity of plant size, the following results build on the un-weighted indexes only, because of efficiency properties.

Table 4: The 10 most concentrated and agglomerated industries (784 LLS): Sample of small plants

	The 10 more concentrated			The 10 more agglomerated	
NACE	3-digits industry	$\hat{\gamma}_{UW}$	NACE	3-digits industry	I_{UW}
172	Textile weaving	0.247	154	Mauf. of vegetable and animal oils and fats	0.125
171	Preparation and spinning of textile fibres	0.244	153	Process. and preserving of fruit and vegetables	0.104
191	Tanning and dressing of leather	0.204	158	Manuf. of other food products	0.082
296	Manuf. of weapons and ammunition	0.164	232	Manuf. of refined petroleum products	0.075
263	Manuf. of ceramic tiles and flags	0.117	266	Manuf. of articles of concrete, plaster and cement	0.073
192	Manuf. of handbags, saddlery, harness	0.067	281	Manuf. of structural and metal products	0.059
244	Manuf. of pharmaceuticals, med. chemicals, etc.	0.065	193	Manuf. of footwear	0.059
173	Finishing of textiles	0.061	203	Manuf. of uilders' carpentry and joinery	0.057
160	Manuf. of tobacco products	0.059	265	Manuf. of cement, lime and plaster	0.051
363	Manuf. of musical instruments	0.049	287	Manuf. other fabricated metal products	0.047

See Appendix B for detailed results on all the 103 3-digit industries.

Table 5: The 10 most concentrated and agglomerated industries (784 LLS): Sample of large plants

	The 10 more concentrated			The 10 more agglomerated	
NACE	3-digits industry	$\hat{\gamma}_{UW}$	NACE	3-digits industry	I_{UW}
223	Reproduction of recorded media	0.393	153	Process. and preserving of fruit and vegetables	0.047
191	Tanning and dressing of leather	0.219	193	Manuf. of footwear	0.039
296	Manuf. of weapons and ammunition	0.216	160	Manuf. of tobacco products	0.038
263	Manuf. of ceramic tiles and flags	0.172	334	Manuf. of optical instruments, photo. equipment	0.034
355	Manuf. of other transport equipment	0.170	363	Manuf. of musical instruments	0.029
363	Manuf. of musical instruments	0.155	152	Process. and preserving of fish products	0.028
362	Manuf. of jewelery and related art	0.129	182	Manuf. of other wearing apparel and accessories	0.027
173	Finishing of textiles	0.089	295	Manuf. of other special purpose machinery	0.026
221	Publishing	0.079	232	Manuf. of refined petroleum products	0.025
244	Manuf. of pharmaceuticals, med. chemicals, etc.	0.078	293	Manuf. of agricultural and forestry machinery	0.022

See Appendix B for detailed results on all the 103 3-digit industries.

A first striking feature arising from the comparison of Tables 4 and 5 is that extreme concentration and agglomeration patterns are triggered by different industries.

Among the most significantly concentrated industries emerge the activities which are at the core of Italian districts: 'Preparation and spinning of textile fibres' (3-digit NACE number 171) and 'Textile weaving' (172) located in the 'Prato' LLS, 'Tanning and dressing of leather' (191) in both the LLS of 'Arzignano' and 'Santa Croce', 'Ceramic tiles and flags' (263) around the LLS of 'Sassuolo', 'Manufacturing of jewelery and related articles' (362) in the LLS of Alessandria', 'Arezzo' and 'Vicenza', and 'Manufacturing of Musical Instruments' (363) in the LLS of 'Ancona'.[17] The districts related to textile industries (171, 172) exhibit an extreme concentration mainly triggered by small firms (less than 20 employees), while the concentration of other districts seem to be more or less equally conveyed by small and large plants (191, 263, 363). These features are therefore coherent with a rough characterization of Italian districts according to their large proportion of small plants, as in Sforzi (1990). Interestingly, while being so concentrated, industries behind the formation of districts are only weakly or sometimes not agglomerated at all, as shown by the non significance of either the weighted or the un-weighted Moran indexes. Despite particularly low plant scales, Italian districts would stem as an exception to the overall trend that small plants would locate according to wide national distance-based patterns. This apparently puzzling feature can be attributed to the fact that the production of many Italian districts is mainly oriented towards foreign markets, as emphasized by Bagella, Becchetti and Sacchi (1998).

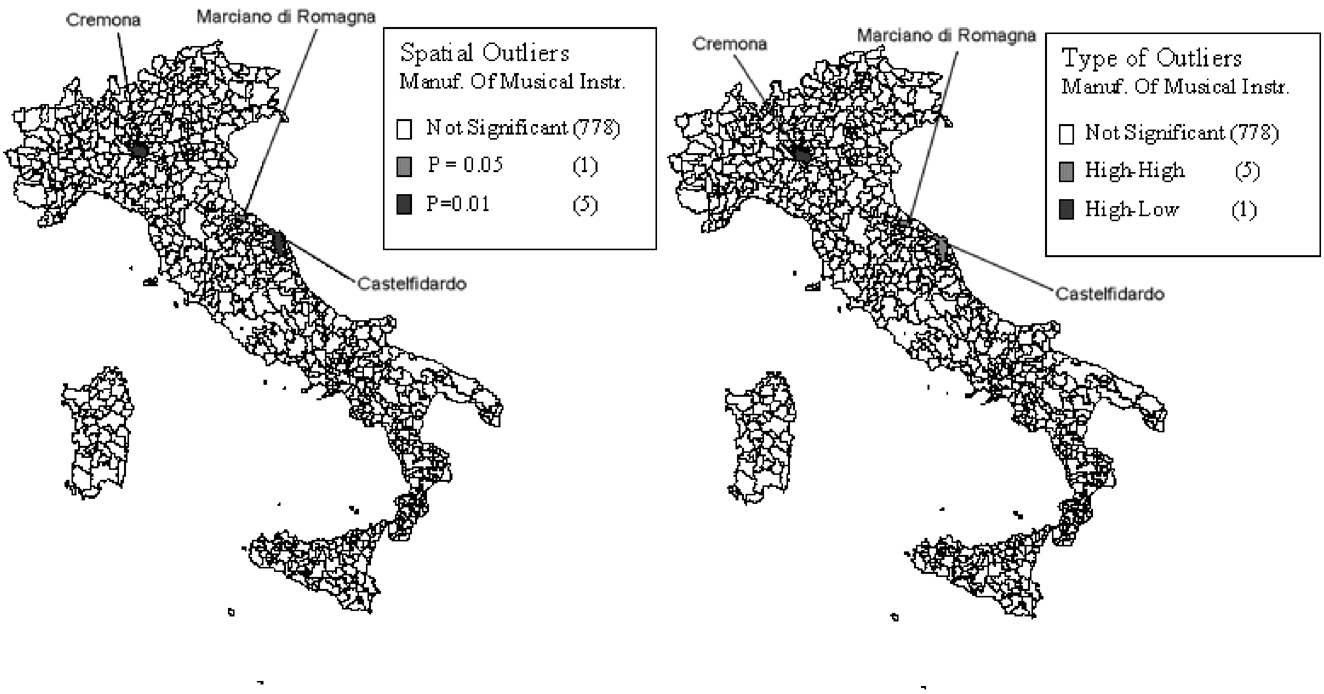
However, a clear exception to this story arises for the 'Manufacturing of Musical Instruments', which is the only district industry that is simultaneously extremely concentrated and agglomerated, independently on the size of its related plants (the industry 363 is present in nearly all columns of Tables 4 and 5). However, complete separation can be restored by showing that the agglomeration of this industry is somehow spurious, as it is triggered by spatial outliers only. Figure 3 reveals that the manufacturing of musical instruments hosts some interesting cases of "hot spots" indeed, as identified by the procedure already described in Section 2.4.

Figure 3-left exhibits the number of spatial outliers in the industry,[18] while Figure 3-right depicts the "type" of spatial correlation observed. As one can see, going from top to bottom, three non-white areas stand as outliers. The first one is located in the LLS of 'Cremona', where there is extreme concentration of plants virtually surrounded by nothing (High-Low). By contrast, the southern location of 'Marciano di Romagna', where plants are also extremely concentrated, is neighbored by LLS that share a small proportion of the same activity (High-High, with the central LLS concentrating

[17] For more details on the mapping of Italian Districts see Sforzi (1990).

[18] Degrees of grey correspond to the significance of the local Moran statistic, and probabilities to the test on local instability.

Figure 3: Spatial Outliers in the 'Manufacturing of Musical Instruments' Industry



most of the activity). Finally, the third eastern-southern area is the well-known district of musical instruments centered around 'Castelfidardo', and which includes the neighboring labor markets of 'Ancona', 'Macerata', 'Osimo', and 'Recanati' in which plants are also extremely concentrated (also High-High, but with both the central and neighboring LLS highly concentrated). When excluding spatial outliers from this industry (which still leads to 110 LLS left with non-zero employment), we find that the 'Manufacturing of Musical Instruments' industry is actually not significantly agglomerated anymore (i.e the Moran index is not significant). Therefore, the extreme case of agglomeration revealed by data on this industry is due to the outlier nature of some LLS only (6 over 116), and does not reflect an overall tendency for the industry of musical instruments to be more agglomerated on average than others.

In the group of the most concentrated industries within big plants (See Table 5), we find the 'Manufacturing of other transport equipment' (355). One can see from Table 15 in Appendix B, that the Moran index for this industry is negative but not significant. Caution is thus needed in interpreting the distribution patterns of this industry. Indeed, in 1996, there were only four Italian plants with at least 20 employees in the transport equipment industry. They were all located in the northern small triangle of 'Bergamo', 'Modena', and 'Imola' LLS. Notice that this number is particularly low in comparison with the 784 LLS geographic units, meaning that the Moran is biased, as recalled in Section 2.4. Mass-production activities such as 'Publishing' (221) or 'Reproduction of recorded media' (223), are also found to be extremely concentrated in the category of large plants, but not agglomerated, as testified by the significant negative values of the related weighted Moran.

These results suggest that extreme concentration patterns occurring within the boundaries of local labor markets, such as the previous, translate into dense clusters of economic activities and therefore may generate productivity gains for the related industries/plants and locations. Such gains could stem from either strong increasing returns to scale (as testified by their extremely low number of large plants) or localized spillovers created through density. Possibly coupled with low international transport costs, they may enable plants to target foreign markets on top of domestic ones.

Among the activities exhibiting the strongest positive spatial auto-correlation within the sample of small plants, the food industries are over-represented (152, 153, 154, and 158). Moreover, as apparent from Table 14 in Appendix B, the number of spatial outliers is particularly large for these industries, meaning that related co-location patterns are triggered by numerous extreme cases of agglomeration. Other activities related to the final stage of production such as 'Manufacturing of footwear' (193) exhibit the same pattern. In the sample of activities displaying the strongest spatial dependence within the counterpart sample of large plants, one can find upstream industries such as 'Manufacturing of other wearing apparel and accessories' (182), 'Manufacturing of other special purpose machinery' (295), or 'Manufacturing of refined petroleum products' (232).

In both previous cases, agglomeration patterns are likely to prevail because firms want to save on transport costs (due to either perishability, voluminosity, specific transport modes or customers' face-to-face requirements), and therefore locate in the close proximity of the potentially largest number of buyers (consumers or downstream industries). High transport costs and demand linkages (final and intermediate) could be at the core of such wide distance-based location patterns.

The comparison of concentration and agglomeration patterns across different industries is therefore insightful in several ways. The results that plants located in the areas where an industry concentrates are larger, on average, than outside such areas, is important as regards efficiency. The productivity gains that could arise from extremely dense areas may enable large firms to serve markets located far beyond the boundaries of neighboring markets. This would translate into (i) a geographic distribution that would not be sensitive to domestic distances, (ii) a production of goods, on average, less domestically customized or more oriented towards distant markets. Industries hosting the largest plants should therefore testify of a larger proportion of either inter-regional or international shipments than of inter-labor market exchanges. By contrast, small establishments, which exhibit the converse tendency of being more sensitive to inter-LLS distances, would need to save on transport costs by locating close to domestic demand, the key determinant of the agglomeration in this case. Most salient exceptions to this overall trend are the Italian districts formed around small concentrated plants. The feature that such districts do not show any distance-based co-location patterns at the scale of LLS is fully compatible with an underlying criterion defining districts on the basis on exports oriented mainly towards foreign (and not domestic) markets.

5 Robustness checks and long-run trends

This section addresses the robustness of the positive (negative) correlation found between concentration (agglomeration) and plant size (Section 5.1). Furthermore it also explores the time-dimension of our panel data, by investigating the evolution of concentration and agglomeration patterns over the period 1981-1996, and by focusing on how changes have been triggered by large rather than small plants, beyond the consideration of specific industry characteristics (Section 5.2).

5.1 Robustness checks

We first investigate the robustness of the results presented in Section 4 to changes in the geographic, industrial, and plant partitions.

Controlling for the MAUP and the distance bias: The case of Italian 'provincie'

Are the trends provided in Section 4 dependent upon the geographic partition of Italian space into Local Labor Systems? In other words, is the positive (negative) correlation found between concentration (agglomeration) and plant size robust to the MAUP? To address this question, we present a brief analysis of the concentration and agglomeration patterns obtained for the 95 Italian NUTS3 regions. As apparent from the comparison of Table 6 and its LLS counterpart (Table 3 presented in Section 4), both the average concentration and agglomeration indexes increase with the geographical scale of study.

Table 6: Concentration and agglomeration indexes (95 'provincie'): Small *vs* large plants

	Sample of small plants				Sample of large plants			
	Concentration		Agglomeration		Concentration		Agglomeration	
	$\hat{\gamma}_{EG}$	$\hat{\gamma}_{UW}$	I_W	I_{UW}	$\hat{\gamma}_{EG}$	$\hat{\gamma}_{UW}$	I_W	I_{UW}
Average value	0.034	0.030	0.024	0.033	0.049	0.046	0.007	0.013
Average st. deviation	0.0025	0.0015	0.0126	0.0133	0.0069	0.0030	0.0124	0.0125
R^2	0.89		0.81		0.82		0.65	
R^2 ranks	0.92		0.70		0.75		0.58	
Number of manuf. plants	549,747		549,747		41,363		41,363	

The result that concentration rises when considering wider spatial units is now well established.[19]

[19]See among others Kim (1995), Ellison and Glaeser (1997), Maurel and Sédillot (1999), Pagnini (2003) and Barrios,

This feature suggests that concentration processes are likely to depend upon other spillovers than those driven, for instance, by labor market pooling. Spatial auto-correlation also seems to occur at a larger scale than LLS. Nevertheless, as differences between the Moran indexes calculated for LLS and provinces are rarely significant, we cannot draw any general conclusion from this result. However, the overall trend found for the relation between concentration, agglomeration, and plant size is similar to that found for LLS. At the scale of Italian administrative NUTS3 regions, large plants still exhibit a clear tendency to concentrate more in the regions where other large plants are already located than elsewhere. As regards agglomeration, small plants display more spatial auto-correlated patterns than large plants.

Furthermore, as shown in Table 7, the consideration of real road distances between regions instead of bilateral great-circle distances, does not lead to drastic changes in the results.

Table 7: Moran indexes computed with real road distances (95 'provincie')

	Sample of small plants		Sample of big plants	
	I_W	I_{UW}	I_W	I_{UW}
Average value	0.032	0.040	0.011	0.016
Average st. deviation	0.0141	0.0148	0.0140	0.0141
R^2	0.79		0.75	
R^2 ranks	0.78		0.70	
Number of manuf. plants	549,747		41,363	

Discrepancies between employment- and plant-based Moran indexes decrease slightly for the sample of large plants (correlations in both level and ranks increase). Although the mean Moran is now larger for both types of plants, agglomeration indexes are still around 3 times larger for small plants than for large establishments. The similarity of the results based on both the effective and linear distances is not surprising, yet. As shown by Combes and Lafourcade (2005) for France, linear distance is indeed a very good substitute to effective distance in the case of *cross-section analysis*. However, as the distance bias worsens when passing from cross-section to time-series analysis, we will have to be cautious in interpreting the long-run trends provided in Section 5.2.

Comparison between 2-digit and 3-digit industries

In order to test whether the results are sensitive to how manufacturing products are defined, we also perform the calculation of indexes using the 2-digit classification of industries. Although the qualitative relation found between concentration, agglomeration and the size of plants is not affected, changes occur in the level of indexes, once again. Focusing on the geographic scale of LLS, we find that the un-weighted index of concentration (agglomeration) decreases (increases) by 58%

Bertinelli, Strobl and Teixeira (forthcoming).

(36%), when computed on this broadly defined category of manufacturing industries. The feature that concentration decreases with the level of industry aggregation suggests that spillovers in the manufacturing industry are less likely to operate between the 3-digit industries than within each industry. Furthermore, this result does not depend upon the definition of regions we choose.[20] This feature is not surprising and was already emphasized by Ellison and Glaeser (1997), and Maurel and Sédillot (1999), as regards the concentration perspective. Our analysis complements their findings in assessing that the distribution of plants within the broad 2-digit category is by contrast characterized by a stronger distance-based pattern (more agglomeration). However, the variances of the 2-digit indexes are so large with respect to the corresponding 3-digit sub-industries that the differences are rarely significant.

Sensitivity to the dichotomic partition of plants and to the plant threshold chosen

The fact that a positive (although strongly reduced) gap between employment- and plant-based indexes still remains after correcting for the heterogeneity of plant size (See Table 3) indicates that more complex partition schemes than the small-large dichotomic one would probably be preferable. We present now the results of splitting the universe of Italian plants into three categories instead of two: small (less than 15 employees), medium (between 15 and 100 employees) and large (more than 100 employees) plants. This partition has the advantages of both considering the cut-off of 15 employees which, as recalled in Section 3.2, may be more relevant for Italy, and of dividing the sample into 3 rather balanced employment groups instead of two.

Table 8: Concentration and agglomeration for 3 sub-samples of plants (784 LLS)

	Concentration ($\hat{\gamma}_{UW}$)			Agglomeration (I_{UW})		
	Small	Medium	Large	Small	Medium	Large
Average value	0.022	0.032	0.053	0.019	0.013	0.005
Average st. deviation	0.0016	0.0020	0.0200	0.0032	0.0027	0.0024
Number of manuf. plants	534,427	51,298	5,385	534,427	51,298	5,385
Number of manuf. workers	1,783,799	1,600,103	1,471,875	1,783,799	1,600,103	1,471,875

As apparent from Table 8, which is the counterpart of the Table 3 presented in Section 4, a further exploitation of the plants employment distribution leads to virtually the same results: We find that large plants are more concentrated than medium establishments, that, in return concentrate more than small plants. And the converse tendency prevails for agglomeration. The correlation story between concentration, agglomeration and plant size thus remains unchanged to that of Section 4. The results presented in this sub-section suggest however that it could be better to model it in a continuous framework: The larger (lower) the employment scale of plants, the larger the tendency to concentrate (agglomerate).

[20]Results on 2-digit industries (for both LLS and NUTS3 regions) are available upon request.

5.2 Time evolution of concentration and agglomeration patterns

In order to further assess the positive (negative) relationship found between concentration (agglomeration) and plant size, we present in Table 9 the result of the following industry fixed-effects panel regression: For the three census years 1981, 1991 and 1996, we use the concentration and agglomeration indexes as independent variables to be regressed on size=ln(average size of establishments) in each industry, with u^s being the industry fixed-effect.

Table 9: Panel regression of indexes on Size=ln(average size of plants) (784 LLS)

	Coefficients or Tests Values			
	Concentration ($\hat{\gamma}_{UW}$)		Agglomeration (I_{UW})	
Size	0.0248*	(0.0039)	-0.0055*	(0.0012)
Constant	-0.0437*	(0.0106)	0.0327*	(0.0033)
R^2	0.17		0.14	
Number of observations	309		309	
Number of years	3		3	
Industry dummies	Yes		Yes	
Time dummies	Yes		Yes	

Note: Standard errors in brackets. * denotes significance at the 1%level.

As apparent from Table 9, the impact of size on concentration (agglomeration) is positive (negative) and significant at 1%, as expected. These results suggest that plant scale has an impact on the spatial distribution of establishments which is not simply driven by (time-invariant) sector specific characteristics such as factor endowments or raw materials.

As for the time evolution of concentration and agglomeration patterns, Table 10 in Appendix A reveals that mean concentration has slightly decreased while mean agglomeration has increased over the period 1981-1996. Kim (1995) finds a similar declining pattern of concentration after the second world war for the U.S. More recent studies for Europe, such as Brülhart (2001) or Midelfart, Overman, Redding and Venables (2002) lead to more controversial results, with some industries experiencing an increase and some others a decrease of concentration.[21] Interestingly, by disentangling the time evolution according to the size of plants (See Tables 11 and 12 in Appendix A), one can see that the dynamics is mainly conveyed by small plants, with big units showing a relatively stabler pattern.

6 Conclusions

This paper analyzes the spatial distribution of manufacturing activities in Italy by focusing on two different features. The first feature, concentration, can be defined as the degree of variability across

[21] Both studies relate the changes in concentration to industry characteristics such as increasing return to scales, skills or R&D intensity.

data for a given partition of space. The second feature, agglomeration, explicitly considers distances among observations and thus their spatial dependence. Although there exists many studies focusing on concentration, agglomeration has received relatively less attention by the profession.

Investigating the influence of plant size on both the concentration and agglomeration distribution patterns is instructive in several ways. Whereas the result that large plants tend to be more concentrated than small units comforts some evidence already pointed by other few studies, the feature that small plants are more agglomerated than large ones is innovative. While large plants would exhibit a clear tendency to cluster within narrow geographical units such as local labor systems, small establishments, by contrast would thus rather co-locate within wider areas in which a distance-based pattern emerges. These features are robust to changes in the partition of space, industries, plants, and in the distance measurement. Controlling for time-invariant sector specific characteristics, such as raw material or natural resources, does not alter the picture either. Such results highlight some of the underlying economic mechanisms driving plant location choices. Differences in transport costs intensity between small and large plants is a plausible explanation of the different distribution patterns obtained. The need for small firms to save on transport costs by locating close to domestic demand, would be a key determinant of the strong distance-based patterns found for the industries hosting small plants, such as food processing. By contrast, industries hosting large plants or Italian districts would testify of a higher proportion of either inter-regional or international activities. Moreover, a closer look at the time evolution of the geographic distribution of Italian firms reveals declining (increasing) concentration (agglomeration) patterns, the dynamics being mainly conveyed by small plants.

Further lines of research would deserve attention for future work. A first valuable contribution would be to measure both the narrow and large scope spillovers within the same integrated theoretical framework, instead of combining two types of indexes. This would enrich the analysis by opening the way to identifying different types of externalities. Another interesting topic is related to the causality of the relationship found between plant size, concentration and agglomeration. As circular causation may be at work, structural econometrics would call for clarifying theoretical contributions.

References

Anselin, L., 1988. *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishers.

Anselin, L., 1995. Local Indicators of Spatial Association-LISA. *Geographical Analysis*, 27(2), 93-115.

Arbia, G., 1989. *Spatial Data Configuration in Statistical Analysis of Regional Economic and Related Problems*. Kluwer, Dordrecht.

Arbia, G., 2001a. Modelling the geography of economic activities on a continuous space. *Papers in Regional Science*, 80, 411-424.

Arbia, G., 2001b. The role of spatial effects in the empirical analysis of regional concentration. *Journal of Geographical Systems*, 3, 271-281.

Bagella, M., L. Becchetti and S. Sacchi, 1998. The positive link between geographical agglomeration and export intensity: The engine of Italian endogenous growth?. *Economic Notes*, Monte dei Paschi di Siena, 27(1), 1-34.

Barrios, S., Bertinelli, L., and Strobl, E., 2003. Geographic Concentration and Establishment Scale: Can Panel Data tell us more?. *CORE Discussion Papers*, 36.

Barrios, S., Bertinelli, L., Strobl, E., and Teixeira, A.C., forthcoming. The Dynamics of Agglomeration: Evidence From Ireland and Portugal. *Journal of Urban Economics.*

Brülhart M., 2001. "Evolving Geographical Specialisation of European Manufacturing Industrie". *Weltwirtschaftliches Archiv*, 137(2), 215-243.

Ciccone, A., 2002. Agglomeration effects in Europe. *European Economic Review*, 46, 213-227.

Ciccone, A., and Hall, R.E., 1996. Productivity and the density of economic activities. *American Economic Review*, 86(1), 54-70.

Cliff, A.D., and Ord, J. K., 1981. *Spatial Processes: Models and Applications. Pion*, London.

Combes, P-P., and Lafourcade, M., 2005. Transport Costs: Measures, determinants and regional policy implications for France. *Journal of Economic Geography*, in press.

Combes, P.-P., and Overman, H.G., 2004. The Spatial Distribution of Economic Activities in the European Union. In *Handbook of Regional and Urban Economics*, Vol.4, J.V. Henderson and J.-F. Thisse (eds.), Elsevier-North Holland, Amsterdam.

Devereux, M.P., Griffith, R., and Simpson, H., 2004. The geographic distribution of production activity in the UK. *Regional Science and Urban Economics*, 34(5), 533-564.

Disdier, A. C., and Head, K., 2004. The Puzzling Persistence of the Distance Effect on Bilateral Trade. Mimeo. http://pacific.commerce.ubc.ca/keith/Papers/meta.pdf.

Duranton, G., and Overman, H.G., 2004. Testing for Localisation Using Micro-Geographic Data. *Review of Economic Studies*, forthcoming.

Ellison, G., and Glaeser, E., 1997. Geographic concentration in US manufacturing industries: A dartboard approach. *Journal of Political Economy*, 105, 889-927.

Fujita, M., and Thisse, J.F. (2001) *Economics of Agglomeration: Cities, Industrial Location, and Regional Growth*, Cambridge University Press, Cambridge, 466p.

Fujita, M., Krugman, P., and Venables, A.J. (1999) *The Spatial Economy: Cities, Regions, and International Trade*, MIT Press, Cambridge, Massachusetts, 367p.

Fujita, M., Henderson, J.V. and Mori, T., 2004. Spatial Distribution of Economic Activities in Japan and China. In *Handbook of Regional and Urban Economics*, Vol.4, J.V. Henderson and J.-F. Thisse (eds.), Elsevier-North Holland, Amsterdam.

Getis, A., and Ord, J.K., 1992. The analysis of spatial association by use of distance statistics. *Geographical Analysis*, 24, 189-206.

Harris, C.D., 1954. The Market as a Factor in the Localization of Industry in the United States. *Annals of the Association of American Geographers*, 44, 315-348.

Holmes, T.J., and Stevens, J.J., 2004. Spatial Distribution of Economic Activities in North America. In *Handbook of Regional and Urban Economics*, Vol.4, J.V. Henderson and J.-F. Thisse (eds.), Elsevier-North Holland, Amsterdam.

Holmes, T.J., and Stevens, J.J., 2002. Geographic concentration and establishment scale. *Review of Economics and Statistics*, 84, 682-690.

Kim, S., 1995. Expansion of Markets and the Geographic Concentration of Economic activities: The Trends in U.S. Regional Manufacturing structure, 1860-1987. *Quarterly Journal of Economics*, 110(4), 881-908.

Lafourcade, M., and Mion, G., 2003. Concentration, Agglomeration and the Size of plants: Disentangling the Source of Co-Location Externalities. *Core discussion Paper* 91, Université Catholique de Louvain.

Marcon, E., and Puech F., 2003. Evaluating the Geographic Concentration of Industries Using Distance-Based Methods. *Journal of Economic Geography*, 3(4): 409-428.

Maurel, F., and Sédillot, B., 1999. A measure of the geographic concentration in French manufacturing industries. *Regional Science and Urban Economics*, 29, 575-604.

Midelfart, K.H., Overman, H.G., Redding, S.J., and Venables, A.J., 2002. "Integration and industrial specialisation in the European Union". *Revue Économique*, 53, 469-481.

Moran, P.A.P., 1950. Notes on continuous stochastic phenomena, *Biometrika*, 37, 17-23.

Pagnini, M., (2003). Misura e Determinanti dell'Agglomerazione Spaziale Nei Comparti Industriali in Italia. *Mimeo*, Bank of Italy.

Sforzi, F., 1990. The quantitative importance of Marshallian industrial districts in the Italian economy. In *Industrial districts and inter-firm co-operation in Italy*, F. Pyke, G. Becattini and W. Sengerberger (eds.), 75-107, Geneva, International Institute for Labor Studies, ILO.

Usai, S., and Paci, R., 2002. Externalities and local economic growth in manufacturing industries. In *European Regional Growth*, Fingleton B. (ed.), Springer-Verlag.

Appendix A: Additional Tables

Table 10: Concentration and agglomeration over time: All plants

	Concentration($\hat{\gamma}_{UW}$)			Agglomeration(I_{UW})		
	1981	1991	1996	1981	1991	1996
Average value	0.026	0.023	0.022	0.014	0.016	0.018
Average st. deviation	0.0004	0.0011	0.0018	0.0027	0.0029	0.0031
Number of industries		103			103	
Number of spatial units		784			784	
Number of manuf. plants	622,353	592,753	591,110	622,353	592,753	591,110

Table 11: Concentration and agglomeration over time: Sample of small plants

	Concentration($\hat{\gamma}_{UW}$)			Agglomeration(I_{UW})		
	1981	1991	1996	1981	1991	1996
Average value	0.026	0.022	0.022	0.017	0.018	0.019
Average st. deviation	0.0009	0.0010	0.0010	0.0030	0.0032	0.0033
Number of industries		103			103	
Number of spatial units		784			784	
Number of manuf. plants	579,676	550,103	549,747	579,676	550,103	549,747

Table 12: Concentration and agglomeration over time: Sample of large plants

	Concentration($\hat{\gamma}_{UW}$)			Agglomeration(I_{UW})		
	1981	1991	1996	1981	1991	1996
Average value	0.032	0.032	0.033	0.010	0.009	0.010
Average st. deviation	0.0016	0.0023	0.0020	0.0025	0.0025	0.0025
Number of industries		103			103	
Number of spatial units		784			784	
Number of manuf. plants	42,677	42,650	41,363	42,677	42,650	41,363

Appendix B: Detailed 3-digit tables

The column 'Sign' takes the value of one if the statistic presented in the previous column is significant according to the two-sigma rule, and of zero otherwise. The column 'Outl' provides the number of spatial outliers in the industry, while "na" means that the relevant variable cannot be computed because there is only one firm.

Table 13: LLS - 3-digit - All plants

NACE	Industry	$\hat{\gamma}_{UW}$	$\sigma(\hat{\gamma}_{UW})$	Sign	$\hat{\gamma}_{EG}$	$\sigma(\hat{\gamma}_{EG})$	Sign	I_{UW}	$\sigma(I_{UW})$	Sign	I_W	$\sigma(I_W)$	Sign	Outl.
151	prod. proc. pres. of meat	0.0109	0.0000	1	0.0085	0.0005	1	0.0146	0.0025	1	0.0143	0.0026	1	14
152	proc. and pres. of fish	0.0218	0.0003	1	0.0200	0.0033	1	0.0389	0.0048	1	0.0124	0.0024	1	17
153	proc. and pres. of fruit	0.0137	0.0001	1	0.0194	0.0006	1	0.0865	0.0106	1	0.0431	0.0053	1	15
154	man. of veg. and anim oils	0.0158	0.0000	1	0.0157	0.0002	1	0.1067	0.0130	1	0.0637	0.0078	1	19
155	man. of dairy prod	0.0071	0.0000	1	0.0036	0.0004	1	0.0352	0.0044	1	0.0181	0.0027	1	17
156	man. of grain mill prod	0.0084	0.0001	1	0.0079	0.0006	1	0.0354	0.0044	1	0.0111	0.0026	1	12
157	man. of prep anim feeds	0.0093	0.0002	1	0.0101	0.0012	1	0.0196	0.0025	1	0.0093	0.0026	1	13
158	man. of other food prod	0.0043	0.0000	1	0.0019	0.0001	1	0.0673	0.0083	1	0.0324	0.0041	1	14
159	man. of beverages	0.0091	0.0000	1	0.0033	0.0003	1	0.0391	0.0049	1	0.0232	0.0030	1	12
160	man. of tobacco prod	0.0324	0.0009	1	0.0081	0.0050	0	0.0357	0.0045	1	0.0215	0.0027	1	18
171	prep. and spin of text fibres	0.2151	0.0000	1	0.0624	0.0003	1	0.0014	0.0012	1	0.0130	0.0023	1	5
172	textile weaving	0.2170	0.0000	1	0.0505	0.0004	1	0.0010	0.0011	1	0.0092	0.0024	1	4
173	finishing of textiles	0.0676	0.0001	1	0.0745	0.0003	1	0.0030	0.0020	1	0.0045	0.0022	1	11
174	man. of made-up text art	0.0057	0.0000	1	0.0101	0.0002	1	0.0030	0.0026	0	0.0075	0.0026	1	7
175	man. of other textiles	0.0142	0.0000	1	0.0125	0.0003	1	0.0068	0.0024	1	0.0153	0.0025	1	6
176	man. of knitt and croch fab	0.0227	0.0000	1	0.0192	0.0002	1	0.0187	0.0024	1	0.0112	0.0025	1	16
177	man. of knitt and croch art	0.0132	0.0000	1	0.0144	0.0001	1	0.0232	0.0029	1	0.0180	0.0026	1	26
181	man. of leather clothes	0.0362	0.0001	1	0.0443	0.0003	1	0.0192	0.0025	1	0.0164	0.0021	1	11
182	man. of other wear apparel	0.0042	0.0000	1	0.0052	0.0000	1	0.0255	0.0032	1	0.0210	0.0027	1	17
183	dress and dyeing of fur	0.0094	0.0001	1	0.0097	0.0003	1	-0.0001	0.0025	0	0.0025	0.0024	0	3
191	tan and dres of leather	0.2061	0.0001	1	0.2082	0.0002	1	-0.0012	0.0021	0	-0.0001	0.0022	0	6
192	man. of luggage, bags	0.0688	0.0000	1	0.0809	0.0001	1	0.0019	0.0011	1	0.0019	0.0011	1	16
193	man. of footwear	0.0288	0.0000	1	0.0274	0.0001	1	0.0551	0.0068	1	0.0437	0.0054	1	9
201	sawmil and impregn of wood	0.0083	0.0000	1	0.0115	0.0002	1	0.0225	0.0029	1	0.0218	0.0028	1	16
202	man. of venter sheets, plywood	0.0205	0.0003	1	0.0177	0.0014	1	0.0150	0.0026	1	0.0051	0.0026	1	9
203	man. of uilders'carp and joinery	0.0052	0.0000	1	0.0051	0.0000	1	0.0425	0.0053	1	0.0243	0.0031	1	13
204	man. of wooden containers	0.0056	0.0001	1	0.0067	0.0003	1	0.0311	0.0039	1	0.0150	0.0026	1	19
205	man. of other prod. of wood	0.0057	0.0000	1	0.0070	0.0001	1	0.0196	0.0025	1	0.0160	0.0026	1	17
211	man. of pulp, paper	0.0105	0.0004	1	0.0052	0.0022	1	0.0170	0.0025	1	0.0030	0.0027	0	6
212	man. of art of paper	0.0030	0.0000	1	0.0037	0.0002	1	0.0065	0.0024	1	0.0009	0.0025	0	15
221	publishing	0.0419	0.0000	1	0.0851	0.0006	1	-0.0032	0.0020	0	-0.0048	0.0017	1	3
222	printing and rel services	0.0061	0.0000	1	0.0115	0.0001	1	0.0058	0.0022	1	-0.0016	0.0021	0	3
223	reproduction of rec media	0.0325	0.0004	1	0.2605	0.0034	1	-0.0044	0.0017	0	-0.0028	0.0006	1	2
231	man. of coke oven prod	0.0111	0.0451	0	0.0941	0.1687	0	-0.0021	0.0024	0	-0.0016	0.0006	0	5
232	man. of refined petrol prod	0.0048	0.0002	1	0.0343	0.0035	1	0.0693	0.0085	1	0.0074	0.0023	1	27
233	processing of nuclear fuel	0.0341	0.1129	0	0.4620	0.8028	0	-0.0024	0.0020	0	-0.0021	0.0005	0	4
241	man. of basic chemicals	0.0045	0.0001	1	0.0100	0.0013	1	0.0065	0.0021	1	0.0016	0.0026	0	28
242	man. of agro-chem prod	0.0099	0.0014	1	0.0293	0.0058	1	0.0042	0.0026	1	0.0039	0.0024	1	17
243	man. of paints, varnish	0.0022	0.0001	1	0.0212	0.0008	1	0.0073	0.0025	1	0.0003	0.0016	0	34
244	man. of pharmac, med chem	0.0670	0.0002	1	0.1210	0.0012	1	-0.0017	0.0017	0	-0.0022	0.0013	0	1
245	man. of soap and deterg	0.0074	0.0001	1	0.0259	0.0014	1	0.0036	0.0020	1	0.0056	0.0022	1	20
246	man. of other chem prod	0.0078	0.0001	1	0.0174	0.0011	1	0.0070	0.0018	1	0.0051	0.0022	1	21
247	man. of man-made fibres	0.0181	0.0021	1	0.0058	0.0070	0	0.0213	0.0027	1	0.0008	0.0026	0	11
251	man. of rubber prod	0.0105	0.0001	1	0.0089	0.0015	1	0.0138	0.0021	1	0.0139	0.0025	1	10
252	man. of plastic prod	0.0016	0.0000	1	0.0022	0.0001	1	0.0284	0.0036	1	0.0259	0.0033	1	11
261	man. of glass	0.0105	0.0000	1	0.0104	0.0009	1	0.0143	0.0021	1	0.0022	0.0025	0	12
262	man. of refr and non-refr ceramics	0.0161	0.0000	1	0.0225	0.0006	1	0.0228	0.0029	1	0.0088	0.0023	1	18
263	man. of ceramic tiles and flags	0.1404	0.0002	1	0.2192	0.0009	1	0.0124	0.0016	1	0.0113	0.0015	1	6
264	man. of bricks, tiles	0.0134	0.0002	1	0.0123	0.0007	1	0.0280	0.0035	1	0.0135	0.0026	1	16
265	man. of cement, lime	0.0126	0.0003	1	0.0081	0.0021	1	0.0469	0.0058	1	0.0056	0.0026	1	22
266	man. of art. of concr	0.0062	0.0000	1	0.0062	0.0001	1	0.0533	0.0066	1	0.0230	0.0029	1	11
267	cutting, finish of stone	0.0105	0.0000	1	0.0172	0.0001	1	0.0341	0.0043	1	0.0223	0.0028	1	17
268	man. of other non-met min prod	0.0024	0.0002	1	0.0070	0.0007	1	0.0131	0.0027	1	0.0023	0.0026	0	18
271	man. of basic iron, steel	0.0115	0.0008	1	0.0520	0.0074	1	0.0179	0.0026	1	0.0001	0.0021	0	8
272	man. of tubes	0.0034	0.0004	1	0.0064	0.0044	0	0.0129	0.0026	1	0.0046	0.0020	1	19
273	other 1st proc of iron, steel	0.0086	0.0001	1	0.0118	0.0011	1	0.0119	0.0020	1	0.0055	0.0023	1	24
274	man. of non-ferr met	0.0083	0.0003	1	0.0156	0.0022	1	0.0140	0.0025	1	0.0028	0.0024	0	19
275	casting of metals	0.0069	0.0001	1	0.0073	0.0007	1	0.0325	0.0041	1	0.0146	0.0026	1	8
281	man. of struct and met prod	0.0028	0.0000	1	0.0022	0.0000	1	0.0472	0.0058	1	0.0207	0.0027	1	14
282	man. of tanks, reserv	0.0031	0.0001	1	0.0064	0.0013	1	0.0114	0.0027	1	0.0061	0.0027	1	29
283	man. of steam gen	0.0258	0.0020	1	0.0108	0.0305	0	0.0037	0.0024	1	-0.0031	0.0018	0	15
284	forg, press, stamp	0.0083	0.0001	1	0.0106	0.0002	1	0.0224	0.0029	1	0.0312	0.0039	1	9
285	treat, coat of met	0.0028	0.0000	1	0.0030	0.0000	1	0.0457	0.0057	1	0.0319	0.0040	1	20
286	man. of cutlery, tools	0.0074	0.0000	1	0.0073	0.0003	1	0.0240	0.0030	1	0.0302	0.0038	1	12
287	man. of other fab metal prod	0.0019	0.0000	1	0.0040	0.0000	1	0.0324	0.0041	1	0.0159	0.0023	1	29
291	man. of machin. for mech power	0.0082	0.0000	1	0.0067	0.0007	1	0.0159	0.0022	1	0.0120	0.0026	1	8
292	man. of other gen purpose machin.	0.0009	0.0000	1	0.0024	0.0001	1	0.0066	0.0025	1	0.0150	0.0025	1	24
293	man. of agric forestry machin.	0.0088	0.0000	1	0.0141	0.0009	1	0.0184	0.0024	1	0.0154	0.0026	1	9
294	man. of machine tools	0.0045	0.0001	1	0.0069	0.0006	1	0.0361	0.0045	1	0.0168	0.0025	1	18
295	man. of other spec purp machin.	0.0034	0.0000	1	0.0046	0.0002	1	0.0276	0.0035	1	0.0174	0.0026	1	14
296	man. of weapons and ammunition	0.1755	0.0008	1	0.0943	0.0137	1	0.0017	0.0013	1	0.0004	0.0022	0	3
297	man. of domestic appliances	0.0045	0.0001	1	0.0183	0.0022	1	0.0171	0.0027	1	0.0041	0.0025	1	25
300	man. of off, comp machin.	0.0147	0.0003	1	0.0436	0.0071	1	-0.0016	0.0024	0	-0.0012	0.0018	0	5
311	man. of elec. motors, gener	0.0025	0.0001	1	0.0057	0.0006	1	0.0055	0.0025	1	0.0079	0.0026	1	20
312	man. of elec. distrib	0.0056	0.0001	1	0.0128	0.0008	1	0.0149	0.0020	1	0.0065	0.0024	1	9
313	man. of insulated wire and cable	0.0059	0.0003	1	0.0105	0.0025	1	0.0179	0.0027	1	0.0014	0.0024	0	25
314	man. of accum, primar cell	0.0075	0.0008	1	0.0256	0.0083	1	0.0211	0.0027	1	0.0033	0.0024	0	9
315	man. of light equip, elect lamps	0.0085	0.0001	1	0.0112	0.0009	1	0.0024	0.0025	0	0.0064	0.0025	1	8
316	man. of electrical equip	0.0031	0.0000	1	0.0094	0.0010	1	0.0127	0.0023	1	0.0047	0.0019	1	15
321	man. of elec. valves, tubes	0.0070	0.0001	1	0.0124	0.0037	1	0.0124	0.0025	1	-0.0001	0.0023	0	12
322	man. of TV, radio for TV	0.0042	0.0000	1	0.0347	0.0014	1	0.0248	0.0031	1	-0.0004	0.0021	0	28
323	man. of TV, radio, sound, video	0.0059	0.0003	1	0.0075	0.0035	1	0.0049	0.0025	1	-0.0019	0.0026	0	19
331	man. of medic surg equip	0.0038	0.0000	1	0.0078	0.0001	1	0.0124	0.0021	1	-0.0023	0.0024	0	21
332	man. of instr. for measur	0.0153	0.0001	1	0.0286	0.0012	1	0.0031	0.0017	1	0.0003	0.0021	0	20
333	man. of ind proc control equip	0.0142	0.0002	1	0.0279	0.0026	1	0.0067	0.0018	1	-0.0002	0.0021	0	13
334	man. of opt instr, photo equip	0.0272	0.0000	1	0.0542	0.0013	1	0.0260	0.0033	1	0.0338	0.0042	1	8
335	man. of watches and clocks	0.0260	0.0011	1	0.0090	0.0068	0	0.0044	0.0020	1	-0.0022	0.0023	0	12
341	man. of motor vehicles	0.0266	0.0022	1	0.1411	0.0083	1	0.0041	0.0022	1	-0.0006	0.0013	0	17
342	man. of bodies for mot vehic	0.0053	0.0002	1	0.0088	0.0016	1	0.0119	0.0026	1	0.0071	0.0026	1	14
343	man. of parts, access for mot vehic	0.0185	0.0001	1	0.0211	0.0007	1	0.0154	0.0020	1	0.0157	0.0021	1	9
351	build and repair of boats	0.0195	0.0001	1	0.0336	0.0019	1	0.0230	0.0029	1	0.0110	0.0026	1	20
352	man. of rail and tram loco	0.0082	0.0012	1	0.0090	0.0042	1	0.0070	0.0026	1	0.0039	0.0026	1	22
353	man. of air and spacecraft	0.0292	0.0012	1	0.0878	0.0062	1	0.0063	0.0024	1	0.0031	0.0021	1	35
354	man. of motor and bicycles	0.0159	0.0001	1	0.0285	0.0046	1	0.0083	0.0024	1	0.0000	0.0017	0	10
355	man. of other transp equip	0.0000	0.0028	0	0.0091	0.0207	0	-0.0024	0.0027	0	-0.0027	0.0016	0	28
361	man. of furniture	0.0117	0.0000	1	0.0161	0.0000	1	-0.0026	0.0023	0	0.0068	0.0025	1	3
362	man. of jewellery	0.0361	0.0000	1	0.0859	0.0001	1	0.0017	0.0023	0	0.0004	0.0023	0	9
363	man. of musical instruments	0.0505	0.0003	1	0.0816	0.0024	1	0.0094	0.0022	1	0.0305	0.0038	1	3
364	man. of sports goods	0.0034	0.0003	1	0.0097	0.0023	1	0.0060	0.0027	1	0.0038	0.0026	0	19
365	man. of games and toys	0.0036	0.0002	1	0.0052	0.0016	1	0.0068	0.0026	1	0.0016	0.0024	0	19
366	miscell man. n.e.c.	0.0049	0.0000	1	0.0080	0.0003	1	-0.0025	0.0026	0	0.0025	0.0022	0	11
371	recycl of met waste and scrap	0.0045	0.0001	1	0.0051	0.0006	1	0.0290	0.0036	1	0.0151	0.0026	1	27
372	recycl of non-met waste and scrap	0.0018	0.0002	1	0.0010	0.0007	0	0.0092	0.0027	1	-0.0007	0.0027	0	33

Table 14: LLS - 3-digit - Sample of small plants

NACE	Industry	$\hat{\gamma}_{UW}$	$\sigma(\hat{\gamma}_{UW})$	Sign	$\hat{\gamma}_{EG}$	$\sigma(\hat{\gamma}_{EG})$	Sign	I_{UW}	$\sigma(I_{UW})$	Sign	I_W	$\sigma(I_W)$	Sign	Outl.
151	prod proc pres of meat prod	0.0092	0.0000	1	0.0114	0.0001	1	0.0155	0.0025	1	0.0145	0.0025	1	11
152	proc and pres of fish prod	0.0206	0.0004	1	0.0292	0.0008	1	0.0360	0.0045	1	0.0182	0.0023	1	14
153	proc and pres of fruit	0.0103	0.0001	1	0.0106	0.0001	1	0.1038	0.0127	1	0.0924	0.0113	1	17
154	man. of veg and anim oils	0.0125	0.0000	1	0.0137	0.0001	1	0.1248	0.0152	1	0.0998	0.0122	1	24
155	man. of dairy prod	0.0055	0.0000	1	0.0067	0.0000	1	0.0405	0.0050	1	0.0331	0.0042	1	21
156	man. of grain mill prod	0.0061	0.0001	1	0.0062	0.0001	1	0.0429	0.0053	1	0.0271	0.0034	1	13
157	man. of prep animal feeds	0.0069	0.0002	1	0.0081	0.0004	1	0.0219	0.0028	1	0.0164	0.0027	1	16
158	man. of other food prod	0.0029	0.0000	1	0.0022	0.0000	1	0.0817	0.0100	1	0.0585	0.0072	1	18
159	man. of beverages	0.0076	0.0000	1	0.0078	0.0001	1	0.0444	0.0055	1	0.0335	0.0042	1	16
160	man. of tobacco prod	0.0586	0.0018	1	0.0293	0.0033	1	0.0276	0.0035	1	0.0185	0.0026	1	9
171	prep. and spin of text fibres	0.2443	0.0000	1	0.2150	0.0001	1	0.0007	0.0011	0	0.0014	0.0012	1	5
172	textile weaving	0.2470	0.0000	1	0.1849	0.0001	1	0.0008	0.0009	1	0.0003	0.0012	0	5
173	finishing of text	0.0610	0.0001	1	0.0861	0.0002	1	0.0035	0.0018	1	0.0032	0.0018	1	12
174	man. of made-up text art	0.0038	0.0000	1	0.0072	0.0001	1	0.0037	0.0026	0	0.0092	0.0025	1	10
175	man. of other text	0.0123	0.0000	1	0.0204	0.0001	1	0.0086	0.0023	1	0.0114	0.0021	1	5
176	man. of knitt and croch fab	0.0187	0.0000	1	0.0182	0.0001	1	0.0180	0.0024	1	0.0138	0.0025	1	13
177	man. of knitt and croch art	0.0099	0.0000	1	0.0103	0.0000	1	0.0260	0.0033	1	0.0254	0.0032	1	21
181	man. of leather clothes	0.0326	0.0001	1	0.0385	0.0002	1	0.0166	0.0023	1	0.0167	0.0022	1	9
182	man. of other wear appar	0.0024	0.0000	1	0.0034	0.0000	1	0.0256	0.0032	1	0.0186	0.0026	1	21
183	dress and dyeing of fur man.	0.0109	0.0000	1	0.0107	0.0001	1	-0.0024	0.0024	0	-0.0014	0.0024	0	2
191	tanning and dres of leather	0.2041	0.0001	1	0.2477	0.0001	1	-0.0021	0.0020	0	-0.0025	0.0020	0	6
192	man. of luggage, bags	0.0667	0.0000	1	0.0872	0.0000	1	0.0002	0.0012	0	0.0004	0.0010	0	8
193	man. of footwear	0.0255	0.0000	1	0.0262	0.0000	1	0.0591	0.0073	1	0.0505	0.0062	1	6
201	sawmil and impregn of wood	0.0060	0.0000	1	0.0100	0.0001	1	0.0289	0.0036	1	0.0238	0.0030	1	21
202	man. of venter sheets	0.0205	0.0004	1	0.0219	0.0006	1	0.0208	0.0027	1	0.0248	0.0031	1	8
203	man. of uilders'carp and joinery	0.0031	0.0000	1	0.0028	0.0000	1	0.0570	0.0070	1	0.0340	0.0043	1	14
204	man. of wooden containers	0.0042	0.0001	1	0.0040	0.0001	1	0.0337	0.0042	1	0.0210	0.0027	1	25
205	man. of oth prod. of wood	0.0042	0.0000	1	0.0037	0.0000	1	0.0185	0.0025	1	0.0114	0.0026	1	21
211	man. of pulp, pap and paperboard	0.0141	0.0006	1	0.0220	0.0010	1	0.0131	0.0026	1	0.0170	0.0024	1	7
212	man. of art of pap and paperboard	0.0046	0.0000	1	0.0052	0.0001	1	0.0015	0.0020	0	0.0019	0.0019	0	13
221	publishing	0.0451	0.0000	1	0.0549	0.0000	1	-0.0034	0.0020	0	-0.0039	0.0020	0	3
222	printing and rel services	0.0078	0.0000	1	0.0088	0.0000	1	0.0033	0.0022	1	-0.0016	0.0020	0	4
223	repro of record media	0.0305	0.0003	1	0.0683	0.0008	1	-0.0043	0.0016	0	-0.0035	0.0012	0	3
231	man. of coke oven prod	0.0057	0.0567	0	0.0058	0.0885	0	-0.0019	0.0023	0	-0.0023	0.0020	0	3
232	man. of refined petrol prod.	0.0036	0.0002	1	0.0042	0.0004	1	0.0754	0.0092	1	0.0595	0.0073	1	37
233	proc of nuclear fuel	na	na	na	na	na	na	-0.0027	0.0004	1	-0.0027	0.0004	1	1
241	man. of basic chemicals	0.0053	0.0001	1	0.0030	0.0002	1	0.0032	0.0019	1	0.0076	0.0025	1	13
242	man. of agro-chem prod.	0.0082	0.0016	1	0.0070	0.0029	1	0.0031	0.0027	0	0.0022	0.0026	0	20
243	man. of paints, varnish	0.0025	0.0001	1	0.0035	0.0002	1	0.0101	0.0025	1	0.0038	0.0024	1	28
244	man. of pharmac, med chem	0.0650	0.0003	1	0.0466	0.0005	1	-0.0022	0.0019	0	-0.0005	0.0020	0	3
245	man. of soap and deterg	0.0087	0.0001	1	0.0125	0.0002	1	0.0021	0.0019	0	0.0064	0.0018	1	18
246	man. of other chem prod	0.0081	0.0001	1	0.0138	0.0002	1	0.0075	0.0018	1	0.0063	0.0018	1	18
247	man. of man.-made fibres	0.0134	0.0056	1	0.0173	0.0076	1	0.0134	0.0026	1	0.0139	0.0025	1	10
251	man. of rubber prod	0.0119	0.0001	1	0.0168	0.0002	1	0.0167	0.0023	1	0.0151	0.0021	1	14
252	man. of plastic prod	0.0029	0.0000	1	0.0032	0.0000	1	0.0305	0.0038	1	0.0379	0.0047	1	12
261	man. of glass and glass prod	0.0093	0.0000	1	0.0089	0.0001	1	0.0113	0.0019	1	0.0037	0.0019	1	8
262	man. of refr and non-refr ceramics	0.0135	0.0000	1	0.0202	0.0001	1	0.0200	0.0026	1	0.0140	0.0026	1	20
263	man. of ceramic tiles and flags	0.1171	0.0004	1	0.1974	0.0007	1	0.0083	0.0013	1	0.0055	0.0011	1	6
264	man. of bricks, tiles and constr	0.0129	0.0003	1	0.0149	0.0007	1	0.0349	0.0044	1	0.0208	0.0027	1	17
265	man. of cement, lime and plaster	0.0127	0.0003	1	0.0103	0.0007	1	0.0513	0.0063	1	0.0297	0.0037	1	20
266	man. of art of concr, plast	0.0039	0.0000	1	0.0037	0.0000	1	0.0730	0.0090	1	0.0534	0.0066	1	17
267	cutting, finish of stone	0.0075	0.0000	1	0.0098	0.0000	1	0.0386	0.0048	1	0.0265	0.0034	1	21
268	man. of other non-met prod	0.0039	0.0002	1	0.0063	0.0003	1	0.0134	0.0026	1	0.0106	0.0026	1	18
271	man. of basic iron, steel	0.0082	0.0015	1	0.0040	0.0028	0	0.0154	0.0026	1	0.0063	0.0027	1	13
272	man. of tubes	0.0066	0.0006	1	0.0068	0.0011	1	0.0146	0.0026	1	0.0144	0.0026	1	15
273	other proc of iron, steel	0.0097	0.0002	1	0.0110	0.0003	1	0.0151	0.0023	1	0.0183	0.0024	1	19
274	man. of non-ferr met	0.0130	0.0003	1	0.0116	0.0007	1	0.0140	0.0024	1	0.0047	0.0025	1	13
275	casting of metals	0.0076	0.0001	1	0.0086	0.0002	1	0.0354	0.0044	1	0.0386	0.0048	1	10
281	man. of struct and met prod	0.0018	0.0000	1	0.0011	0.0000	1	0.0593	0.0073	1	0.0250	0.0032	1	18
282	man. of tanks, met cont	0.0036	0.0002	1	0.0046	0.0003	1	0.0070	0.0026	1	0.0080	0.0027	1	24
283	man. of steam gen, exc centr heat	0.0326	0.0026	1	0.0447	0.0043	1	0.0031	0.0024	0	0.0014	0.0021	0	12
284	forg, press, roll of met	0.0118	0.0001	1	0.0103	0.0001	1	0.0193	0.0025	1	0.0251	0.0032	1	10
285	treat, coat of met, gen mech	0.0044	0.0000	1	0.0050	0.0000	1	0.0467	0.0058	1	0.0447	0.0055	1	18
286	man. of cutlery, and gen hard	0.0096	0.0000	1	0.0089	0.0001	1	0.0249	0.0032	1	0.0384	0.0048	1	13
287	man. of other fab metal prod	0.0013	0.0000	1	0.0022	0.0000	1	0.0472	0.0058	1	0.0296	0.0037	1	27
291	man. of machin for mech power	0.0089	0.0000	1	0.0116	0.0001	1	0.0172	0.0022	1	0.0218	0.0028	1	8
292	man. of other gen purpose machin	0.0021	0.0000	1	0.0029	0.0000	1	0.0089	0.0024	1	0.0114	0.0023	1	26
293	man. of agric forestry machin	0.0062	0.0000	1	0.0066	0.0001	1	0.0213	0.0027	1	0.0210	0.0027	1	10
294	man. of machine tools	0.0069	0.0001	1	0.0064	0.0001	1	0.0339	0.0042	1	0.0401	0.0050	1	11
295	man. of other purpose machin	0.0044	0.0000	1	0.0049	0.0000	1	0.0274	0.0035	1	0.0318	0.0040	1	11
296	man. of weapons and ammunition	0.1636	0.0008	1	0.1888	0.0018	1	0.0020	0.0012	1	0.0030	0.0015	1	4
297	man. of domestic appliances	0.0055	0.0001	1	0.0067	0.0003	1	0.0128	0.0025	1	0.0141	0.0027	1	26
300	man. of off, account, comp machin	0.0203	0.0003	1	0.0172	0.0004	1	-0.0022	0.0022	0	0.0001	0.0022	0	6
311	man. of elec motors, gener	0.0034	0.0001	1	0.0042	0.0001	1	0.0092	0.0023	1	0.0140	0.0024	1	24
312	man. of electr dist, contr appar	0.0090	0.0001	1	0.0091	0.0001	1	0.0171	0.0022	1	0.0162	0.0021	1	8
313	man. of insulated wire and cable	0.0068	0.0004	1	0.0089	0.0008	1	0.0255	0.0032	1	0.0216	0.0028	1	24
314	man. of accum, and batt	0.0098	0.0009	1	0.0121	0.0018	1	0.0179	0.0026	1	0.0032	0.0026	0	7
315	man. of light equip, elect lamps	0.0093	0.0001	1	0.0151	0.0001	1	0.0003	0.0024	0	0.0032	0.0023	1	8
316	man. of electrical equip	0.0058	0.0000	1	0.0056	0.0000	1	0.0144	0.0022	1	0.0174	0.0023	1	15
321	man. of electr valves, tubes	0.0099	0.0001	1	0.0118	0.0002	1	0.0149	0.0025	1	0.0122	0.0024	1	10
322	man. of TV, radio, app for TV	0.0047	0.0000	1	0.0079	0.0000	1	0.0176	0.0023	1	0.0015	0.0023	0	15
323	man. of TV, radio, sound, video	0.0080	0.0003	1	0.0103	0.0005	1	0.0034	0.0023	1	0.0040	0.0023	1	26
331	man. of medic surg equip	0.0051	0.0000	1	0.0061	0.0000	1	0.0079	0.0023	1	0.0005	0.0023	0	14
332	man. of instr for measur	0.0180	0.0001	1	0.0223	0.0001	1	0.0041	0.0017	1	0.0061	0.0017	1	21
333	man. of ind proc control equip	0.0191	0.0002	1	0.0165	0.0004	1	0.0076	0.0018	1	0.0113	0.0021	1	13
334	man. of opt instr, photo equip	0.0242	0.0000	1	0.0468	0.0001	1	0.0247	0.0031	1	0.0269	0.0034	1	8
335	man. of watches and clocks	0.0338	0.0011	1	0.0293	0.0023	1	0.0060	0.0020	1	0.0045	0.0024	1	9
341	man. of motor vehicles	0.0018	0.0074	0	-0.0075	0.0097	0	0.0018	0.0026	0	0.0011	0.0026	0	14
342	man. of bodies for mot vehic	0.0042	0.0003	1	0.0053	0.0004	1	0.0128	0.0027	1	0.0083	0.0027	1	22
343	man. of parts for mot vehic	0.0198	0.0001	1	0.0246	0.0003	1	0.0145	0.0019	1	0.0134	0.0018	1	11
351	build and repair of boats	0.0164	0.0000	1	0.0235	0.0001	1	0.0222	0.0028	1	0.0147	0.0026	1	23
352	man. of rail and tram loco	0.0064	0.0031	1	0.0052	0.0059	0	-0.0022	0.0026	0	-0.0014	0.0026	0	10
353	man. of air and spacecraft	0.0140	0.0021	1	0.0098	0.0041	1	0.0032	0.0026	0	-0.0005	0.0026	0	25
354	man. of motor and bicycles	0.0164	0.0001	1	0.0220	0.0003	1	0.0094	0.0024	1	0.0080	0.0024	1	9
355	man. of other transp equip	0.0019	0.0027	0	0.0011	0.0059	0	-0.0041	0.0027	0	0.0009	0.0026	0	37
361	man. of furniture	0.0094	0.0000	1	0.0128	0.0000	1	-0.0023	0.0021	0	0.0021	0.0023	0	5
362	man. of jewellery	0.0327	0.0000	1	0.0747	0.0000	1	0.0007	0.0023	0	-0.0005	0.0022	0	8
363	man. of musical instruments	0.0488	0.0002	1	0.0654	0.0006	1	0.0070	0.0022	1	0.0145	0.0019	1	3
364	man. of sports goods	0.0036	0.0003	1	0.0049	0.0006	1	0.0054	0.0027	1	0.0070	0.0027	1	18
365	man. of games and toys	0.0039	0.0002	1	0.0047	0.0004	1	0.0065	0.0026	1	0.0133	0.0026	1	23
366	miscell man.	0.0058	0.0000	1	0.0070	0.0001	1	-0.0050	0.0025	0	0.0007	0.0024	0	10
371	recycl of met waste and scrap	0.0045	0.0001	1	0.0040	0.0002	1	0.0275	0.0035	1	0.0232	0.0029	1	31
372	recycl of non-met waste and scrap	0.0013	0.0002	1	0.0011	0.0004	1	0.0109	0.0027	1	-0.0003	0.0027	0	32

Table 15: LLS - 3-digit - Sample of large plants

NACE	Industry	$\hat{\gamma}_{UW}$	$\sigma(\hat{\gamma}_{UW})$	Sign	$\hat{\gamma}_{EG}$	$\sigma(\hat{\gamma}_{EG})$	Sign	I_{UW}	$\sigma(I_{UW})$	Sign	I_W	$\sigma(I_W)$	Sign	Outl.
151	prod proc pres of meat prod	0.0109	0.0003	1	0.0098	0.0013	1	0.0128	0.0025	1	0.0113	0.0026	1	21
152	proc and pres of fish prod	0.0216	0.0021	1	0.0243	0.0061	1	0.0276	0.0035	1	0.0084	0.0023	1	23
153	proc and pres of fruit	0.0260	0.0006	1	0.0269	0.0013	1	0.0475	0.0059	1	0.0310	0.0039	1	10
154	man. of veg and anim oils	0.0214	0.0018	1	0.0168	0.0032	1	0.0162	0.0026	1	0.0074	0.0026	1	18
155	man. of dairy prod	0.0068	0.0005	1	0.0028	0.0015	0	0.0077	0.0027	1	0.0103	0.0027	1	24
156	man. of grain mill	0.0104	0.0013	1	0.0103	0.0036	1	0.0049	0.0027	1	0.0013	0.0026	0	31
157	man. of prep anim feeds	0.0115	0.0013	1	0.0132	0.0031	1	0.0117	0.0027	1	0.0063	0.0026	1	30
158	man. of other food prod	0.0021	0.0002	1	0.0062	0.0012	1	0.0105	0.0027	1	-0.0008	0.0025	0	19
159	man. of beverages	0.0065	0.0004	1	0.0035	0.0009	1	0.0193	0.0027	1	0.0041	0.0027	1	18
160	man. of tobacco prod	0.0176	0.0020	1	0.0098	0.0059	0	0.0382	0.0048	1	0.0220	0.0028	1	24
171	prep. and spin of text fibres	0.0556	0.0003	1	0.0389	0.0007	1	0.0164	0.0024	1	0.0267	0.0034	1	4
172	textile weaving	0.0644	0.0003	1	0.0382	0.0008	1	0.0098	0.0024	1	0.0172	0.0025	1	11
173	finishing of text	0.0894	0.0003	1	0.0792	0.0005	1	0.0032	0.0022	1	0.0040	0.0022	1	9
174	man. of made-up text art	0.0174	0.0008	1	0.0165	0.0015	1	0.0018	0.0026	0	0.0075	0.0026	1	12
175	man. of other text	0.0128	0.0005	1	0.0094	0.0010	1	0.0133	0.0026	1	0.0155	0.0027	1	15
176	man. of knitt and croch fab	0.0225	0.0010	1	0.0159	0.0014	1	0.0075	0.0026	1	0.0074	0.0026	1	11
177	man. of knitt and croch art	0.0182	0.0002	1	0.0212	0.0005	1	0.0171	0.0026	1	0.0125	0.0025	1	16
181	man. of leather clothes	0.0573	0.0029	1	0.0594	0.0037	1	0.0065	0.0021	1	0.0085	0.0022	1	25
182	man. of other wear appar	0.0106	0.0001	1	0.0082	0.0002	1	0.0271	0.0034	1	0.0221	0.0028	1	23
183	dress and dyeing of fur man.	0.0033	0.0073	0	0.0008	0.0121	0	0.0061	0.0027	1	0.0040	0.0023	1	13
191	tanning and dres of leather	0.2189	0.0004	1	0.2020	0.0007	1	0.0016	0.0022	0	0.0027	0.0020	1	9
192	man. of luggage, bags	0.0659	0.0006	1	0.0668	0.0011	1	0.0042	0.0016	1	0.0034	0.0018	1	26
193	man. of footwear	0.0312	0.0001	1	0.0320	0.0003	1	0.0385	0.0048	1	0.0342	0.0043	1	15
201	sawmil and impregn of wood	0.0150	0.0013	1	0.0134	0.0018	1	0.0197	0.0026	1	0.0203	0.0026	1	15
202	man. of venter sheets	0.0195	0.0011	1	0.0200	0.0022	1	0.0047	0.0026	1	0.0020	0.0026	0	14
203	man. of uilders'carp and joinery	0.0094	0.0005	1	0.0096	0.0009	1	0.0156	0.0025	1	0.0134	0.0026	1	19
204	man. of wooden containers	0.0123	0.0012	1	0.0154	0.0020	1	0.0118	0.0026	1	0.0077	0.0026	1	17
205	man. of oth prod. of wood	0.0181	0.0007	1	0.0245	0.0010	1	0.0154	0.0026	1	0.0164	0.0026	1	14
211	man. of pulp, pap and paperboard	0.0096	0.0011	1	0.0059	0.0028	1	0.0101	0.0026	1	0.0028	0.0027	0	8
212	man. of art of pap and paperboard	0.0034	0.0002	1	0.0054	0.0005	1	0.0036	0.0026	0	-0.0001	0.0025	0	9
221	publishing	0.0788	0.0005	1	0.1080	0.0019	1	-0.0047	0.0018	0	-0.0050	0.0016	1	3
222	printing and serv rel to print	0.0117	0.0002	1	0.0202	0.0009	1	-0.0004	0.0020	0	-0.0014	0.0021	0	16
223	reproduction of record media	0.3930	0.0104	1	0.5573	0.0138	1	-0.0025	0.0011	0	-0.0025	0.0006	1	3
231	man. of coke oven prod	na	na	na	na	na	na	-0.0015	0.0005	0	-0.0015	0.0005	0	1
232	man. of refined petrol prod	0.0068	0.0010	1	0.0468	0.0056	1	0.0249	0.0032	1	0.0058	0.0023	1	28
233	proc of nuclear fuel	na	na	na	na	na	na	-0.0022	0.0005	0	-0.0022	0.0005	0	1
241	man. of basic chem	0.0067	0.0004	1	0.0106	0.0017	1	0.0091	0.0024	1	0.0009	0.0026	0	16
242	man. of agro-chem prod	0.0369	0.0067	1	0.0402	0.0096	1	0.0019	0.0024	0	0.0036	0.0024	1	14
243	man. of paints, varnish	0.0115	0.0008	1	0.0314	0.0017	1	0.0018	0.0022	0	0.0001	0.0017	0	15
244	man. of pharmac, med chem	0.0776	0.0004	1	0.1188	0.0014	1	-0.0011	0.0015	0	-0.0023	0.0013	0	4
245	man. of soap and deterg	0.0212	0.0008	1	0.0295	0.0027	1	0.0102	0.0020	1	0.0046	0.0023	1	8
246	man. of other chem prod	0.0246	0.0006	1	0.0175	0.0022	1	0.0036	0.0017	1	0.0034	0.0023	1	13
247	man. of man-made fibres	0.0203	0.0036	1	0.0072	0.0081	0	0.0137	0.0025	1	-0.0011	0.0026	0	16
251	man. of rubber prod	0.0163	0.0005	1	0.0054	0.0025	1	0.0065	0.0020	1	0.0123	0.0026	1	10
252	man. of plastic prod	0.0028	0.0001	1	0.0026	0.0002	1	0.0072	0.0027	1	0.0076	0.0027	1	14
261	man. of glass and glass prod	0.0231	0.0005	1	0.0160	0.0028	1	0.0041	0.0025	1	0.0019	0.0025	0	22
262	man. of refr and non-refr ceramics	0.0478	0.0007	1	0.0372	0.0018	1	0.0064	0.0021	1	0.0045	0.0021	1	19
263	man. of ceramic tiles and flags	0.1724	0.0005	1	0.2229	0.0011	1	0.0154	0.0020	1	0.0120	0.0016	1	6
264	man. of bricks, tiles and constr	0.0159	0.0008	1	0.0165	0.0012	1	0.0140	0.0026	1	0.0127	0.0026	1	15
265	man. of cement, lime and plaster	0.0114	0.0015	1	0.0095	0.0031	1	0.0153	0.0026	1	0.0037	0.0026	0	27
266	man. of art of concr, plast	0.0091	0.0003	1	0.0097	0.0004	1	0.0158	0.0024	1	0.0091	0.0025	1	11
267	cutting, shap, finish of stone	0.0457	0.0005	1	0.0546	0.0008	1	0.0177	0.0024	1	0.0183	0.0024	1	7
268	man. of other non-met min prod	0.0046	0.0016	1	0.0083	0.0024	1	-0.0021	0.0027	0	-0.0020	0.0026	0	32
271	man. of basic iron, steel	0.0204	0.0016	1	0.0549	0.0085	1	0.0113	0.0026	1	0.0006	0.0021	0	11
272	man. of tubes	0.0024	0.0013	0	0.0071	0.0059	0	0.0025	0.0027	0	0.0028	0.0020	1	38
273	other proc of iron, steel	0.0102	0.0007	1	0.0125	0.0019	1	0.0076	0.0021	1	0.0015	0.0024	0	17
274	man. of non-ferr met	0.0088	0.0011	1	0.0166	0.0029	1	0.0137	0.0026	1	0.0028	0.0024	0	14
275	casting of metals	0.0100	0.0004	1	0.0089	0.0013	1	0.0203	0.0026	1	0.0062	0.0026	1	13
281	man. of structural prod	0.0045	0.0001	1	0.0059	0.0002	1	0.0189	0.0024	1	0.0180	0.0025	1	13
282	man. of tanks, reserv	0.0067	0.0008	1	0.0106	0.0023	1	0.0094	0.0027	1	0.0035	0.0026	0	27
283	man. of steam gen, exc heat	0.0190	0.0073	1	0.0156	0.0405	0	0.0008	0.0026	0	-0.0039	0.0018	0	14
284	forg, press, roll of met	0.0113	0.0003	1	0.0120	0.0005	1	0.0194	0.0025	1	0.0257	0.0033	1	8
285	treat, coat of met, gen mech	0.0039	0.0001	1	0.0036	0.0002	1	0.0062	0.0025	1	0.0014	0.0025	0	14
286	man. of cutlery, and gen hard	0.0087	0.0003	1	0.0092	0.0007	1	0.0203	0.0026	1	0.0140	0.0027	1	12
287	man. of other fab metal prod	0.0077	0.0001	1	0.0093	0.0003	1	0.0099	0.0024	1	0.0078	0.0024	1	16
291	man. of machin for mech power	0.0124	0.0002	1	0.0063	0.0011	1	0.0173	0.0026	1	0.0062	0.0026	1	11
292	man. of other gen purp machin	0.0023	0.0001	1	0.0034	0.0004	1	0.0188	0.0026	1	0.0139	0.0026	1	19
293	man. of agric. forestry machin	0.0159	0.0007	1	0.0273	0.0033	1	0.0223	0.0028	1	0.0116	0.0025	1	28
294	man. of machine tools	0.0070	0.0003	1	0.0073	0.0013	1	0.0172	0.0026	1	0.0070	0.0026	1	16
295	man. of other pure machin	0.0039	0.0001	1	0.0045	0.0003	1	0.0260	0.0033	1	0.0122	0.0026	1	21
296	man. of weapons and ammunition	0.2159	0.0051	1	0.0849	0.0193	1	0.0008	0.0016	0	-0.0001	0.0023	0	3
297	man. of domestic appliances	0.0106	0.0006	1	0.0212	0.0028	1	0.0117	0.0026	1	0.0034	0.0026	0	14
300	man. of account, comp machin	0.0239	0.0016	1	0.0424	0.0123	1	-0.0002	0.0023	0	-0.0019	0.0018	0	15
311	man. of elec motors	0.0067	0.0005	1	0.0064	0.0014	1	0.0074	0.0026	1	0.0035	0.0027	0	19
312	man. of elec distrib	0.0037	0.0005	1	0.0141	0.0016	1	0.0020	0.0025	0	0.0033	0.0024	0	21
313	man. of insulated wire and cable	0.0094	0.0013	1	0.0065	0.0037	0	-0.0005	0.0026	0	-0.0001	0.0024	0	27
314	man. of accum, primar cell	0.0126	0.0056	1	0.0349	0.0130	1	0.0060	0.0027	1	0.0034	0.0025	0	21
315	man. of light equip, elect lamps	0.0248	0.0010	1	0.0077	0.0031	1	0.0074	0.0021	1	0.0045	0.0025	1	17
316	man. of elect equip	0.0035	0.0002	1	0.0067	0.0029	1	0.0040	0.0026	1	0.0022	0.0019	0	29
321	man. of electr valves, tubes	0.0070	0.0008	1	0.0076	0.0060	0	-0.0003	0.0026	0	0.0000	0.0024	0	31
322	man. of TV, radio, app. for TV	0.0195	0.0005	1	0.0489	0.0031	1	0.0008	0.0023	0	-0.0003	0.0021	0	5
323	man. of TV, radio, sound, video	0.0098	0.0021	1	0.0054	0.0074	0	-0.0003	0.0026	0	-0.0034	0.0026	0	22
331	man. of medic surg equip.	0.0290	0.0008	1	0.0429	0.0019	1	0.0012	0.0024	0	-0.0015	0.0023	0	12
332	man. of instr for measur	0.0247	0.0006	1	0.0324	0.0024	1	0.0037	0.0014	1	-0.0007	0.0021	0	16
333	man. of ind proc control equip.	0.0128	0.0011	1	0.0298	0.0050	1	0.0045	0.0023	1	-0.0020	0.0022	0	24
334	man. of opt instr, photo equip.	0.0677	0.0008	1	0.0699	0.0037	1	0.0343	0.0043	1	0.0295	0.0037	1	6
335	man. of watches and clocks	0.0217	0.0137	0	0.0164	0.0248	0	-0.0062	0.0025	0	-0.0057	0.0021	1	9
341	man. of motor vehicles	0.0379	0.0033	1	0.1319	0.0092	1	0.0048	0.0020	1	-0.0006	0.0014	0	15
342	man. of bodies for mot vehic	0.0093	0.0009	1	0.0098	0.0028	1	0.0052	0.0026	1	0.0065	0.0026	1	15
343	man. of parts for mot vehic	0.0255	0.0003	1	0.0197	0.0009	1	0.0128	0.0018	1	0.0140	0.0023	1	8
351	build and repair of boats	0.0430	0.0008	1	0.0433	0.0047	1	0.0112	0.0026	1	0.0085	0.0026	1	20
352	man. of rail and tram loco	0.0113	0.0021	1	0.0112	0.0047	1	0.0096	0.0027	1	0.0055	0.0026	1	26
353	man. of air and spacecraft	0.0640	0.0027	1	0.0872	0.0070	1	0.0064	0.0022	1	0.0030	0.0021	1	27
354	man. of motor and bicycles	0.0225	0.0010	1	0.0414	0.0084	1	0.0060	0.0026	1	0.0003	0.0017	0	15
355	man. of other transp. equip	0.1705	0.0501	1	0.0719	0.0754	0	-0.0021	0.0020	0	-0.0042	0.0016	0	6
361	man. of furniture	0.0248	0.0001	1	0.0241	0.0002	1	0.0134	0.0026	1	0.0153	0.0026	1	11
362	man. of jewellery	0.1287	0.0005	1	0.1154	0.0010	1	0.0010	0.0023	0	0.0018	0.0024	0	11
363	man. of musical instruments	0.1546	0.0060	1	0.1093	0.0106	1	0.0286	0.0036	1	0.0343	0.0043	1	4
364	man. of sports goods	0.0105	0.0038	1	0.0179	0.0075	1	0.0016	0.0027	0	0.0005	0.0026	0	25
365	man. of games and toys	0.0035	0.0028	0	0.0056	0.0057	0	0.0026	0.0026	0	-0.0020	0.0023	0	28
366	miscell man. n.e.c.	0.0173	0.0006	1	0.0119	0.0014	1	-0.0006	0.0019	0	0.0019	0.0023	0	14
371	recycl of met waste and scrap	0.0125	0.0098	0	0.0408	0.0136	1	0.0008	0.0026	0	0.0024	0.0023	0	15
372	recycl of non-met waste and scrap	0.0003	0.0043	0	-0.0035	0.0050	0	-0.0022	0.0027	0	-0.0038	0.0027	0	29