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The Bright Side of MAUP: an Enquiry on the Determinants of Industrial Agglomeration in the United States

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Abstract
Using county employment data for US and two appositely developed zoning algorithms, I compare the industrial concentration of manufacturing sectors calculated following the standard metropolitan and micropolitan statistical areas definition with two other counterfactuals, obtained by "gerrymandering" the original sample of counties. The methodology allows i) to obtain an unbiased estimate of industrial agglomeration which significantly improves on existing indices, and ii) to provide a ranking of industries according to their responsiveness to labour market determinants of agglomeration. Results show that labour market determinants explain one quarter of the variation of spatial agglomeration across industries.

Keywords
Industrial Agglomerations;, MAUP, Industrial Concentration

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1. Introduction

The high degree of spatial concentration of firms belonging to the same industry is a striking real world fact. A widely accepted theoretical explanation of its determinants has been proposed more than one century ago by Alfred Marshall (1890), who identifies the labour market pooling, input sharing and knowledge spillovers as the main drivers of the process. Empirical evidence, however, has not been satisfactorily eloquent in assessing the relative importance of the different determinants.

In this paper, I develop a new methodology aimed at disentangling the effects of the "labour market" determinants of agglomeration. Starting from an exploration of the Modifiable Areal Unit Problem (henceforth MAUP), i.e., the apparently unpredictable dependence of results on the size and the shape of spatial units, I argue that this variation can rather be interpreted as useful information, once in command of the process generating the spatial classification. More specifically, I compare the level of concentration of each industry calculated using the commuting-defined US metropolitan areas (Core Based Statistical Areas - CBSAs) against the level of concentration of the same industry in a counterfactual of randomly aggregated spatial units, arguing that the industry-specific difference in spatial concentration between the two datasets is proportional to the importance of the labour market determinants.

The reclassification of the aforementioned Marshallian determinants under the more general categories of "labour market related" and "non labour market related" is motivated by the empirical strategy, but it is also relevant for policy. Examples of labour market determinants may be the need for specific skills, for low wages, or for an environment where workers can enjoy frequent interactions with an heterogeneous labour force, or also some local amenities which make the location particularly appealing for specific groups of workers; more generally, everything is capitalized by the firm through the labour force (via lower wages or higher productivity). Examples of non labour market determinants are input-output linkages between firms, access to local natural resources, lower prices for inputs other than labour. The aim of this paper is to assess which industries are most dependent on labour market determinants in their spatial concentration pattern, as opposed to other Marshallian determinants.

Labour market determinants may have a non-linear, and even non-monotonic, relationship with the variables that are commonly used to proxy the input intensity of industries (average wage, total labour compensation over total value of shipment, capital intensity, etc.). E.g., a particular industry may target a local endowment of low-wage labour force, another a highly skilled one. Both the industries may consider labour supply as the most important determinant of their location, but they completely differ in the average wage level. Moreover, the hi-skill industry may be capital intensive, which implies that it allocates a low share of total costs to labour compensation, while the low-skill one is likely to have a large labour force and thus a bigger share of labour cost. Alternatively, capital intense production may require also repetitive and unqualified labour, which translates into a low average wage. Therefore, results from a cross-industry linear regression of a concentration index on measures of input intensity can be inconsistent.[1] This provides the main argument for developing a different approach, which does not require to estimate *a priori* how industries relate to local labour markets.

Functional areas based on the self-containment of commuting flows are generally used as an approximation of the spatial extent of single labour markets. We can therefore assume that commuting-defined areas exhibit the maximum value (among all the possible spatial classification based on the same building blocks) of "within homogeneity" and "between heterogeneity" of labour markets characteristics. At the same time, the effects of the determinants of agglomeration which are not dependent on the labour market (i.e., input-output linkages, market access and transport costs, natural advantages) are not affected by labour heterogeneity; the only spatial characteristics which matter, in this case, are location and distance. It follows

[1] One could theoretically interact industry input intensity with local factor endowments (as done, for instance, by Midelfart-Knarvik et al., 2000), but obtaining the necessary geographic and industrial data is impossible in most of the cases; moreover, one would still need to assume the process is monotonic in the interaction variable.

that the amount of concentration of each industry I find using a commuting-defined area should not be smaller than that found in a comparable dataset of randomly shaped spatial units (i.e., where the "ceteris paribus" condition holds for everything except the self-containment of commuting flows), and that this difference depends on the importance of the labour market determinants for that industry.

I also contribute to the existing literature by developing a new technique for correctly estimating the amount of spatial concentration of each industry. It is widely known that the traditional concentration measures (e.g., Gini or Krugman indices) are affected by the "dartboard effect" bias[2] (Ellison and Glaeser, 1997), i.e., the amount of spurious concentration given by the "lumpiness" of industrial establishment and the discrete classification of the space. Another, less known, source of bias for concentration indices is essentially geographic and is given by the arbitrary aggregation (or disaggregation) of events in a continuous space using exogenously defined spatial units.

Generally, however, scholars tend to ignore the geographical component of the bias, limiting themselves to controlling for the industry-specific plant employment concentration (e.g. Ellison and Glaeser, 1997; Maurel and Sedillot, 1999). Alternative approaches to the description of the pattern of industrial concentration are based on Point Pattern Analysis and on a continuous definition of space (Marcon and Puech, 2003; Duranton and Overman, 2005). These studies offer a more precise description of the concentration pattern via the elimination of the discrete spatial unit; but the latter is often a direct source of data and a natural target for policy, thus the approach may be limiting in few circumstances.

I propose a different approach, which consists in estimating the "noise" with a Monte Carlo procedure, and then in filtering out the industry-specific estimated noise from the estimates of industrial concentration. The vector of

[2] The definition comes from the metaphor used by Ellison and Glaeser (1997): if an industry exhibits high concentration of plant employment, then traditional indices will found positive concentration just for a statistical effect, even if the underlying spatial process is completely random (that is, even if one randomly throws plants to a map).

industry-specific values of the noise is given by the average concentration value (as measured by a “raw concentration index”) in a distributions of 1000 random counterfactuals, each of them obtained by i) randomly “shuffling” plants across the space and ii) randomly aggregating small (not necessarily contiguous) portions of space (US Zip Code Areas – ZCAs) into spatial units of the same size of the real ones (CBSAs). Step i) captures the “lumpiness” effect, and step ii) the geographical bias. By applying this procedure I obtain a distribution of "spurious concentration" for each industry, which I can easily use to estimate the amount of “true” concentration (and to test its significance).

Thus, I will assess the level of concentration of each industry in a way which meets all the criteria listed by Combes and Overman (2004): measures are comparable across activities and spatial scales, they take a unique known value under the null hypothesis of no systematic component in the location process, it is possible to report their significance, the spatial and industrial classification are controlled for, and the estimation technique is related to explicit assumptions about theory.

To sum up, I use year 2000 data from the County Business Patterns (CBP) from US Census to calculate the industrial concentration for the manufacturing 6-digit sectors in three different settings: in the first one the spatial unit is the CBSA, in the second one (the noise) it is a random aggregation of non contiguous ZCAs, and in the third one (the counterfactual) it is a random aggregation of contiguous counties. The size distribution and the number of spatial units will be the same in the three datasets. I calculate the difference between the first two values as an unbiased index of industrial concentration, and the ratio between the first and the third values as an estimate of the relative importance of labour market determinants for each industry.

2. The Determinants of Concentration: Theory and Evidence

Industrial clustering is a striking real world fact and economists have been speculating on its determinants since more than a century. The principal theoretical reference is Marshall's *Principles in Economics* (1890), which identifies in labour market pooling, knowledge spill-over, and input-output linkages the drivers of industrial clustering. More recent works formalize original Marshall's intuitions, reclassifying the determinants according to a more theoretical informed taxonomy, composed by matching, sharing, and learning mechanisms (Duranton and Puga, 2004, who also provide an excellent survey on the topic). However this and similar contributions refer mostly to the agglomeration of economic activities as a whole (e.g., why cities exists), while little is told about the different concentration patterns of individual industries.

Despite the long-established theoretical foundations, empirics of concentration have not been conclusive so far. Contributions can be separated into two general categories: the *description* (or measurement) of the concentration pattern, and the *inference* on its determinants at industry level. It is obvious that if the former is misleading, also the results of the latter are unreliable.

The first issue has been recently critically surveyed by Combes and Overman (2004), who effectively point out all the limits of "attempts to collapse the entire structure of industrial production down to one number that can be compared across time and across countries" (p. 2855). These limits are particularly evident in the so-called first generation concentration (and specialization) indices – namely the Krugman index and Location Gini index – in the light of the failure to control for the aforementioned "dartboard" bias, and more generally to meet the target requirements identified by Combes and Overman.

The second generation indices, i.e., the EG index and similar (Ellison and Glaeser, 1997; Maurel and Sedillot, 1999), represent a significant improvement,[3] but are still fraught with problems. The Ellison-Glaeser index for industry k is equal to:

[3] Actually this assertion is questionable: although the second generation indices are more theoretical informed, on the other side in few cases a raw employment index is more policy relevant – for instance when we need to assess how much an industry shock translates into a regional shock. In such a case, the only thing that matters is the concentration of employment, irrespectively of the dartboard bias. In the context of this paper the advantages

$$\gamma_k = \frac{G_k - \left(1 - \sum_i x_i^2\right) H_k}{\left(1 - \sum_i x_i^2\right)(1 - H_k)} \qquad (1)$$

Where G is defined as

$$G_k = (s_i^k - x_i)^2 \qquad (2)$$

where *s* and *x* correspond to the share of total employment of region *i* for industry *k* and in the aggregate, respectively, and *H* is the plant employment Herfindahl index, corresponding to the sum of the squares of the share of employment of each plant, over the total employment of the industry. The EG index has the property of controlling simultaneously for the employment distribution among plants and regions. The authors demonstrate that their index takes the value of zero under the null hypothesis of random location conditional on the aggregate manufacturing employment in that region. Formally, the index derives from a simple model where firms choose their location according to natural advantages (first order spatial process), and intra-industry spillovers (second order spatial process). The processes are observationally equivalent, as both translate into an industry employment share higher than the aggregate one.

The EG index generated a *Pax Romana* in the field. However, there are a few aspects which may still be improved. First, the Herfindahl index takes into account only the fewness, the average size, and the variance[4] of the size distribution of plants and regions; under the underlying statistical and theoretical hypotheses, this is sufficient to prove the unbiasedness of the index. However, more flexible approaches has proved to give rather different results

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of the second generation indices are evident, but it may be useful to keep in mind and that may not always be the case.

[4] As it is widely known, the Herfindahl index can be expressed as $1/n+n\sigma^2$, where σ^2 is the variance of the employment shares of plants. It therefore depends on the number of plants/regions, their average size, and the variance of their size.

(Duranton and Overman, 2005). My methodology will therefore exploit all available information on the two size distributions without need to rely on any statistical assumption. Second, equating the probability of a plant to “fall” in a given region to the region’s aggregate share of employment may not be the most logical null hypothesis (especially if there are many small regions and few plants for industry), as the size of plants may be endogenously determined by the industry pattern of concentration (as shown by Holmes and Stevens, 2002). I will follow a different approach, based on the number of manufacturing plant sites, rather than on the employment share (which is the same “null hypothesis” adopted by Duranton and Overman, 2005). Third, the variance of the employment size of regions is not the only geographical characteristic which contributes to generate the bias. As Arbia (2001), Overman and Combes (2004), and Duranton and Overman (2005) clearly explained, is the whole process of “taking points on a map and allocating them to units in a box” (Combes and Overman, 2004) that is arbitrary and likely to introduce a spurious component in the results. This happens because our “boxes” are generally not regular nor homogenous in both shape and size. Moreover, in the process we loose all the spatial information embedded in the data, and distance is collapsed to a binary variable in/out.

Regarding empirical inference, only few contributions provide evidence on the Marshallian microfoundations of agglomeration economies at industry level (Ellison and Glaeser, 2001; Rosenthal and Strange, 2001 and 2004). These studies are based on a linear regression of the EG index on industry-specific input intensity proxies. Results are not conclusive, however, for many possible reasons. The first one is data scarcity, both at geographical and industry level, with the results that the concentration pattern and the input intensity of industries are extremely difficult to quantify. Generally scholars use share of total cost as proxies but these are clearly endogenous, as firms chose locations (and therefore concentrate) in order to minimize costs. This has been acknowledged (e.g. Rosenthal and Strange, 2001) but not satisfactorily solved, to the best of my knowledge. Moreover, as already mentioned before, if the EG index contains a bias, this is transferred into the regression output.

Second, the effect of the determinants may be non linear and, more generally, difficult to parameterize. Third, path dependencies, local idiosyncratic dynamics, and unobserved factors may play a major role in explaining industrial concentration. All these elements provide the need for developing an alternative tool to explore the topic.

3. The MAUP and the Gerrymandering Approach

3.1. The Dark Side

Every geographical area may be divided in a theoretically infinite number of ways, and economic estimates may present huge variation among them. Moreover, differently from international comparison – where country borders have an economic and political meaning that is not comparable with any other geographic classification – in a sub-national setting researchers face a variety of administrative and functional divisions – each of them with its pros and cons – with the result that the choice of the spatial unit is often arbitrary, even in the rare cases in which it is not constrained by data availability. The complex and apparently unpredictable variation which the results of investigations based on "modifiable units" are prone to is called the "Modifiable Areal Unit Problem" (MAUP). The issue had first been raised by Gehlke and Biehl (1934), who essentially focussed on the scale problem. Openshaw and Taylor (1979) provided evidence of how the "shape" component of the MAUP plays an important role too. In their application, they generated several distributions of 10,000 random aggregations of the 99 Iowa Counties, varying the average size of the spatial units and calculating at each time the correlation between the shares of Republican votes and of elderly population. The magnitude of the range of values they obtained is extreme (-0.97 : + 0.99) and increases proportionally to the average size of spatial units. More recently, Briant et al. (2007) reconsider the role of MAUP with an application to French data. They perform standard economic geography analyses (applied to agglomeration, concentration, and trade), using administrative, functional, and random (geometric) spatial units. Although they find some variations in the results, they eventually reach the conclusion that "the MAUP induces much smaller distortions than economic misspecification" (p. 25). Two caveats, however, have to be kept in mind while assessing their findings: first, the random counterfactual is based on a single iteration, thus is not possible to test the statistical significance of their results; second, the French political geography may presents some peculiarities which limit the extendibility of their conclusions, as the authors themselves acknowledge.

A formal treatment of the topic is due to Arbia (1989), which shows how the distortions arising from scale and shape effects would be minimized if the units of analysis were: i) identical, in terms of shape, size and neighbouring structure; and ii) spatially independent. Given the difficulty of contemporaneously satisfying the two conditions, in the last years the MAUP has generally become part of the subconscious of spatial economists and regional scientists, and has seldom been taken into explicit consideration. In the rare case it happened, efforts to deal with it have been concentrated on obtaining a dataset of spatial units which would be "geographically meaningful" in relation to the enquired phenomenon,[5] or in getting rid of the spatial unit altogether by using a continuous definition of space (e.g., Duranton and Overman, 2005).

3.2. The Bright Side

My methodology is based on the hypothesis that the variation of outcomes given by the MAUP has an informative content, which can be exploited by confronting the properties of differently shaped datasets according to a known economic rationale. The idea that the MAUP, once under control of the researcher, may become a powerful tool has already been suggested by Openshaw (1977), but to the best of my knowledge no applications have been proposed so far.

[5] See Cheshire and Hay (1989) and Magrini (1999 and 2004), for an economic approach; quantitative geography also offer a wide literature on "optimal zoning" of areal units, e.g. Openshaw and Rao (1995).

In the present paper I examine the spatial distribution of industries across the United States, with the aim of assessing the role of labour market determinants as opposed to technological spillovers, input-output linkages, and natural advantages. In order to do that, I confront the level of concentration of each industry in the US "travel-to-work" regions (CBSAs – Core Based Statistical Areas) against the level of concentration of the same industries in a distribution of spatial units of the same average size, obtained by randomly aggregating the same sample of counties which form the CBSAs.

The US Office of Management and Budget defines the CBSAs by identifying a central county with a significant share of urban population and by subsequently aggregating the neighbouring counties which have high commuting linkages with the central one. The aim of this definition is to contain in the same spatial unit the place of work and of residence of workers.[6]

The spatial structure of CBSAs – based on a commuting-defined size and a densely populated centre – is crucial in order to introduce an important assumption, i.e., the borders of the CBSAs approximate the borders of individual labour markets. The coincidence of a spatial unit defined on the maximization of the self-containment of the commuting flows with the concept of "local labour market" is quite debated in the literature and complicated by the slippery definition of the latter. The labour market may be defined as a continuum not only in the spatial, but in almost any of its dimensions (Cheshire, 1979). Moreover, workers may have different commuting patterns according to their income and skills. However, some consensus has emerged in the last years on the comparative advantages of a zoning procedure which maximizes the self-containment of commuting flows (see Cheshire and Hay, 1989, p. 21-25, for a detailed discussion). The rationale for that rests on the consideration that the most immediate channel of adjustment and price-clearing within a spatial labour market is occupational mobility constrained to

[6] More information on the CBSA definition can be found in the US Census website (http://www.census.gov/population/www/estimates/metrodef.html) and in the part IX of the Office and Management and Budget Federal Register of 27/12/2000 (OMB, 2000).

residential immobility (people change the job but not the house).[7] In the following of the paper I will present an empirical exercise which corroborates the "labour market homogeneity" hypothesis.

In this context, however, I need a weaker assumption, because the focus is on a stylized location choice of firms, which may be assumed to be information constrained. Therefore, there is no need to take into account all the complex economic interactions between and within labour markets, but – more simply – the local labour supply "perception" of the firm; and this can reasonably be approximated by the commuting area. In other words, I simply assume that a firm which chooses to locate within a given CBSA expects to face a supply of workers which is spatially constrained by the extent of the estimated commuting area.

The CBSAs are merely statistical entities, they do not have any political or administrative meaning and may cross State borders. Hence, if we assume that the intensity of the "non labour market" determinants of concentration varies continuously across the physical space,[8] it follows that a couple of contiguous counties shares the same average intensity of input-output linkages, natural advantages, political environment, market access, etc.; but firms in each of the two counties are more likely to hire workers living in the CBSAs they belong to, so the intensity of the action of the labour market determinants will be different if they belong to a different CBSA.

It follows that two firms A and B located within a given CBSA are assumed to face the same labour supply irrespectively of bilateral distance between the two firms, because the closest predominant agglomeration of workers (the city) is the same. On the other side, two firms C and D situated at the same distance as A and B, but respectively linked to two different cities by the predominant commuting flows, face a supply of labour that is partly different. Consequently, the difference between A-B and C-D in the likelihood

[7] Functional areas have then a wider economic meaning, which is essentially given by containing within the same spatial unit the place of work and of residence of the majority of the inhabitants (or workers); but this is not relevant here.

[8] Considering that our sample is limited to the counties belonging to the CBSAs, i.e., to counties where a significant level of population or employment is present, the notion of distance we use is corrected for the general spatial distribution of economic activity.

to belong to the same industry is proportional to the importance of the labour market determinants for that industry. Generalizing the argument, if an industry is highly dependent on labour market characteristics, its heterogeneous distribution across space will follow the heterogeneous distribution of the labour endowment. Considering that higher spatial concentration equals higher heterogeneity among spatial units, it follows that the amount of concentration determined by the labour market characteristics is expected to be higher in a dataset in which the spatial units are defined in a way that maximizes the "within homogeneity" and the "between heterogeneity" of labour market characteristics, than in any other comparable dataset.

In order to clarify the concept, I introduce a simple example (Figure 1). Consider a one-dimensional space where there are four cities (1, 2, 3, and 4) and six industrial districts, belonging to four different industries (A, B, C, and D). Workers commute from cities to the nearest industrial district, thus forming the commuting area delimited by the ellipsoids in the upper diagram of Figure 1. Labour is the only input and the location of the different industries is only due to labour market determinants. A commuting-based classification (like the CBSAs) will subdivide the space into the four regions reported as rectangular polygons in the second line of the diagram, thus minimizing the commuting flows across different spatial units. In the bottom line we report another random classification, in which spatial units have the same size but the commuting flows are not taken into account. It immediately appears from the example that the amount of concentration we can measure using the commuting-based spatial classification is bigger than what we would find using any other spatial classification.

The methodology may recall the so-called "regression discontinuity approach", which has recently been applied in a geographical setting by Holmes (1998) and Duranton et al. (2006), among others. However the apparent analogy is misleading, because the discontinuity I exploit in this case is only approximate, given that we expect that some commuters will cross CBSAs borders. It is probably more useful to think of the CBSAs as the spatial classification which minimizes the cross-unit commuting flows.

In order for my methodology to be meaningful, I need to provide evidence that the CBSA classification presents similar characteristics to the stylized example. More specifically, the consistency of the methodology requires that (i) CBSAs have a highly populated centre and a set of outlying counties which are lower populated, where workers commute to and from; and (ii) almost the totality of the population lives and work in the same CBSA (but generally not in the same county), even those who reside close to the CBSA border.

The first condition is given by the definition properties of CBSAs, which are identified around an urban centre and comprehend the neighbouring, external counties. In the map in Figure 2 I report the CBSA borders layer together with a map of populated places; the map clearly shows a common pattern of urbanization in the central area of CBSAs.

To test the second condition, I used journey-to-work data from the 2000 Census, with the result that only the 9% of employees living in a CBSA work outside the same CBSA where they reside. On the other side, the 25% of workforce resident in a CBSA commute outside the County they reside in. This confirms that CBSAs truly contain the commuting flows, and, at the same time, there is a significant cross-county commuting activity.

3.3. A Real World Example

Figure 3 reports a closer view of the CBSA map, in order to provide an useful insight of how my assumptions fit the real world. The thick lines report CBSA borders, the thin lines the County borders, and the black polygons the "populated places". The digital maps are available from the US National Atlas website and refer to the period of analysis. The general pattern that emerges is a constellation of small one-county micropolitan areas which surround a few big metropolitan areas, composed of several counties. In both the micropolitan and metropolitan areas there is a populated agglomeration, normally the main city, at the centre of spatial units, and smaller villages around.

Looking at the picture, it should clearly appear how – in a world where the labour market does not matter for agglomeration – there is no reason to expect that the CBSA classification would better match the clustering of economic activities than any other random aggregation of counties. For instance, if in the North and South parts of the Indianapolis CBSA (at the centre of the picture) we register the presence of plants of the same industry and this industry is not present in Anderson, Columbus and Bloomington (neighbouring CBSAs on the southern side), then this is because of – according to my previous hypothesis – a specific need of that industry for the labour force residing in Indianapolis. Conversely, if firm location is driven by the need to supply another firm in Indianapolis, it can easily be located in Columbus or in Bloomington, because the only thing which matters in this case is the distance – there is no reason for this firm to prefer to locate inside the commuting area of Indianapolis, everything else being equal.

Of course there may be many other unobservable and idiosyncratic factors driving the firm location but, in a sample of 876 spatial units and more than 320,000 manufacturing plants, a general pattern should emerge, where the difference of concentration between the CBSA and a random classification is related to a "labour market determinants" story. This is, in a nutshell, the meaning of my work.

The reader may argue that the methodology is affected by a reverse causality problem, that is, the commuting flows are determined by industrial clustering and the labour market areas are shaped after the industrial clusters, rather than being their determinant. I think that this may seldom be the case, as I am considering only the manufacturing sector, which employs less than the 20% of the workforce, while the commuting flows are calculated on the whole sample of workers; moreover, often commuting patterns are determined by exogenous factors, like physical geography or long term investments in commuting infrastructures.

However, even it were the case, it would not affect the causal linkage that I am inferring here: the fact that the commuting flows *follow* industries' location does not necessarily imply that they come from the *same origin*, which is implied by being within the same CBSA. The evidence that they come from the same origin, i.e., that a given industrial cluster is drawing workers from a single labour market, and that this systematically happens over a big sample of spatial units, is, in my opinion, difficult to explain with a causality going on the opposite direction respect to what I assume in this paper.

4. Data

I use six-digit NAICS employment data for Zip Code Areas (ZCAs) and Counties in the year 2000, freely available from the County Business Patterns (CBP) of US Census Bureau, in the form of the dataset collected by Prof. Thomas Holmes, University of Minnesota, and freely downloadable from his website.[9] I also use a shape file from the National Atlas of the United States and the Luc Anselin's GeoDa software[10] to calculate a first order rook contiguity matrix[11] needed by the PSA algorithm (described in the next section).

Because of confidentiality issues, in the CBP database many employment records are reported only in approximated form, i.e., we only know the size class of the plant. There are various ways to overcome this problem (see Isserman and Westervelt, 2006, for a survey). As I do not need a precise locality-specific estimate, I followed the most straightforward route: I ascribed to every plant the average employment of the class it belongs to (as done, for example, also by Holmes and Stevens, 2004). Another minor problem is given by the fact that ZCAs employment data over 1000 employees are merged in only one class, instead of four as it is in counties data. In order to obtain comparable data (and, again, considering that the exact estimate of the employment of each ZCA is not relevant here), I attributed to ZCAs the distribution of employment class size of the counties data (industry-wise).

From the 3079 counties composing the Continental US (therefore excluding the States of Alaska, Porto Rico and Hawaii) I selected the records

[9] http://www.econ.umn.edu/~holmes/data/CBP. The dataset is described in Holmes and Stevens (2004).
[10] Freely downloadable from https://www.geoda.uiuc.edu/
[11] A first order rook contiguity matrix is a symmetric, square NxN matrix, where N is the number of spatial units, in which the element *mk* is equal to 1 if region m and k share a common border (longer than one pixel in the map), and equal to zero otherwise.

of the 1734 counties which are included in the 2000 standards Core Based Metropolitan and Micropolitan Statistical Areas (CBSAs). From these I eliminated 26 Micropolitan Statistical Areas which are isolated, i.e., do not share any border with other CBSAs and therefore would not show any variability among the random aggregations. I end up with a dataset of 1707 counties which account for the 97% of the total (continental) US population, and form 876 CBSAs, of which 306 are Metropolitan Statistical Areas and 570 are Micropolitan Statistical Areas. The definition procedure of Metropolitan and Micropolitan areas is exactly equivalent, but for the latter the population of the core county has to be smaller than 50,000. However, the overwhelming majority of Micropolitan Statistical Areas are composed by only one county, as a consequence of the fact that the commuting flows with the neighbouring counties are limited.

The same selection of the US territory is applied to the ZCAs dataset, using the ZCAs-counties geographical equivalence list, also available in Prof. Holmes website.[12]

5. Building the Counterfactuals

5.1. The Noise

As I mentioned earlier in the paper, the amount of concentration detected using raw employment concentration indices is affected by the "dartboard effect", i.e., the bias due to the interaction of the "lumpiness" of industrial establishments and of the discrete classification of space.

Trying to eliminate the bias without renouncing to a discrete classification of space may be extremely complex and beyond the scope of the present paper. It is relatively easy, instead, to create a counterfactual where the amount of concentration measured by a raw concentration index is totally

[12] As explained in the website, in few cases ZCAs can cross counties boundaries. Therefore, our selection may introduce a difference between the ZCAs dataset the CBMSA one. However the difference in total employment between the two datasets after the selection is extremely small (0,3%), which seems to be a negligible difference.

spurious, i.e., is given only by noise, in order to have an estimate of the bias specific to the given joint combination of the industry and spatial classifications.

Therefore, I apply a simple technique which exploits all the information contained in the plant employment distribution and in the spatial classification system. My approach consists in composing a distribution of 1000 datasets, each of them created by applying the following two-step algorithm to the original sample of plants under analysis:

a) The plants are "shuffled" across ZCAs (Zip Code areas, the smallest spatial units at which industry data are available), simulating a scenario where plant location is random *given* the spatial distribution pattern of all manufacturing plants. This means that every ZCA ends up with a random – in term of employment and industry – sample of plants, but with exactly the same number of plants it originally had.

b) The ZCAs are randomly aggregated – without any contiguity constraint – into bigger spatial units. The number of these spatial units is equivalent to the number of CBSA and every time a new spatial unit is created, its maximum employment size is drawn (without replacement) from the actual CBSA size distribution, in order to mimic the total employment distribution of the CBSA dataset. This step is meant to absorb the geographical bias embedded in the CBSA dataset, by reproducing an equivalent spurious aggregation of points into comparable "boxes" deprived of any spatial meaning (internal connectivity).

At every iteration, [13] a raw concentration index (the G concentration index) end the EG are calculated and stored. At the end of the process we obtain a distribution of values of the indices for each industry. Interestingly, for many industries the average G values are definitely high, while the values of the EG index are generally close to zero, but with significant exceptions,

[13] The assignment of plants to PSAs is a slow procedure – it takes around nine minutes with a standard PC. Repeating it 1000 times will take around 150 hours. Therefore, in order to speed up the algorithm, the step b) is repeated only every 50 iteration. However, the random variation of the results at every iteration is assured by the reshuffling of the plants in step a).

especially for industries with a small number of establishments. A more precise description of the "noise pattern" is reported in the next section.

5.2. The Pseudo Statistical Areas (PSAs)

In order to obtain a relative estimate of the importance of the labour market determinants for each industry, I need a counterfactual in which the spatial units are in all comparable to the CBSAs, except for the containment of the commuting flows. This implies two main requirements: i) the "Pseudo Statistical Areas" (PSAs) must be internally connected, and ii) they must follow the same size distribution of the CBSAs (in terms of total employment and area).

Therefore, I composed an algorithm[14] which randomly assigns the 1707 counties to 876 internally connected spatial units (every county which is going to be added to a PSA must be contiguous to at least one of the counties already composing the PSA). Its functioning can be summarized as follows: for every county that has not been assigned already, a random neighbour is chosen and added to a PSA-to-be. A vector including all the neighbours of the two counties is then created, from which a random contiguous county is chosen and included to the PSA-to-be. The process continues until the size and employment limit is reached, or all the counties around the PSA-to-be are assigned. In order to maximize the degree of internal connectivity, and therefore to avoid to shape PSAs as long rows of counties, the likelihood for a county to be added to a PSA is exponentially proportional to the number of contiguous counties already composing that PSA. For instance, if an unassigned county *i* is surrounded by counties which have already been assigned to the forming PSA, its probability to be assigned is much higher than it is for a county that has only one contiguous neighbour already assigned to the forming PSA.[15]

[14] The algorithm has been developed by the author and compiled in Matlab® language. Original scripts and more information on its functioning are available on request. Although many contributions have already been proposed on Automated Zoning Procedure (since, e.g., Openshaw 1977), to the best of my knowledge none of them satisfies the properties which I need in this case.

[15] The neighbour vector is sorted in decresing order according to the number of times every county is repeated; then a random number is drawn from an exponential distribution with

The algorithm is also aimed at closely mimicking the employment size distribution of CBSAs. This is obtained by imposing to every forming PSA a total employment limit drawn (without replacement) from the actual CBSA size distribution. For the bigger PSAs, the limit may not be reached, because contiguous counties have already been assigned. To avoid that, at every iteration the twenty biggest PSAs are the first to be composed, aggregating random counties around the twenty biggest counties.

Although there is a clear trade-off in replicating the size distribution without limiting the randomness of the aggregation, on average the moments of the PSA distribution are close to the ones of the CBSA distribution (Table 1, first two rows). While the focus is prevalently on the employment distribution, the algorithm contains also some instruction aimed at replicating the CBSA area distribution (Table 1, third and forth rows). The joint replication of both the distributions is important for two reasons: first, it avoids that the difference in concentration between the CBSA and PSA dataset contains a spurious component due to a different size distribution; second, it also contributes to keep the distributions of central and outlying counties across spatial units similar in the two datasets. In fact, as central counties are much denser populated than the outlying ones, a different repartition of them would necessarily end up in a different employment or area distribution.

The outcome of a single iteration of the algorithm are visualized in Figure 4, which reports the same area of Figure 2, substituting the CBSAs' borders with the PSAs' ones. The picture shows how the size and the shape of the spatial units are extremely similar to the original CBSA classification. Moreover, there are two other reasons which support the robustness of the results to potential isolated "strange geometries": first, they would generate a bias only for industry with a significant share of plants located in that area; second, and most important, the algorithm executes 1000 iterations, which implies that to have a bias we would also need the "strange geometries" not be

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the lambda parameter equal to three (thus skewed to the left) and bounded by the length of the vector of counties. The random number correspond to the position of the chosen county in the vector; lower is the number, more frequently the county is repeated in the vector. This implies that counties which are repeated most are more likely to be selected.

created always in the same location. At every iteration, a raw concentration index (the G index, defined in the following section) is calculated and stored.

As I mentioned earlier in the paper, I assume that the PSA counterfactual will be more heterogeneous in terms of labour market characteristics than it is in the CBSA dataset. I did a simple exercise to test this assumption: I calculated the coefficient of variation of an immediate proxy of labour market characteristics – the unemployment rate – in the CBSA and PSA dataset. In the CBSA dataset the value is equal to 0.377. In 1000 iterations of PSA dataset I obtain a mean of 0.331, a 90th percentile of 0.348, and a maximum of 0.366. It implies that the variation of the unemployment rate is higher in the CBSA dataset than in any of the 1000 counterfactuals, which in turn means that the requirement of a significantly bigger level of "between heterogeneity" of labour market characteristics is satisfied.

6. Results

For every industry, my "raw" results consist of the G values, calculated following the specification reported in (2), for three different groups of analysis: the CBSAs (a single value for each industry), the PSAs (random aggregation of contiguous counties, distribution of 1000 values for each industry), and the "noise" (random aggregation of non necessarily contiguous Zip Code Areas, distribution of 1000 values for each industry).

The meaning of these values is the following: the CBSA values at net of noise report the maximum, unbiased amount of concentration given by the action of all the determinants, while the PSA values at net of the noise should be smaller, because the effect of the labour market determinants is lower. The first value is calculated as the difference between the CBSA values and the average values of the "noise" distribution, while the second one is the difference of the average values of the two respective distributions (the PSA one and the noise). I also test the hypothesis that this difference is statistically null and I report the p-value of the test.

a) Noise: the values of the estimated "noise" provide extremely useful information for assessing the bias of the concentration index (Table 2). A first, striking result is that the noise is extremely “loud”: the average value of the G across the 473 manufacturing industries is 0.032, which in previous studies based on the value of that index would have been interpreted as a remarkable signal of concentration (with the caveat, however, that the small dimension of our spatial units and the highly detailed industrial classification partly contributes to generate big values).

b) CBSAs minus noise: 298 out of 473 manufacturing industries present a concentration at the CBSA level that is not compatible with the “noise” counterfactual at 5% level of confidence (215 at 1% level). On the contrary, only three industries exhibit a 5% significant negative value (Magnetic and optical recording media mfg; Biological product mfg; Quick printing). The most concentrated industries, once the noise is eliminated, are “Jewelers' material & lapidary work mfg”, “Sugarcane mills” and “Women's, girls' cut & sew dress mfg” . The Spearman rank correlation with the EG calculated on the same data and spatial classification is equal to 0.51. Therefore, there is a significant positive correlation, but the matching is far from being complete. Overall, my methodology seems to add some precision to the estimate, while the EG index does not eliminate the risks of misleading estimates for few industries, as shown in Table 2.

c) CBSA minus PSA: this difference is uninformative in its absolute value, because we cannot know how much of the labour market determinants effect is absorbed by the PSAs definition, given that it is a random counterfactual; but we can plausibly assume that it is a share of the total effect, and that it is constant across industries. A closer examination reveals that the latter assumption is much weaker than it may appears: the effect absorbed by the PSAs definition depends on how much the PSAs are geographically similar to the CBSAs, which in turn affect the values of all the industries in the same way. Considering that every industry has many plants in many locations, the space under analysis is the same for all the industries, and the values I use are averaged across 1000 iterations, the assumption is completely plausible.

An extremely simple formalization may clarify the meaning of the value. Let’s define the total concentration of industry k in the CBSAs dataset as

$$X_k = a_k + b_k$$

where *a* and *b* are the effect of labour and non labour market determinants, respectively. Let's then define the total concentration of industry *k* in the PSAs dataset as

$$Z_k = ma_k + b_k$$

where *m* is the unknown (but constant across industries) share of labour market effect captured by the PSA definition. It follows that the difference between the concentration in the CBSA-PSA dataset, industry-wise, is equal to:

$$X_k - Z_k = a_k - ma_k = j_k$$

which is directly proportional to *a* and is the value I will analyse.

The sign of the CBSA-PSA difference[16] is significantly positive at the 5% level in 125 cases (71 at 1%). It means that for around one quarter of manufacturing industries the level of spatial concentration given by the CBSA classification is significantly bigger (i.e., the industry employment has a more heterogeneous distribution across space) than when we use the PSA counterfactual.

Table 5 reports the first 50 industries according to the CBSA-PSA value, limited to the sample of industries with a 5% significant difference both in the CBSA-PSA and CBSA-noise difference. Interestingly, these industries do not show an immediate clear similarity in labour or skill intensity: both hi-tech and labour-intensive industries are in the list. E.g., among the first ten industries in the ranking, we find a few textile industries, as well as space vehicle manufacturing and optic fibre manufacturing. The hypothesis of a non monotonic relationship between input intensity and spatial concentration is thus validated, and confirms the advantages of a non parametric approach.

There are also few industries for which the CBSA-PSA difference is significantly negative: they are 23 in total, but only nine if the analysis is restricted to the industries with a 5% significant CBSA-noise difference. These nine industries are: *Electrometallurgical ferroalloy product mfg; Oil and gas field machinery and equipment mfg; Petrochemical mfg; Schiffli machine*

[16] From this point on, every mention of Noise and PSA values refers to the average value across 1000 iterations of the zoning algorithm.

embroidery; Animal (except poultry) slaughtering; All other basic organic chemical mfg; Sugarcane mills; Carbon black mfg; Softwood veneer and plywood mfg; Dried and dehydrated food mfg. For them, the employment ends up to be more heterogeneously distributed in the PSA counterfactual than in the CBSA dataset. This may depend on the specific pattern of within-CBSA location of these industries. An industry that is systematically located in "outer counties" of CBSAs may be more concentrated in the PSA dataset because there the outer counties are slightly more heterogeneously distributed than in the CBSA one. However, given that both the employment and area distributions of the PSA dataset mimic the correspondent distribution in the CBSA one, and considering that the central counties are more densely populated, unbalances between the number of central and outer counties in the PSA dataset should be limited, thus the bias is probably limited to a restricted number of outliers.

The CBSA and PSA difference is an absolute measure of the effect of labour market determinants. In order to assess the labour market effect conditional on the total amount of concentration, I calculate the ratio between the two "de-noised" values:

$$LMDI = (CBSA - noise)/(PSA - noise) \qquad (2)$$

I define this the "Labour Market Determinant s Index" (LMDI). This value provides us with an industry-specific estimate of the importance of the labour market determinants, relative to the whole sample of industries and the effects of the other concentration determinants. The subtraction of the noise from both the numerator and denominator allows to remove the spurious concentration component and to not underestimate the index when this component is large. The value is reported in the last column of table 5, and it is generally highly correlated with the CBSA – PSA one (which is logically implied by the low correlation of the total concentration with the CBSA – PSA difference).

6.1. Comparison of the “CBSA minus noise” values with the Ellison-Glaeser Index

A comparison of the results I obtain by using my noise algorithm provide empirical support for the discussion on the limits of the EG procedure. A similar exercise has already been done by Duranton and Overman (2005), who compared the results from a Point Pattern Analysis (PPA) of concentration of UK manufacturing to the values of the EG index at County level. They find a remarkable difference in the industry ranking, quantifiable in a Spearman rank correlation of 0.41.

Interestingly, while comparing my unbiased measure of concentration (CBSA – Noise) with the EG index calculated on the same data and spatial units (CBSA), I find a similar result, i.e., a Spearman rank correlation of 0.51 across all the 473 industries in the sample. However, while the difference with a Point Pattern Analysis may be attributable to a different concept of space definition – continuous vs. discrete – I calculate the two concentration measures using the same zoning criterion and exactly the same spatial units, thus providing stronger evidence on the limits of the EG approach. On the other side, this may suggest that my procedure gives results coherent with the PPA, but with the advantage of keeping a discrete spatial unit, which is often essential in order to match the concentration measure with other geographical datasets.

Another confirmation of the bias of the EG index – at least in this specific sample – comes from the analysis of its values in the noise counterfactual (average across 1,000 iterations). Given that it reproduces a completely random location process, we would ideally expect un unbiased index to give values close to zero. The EG index, however, may absorb some spurious concentration as it is prone to the geographical bias and to the other potential misspecifications discussed earlier. This is confirmed by data: I obtain an average of 0.02 across the 473 industries in the sample, which, according to Ellison and Glaeser (1997) indications, should be interpreted as evidence of localization. The distribution appears to be strongly skewed toward the right hand side, which means that the overestimate is particularly high for few industries (Table 4). Overall, 102 industries present a value bigger than 0.02, which implies that the bias is substantial for more than one fifth of industries. Therefore, the Noise counterfactual can provide the basis for further research on the distribution of the EG index under the null hypothesis of random location pattern.

6.2. Analysis at 4-digit level

In this section I present the results obtained using a wider industry classification, i.e., the 86 manufacturing sectors reported at the 4-digit industry level. There are three main reasons why this may be useful: first, the 6-digit is an extremely detailed classification and results, although very informative, may be biased by the presence of few peculiar sub-sectors, which may behave as outliers. Second, the sectors reported in CBP refer to the prevalent activity of the plants; it is likely that some plants are actually multi-product, thus, again, a too detailed classification may be misleading. Finally, the analysis at a higher level of industry classification disclose also new information *per se*.

The results – reported in table 6 – are coherent with the 6-digit analysis. The Spearman rank correlation between the G index at 4 and 6 digits is positive and significant for all the three different datasets (CBSAs, PSAs, Noise). 31, out of 86, manufacturing sectors exhibit a positive and significant (at 5%) CBSA – PSA difference, while the CBSA – Noise difference is significantly positive in 74 cases.

Similarly to the 6-digits analysis, the top sectors in the CBSA-PSA ranking do not show a linear dependence on labour input intensity, and a mix between low and high skill activities emerges. Again, it would be extremely complex to recognize such a pattern with a parametric analysis.

6.3. Does the labour market matter for concentration?

In order to assess to what extent the concentration driven by labour market determinants explains the general pattern of concentration, I regress the index reporting the total amount of concentration (CBSA – Noise) on the estimation of the labour market effect (CBSA – PSA). A positive and significant coefficient would reveal a systematic effect of the labour market determinants in explaining the overall pattern of spatial concentration.

At 6-digit level, results are dubious: the value of the coefficient is highly significant using OLS, but standard errors hugely increase after applying the White correction for heteroschedasticity, with the result that the t-statistics decrease from 3.61 to 1.01. The R^2 is equal to 0.04 in the two specifications. The association thus appears quite weak and highly variable across observations.[17] Nevertheless, both the standard and Spearman correlation coefficient are significant, showing a value of 0.18 and 0.26, respectively.

At 4-digit level, however, the CBSA – PSA difference explains much more of the variations in the CBSA minus Noise values. The regression of the latter variable on the former now produces a robust t statistic equal to 2.69 and a R^2 of 0.25. This is definitively a robust association, clearly implying a strong effect of labour market determinants in explaining the spatial concentration of industries, on one side; on the other side, it suggests that the 6-digit level may be too "noisy" and detailed to investigate the relationship.

Moreover, the CBSA – PSA difference appears to be significantly and positively associated with average plant size, as measured by both pairwise correlation and multivariate regressions.[18] Interestingly, this is in line with findings from Lafourcade and Mion (2007), who showed that in Italy "large plants tend to cluster within narrow geographical areas such as labour market" (p. 48), while smaller plants tend to exhibit colocation at a wider geographical level. The authors comment on their results arguing that large plants are more export oriented, which in turn implies that their location is more sensitive to Marshallian labour market externalities rather than local market potential.

[17] Results are extremely similar while using the complete sample of all the industries with a positive and significant CBSA-Noise difference, or limiting it to the 105 industries with a 5% significant difference in both the CBSA-PSA and CBSA-noise values.

[18] In the light of my critique to parametric approaches to concentration, regression results are expected to be biased and therefore they are not reported for brevity. They are available from the author upon request.

7. Conclusions

In this paper I develop a new methodology to evaluate the effect of the "labour market" determinants of agglomerations, as opposed to the effect of all the other "non labour market related" determinants (e.g., input-output linkages, natural advantages, market access). Past contributions on the field have provided rather feeble results, and this may be due to the unfitness of standard parametric techniques to approach the issue.

In the light of that, I develop an original non parametric approach, which exploits the "bright side" of the Modifiable Areal Unit Problem (MAUP), i.e., the apparently unpredictable variation of the results depending on the size or shape of spatial units. I argue that, once in control of the process generating the spatial classification, this variation can rather be seen as useful information.

I therefore calculate the value of an industry concentration index applying two different zoning procedures to the same partition of US territory. The first procedure follows the commuting-based Core Based Statistical Areas (CBSA) definition, which is expected to maximize (among all the possible alternatives) the within-homogeneity and between-heterogeneity of labour market characteristics across spatial units. In this dataset, the effect of the "labour market" determinants is maximized. The second procedure creates a distribution of 1000 counterfactuals, each of them is composed by randomly aggregating the same counties which form the CBSAs into internally connected "Pseudo Statistical Areas" (PSAs). In this second dataset, all the "non labour market" determinants have the same effects of the previous one, while the "labour market determinants" effect is reduced. The difference from the concentration value found with the first procedure and the average across the 1,000 iterations of the second counterfactual quantifies the effect of labour market determinants for a given industry. I find this value to be significantly positive in 125, out of 473, manufacturing sectors.

I also propose a new approach to obtain unbiased estimates of industry concentration. I empirically estimate the bias who affects raw concentration indices by creating a distribution of “noise counterfactuals”, where plants are randomly shuffled across plant sites, and then small spatial units (Zip Code Areas) are randomly aggregated into bigger spatially units – of the same size of the CBSAs – without any contiguity constraint. The first step captures the spurious concentration component given by the industry plant size distribution, while the second step absorbs the geographical bias given by the arbitrary aggregation of events into exogenous spatial units. The amount of industry-specific concentration found in the noise scenario corresponds to the spurious component comprised in the CBSAs dataset, while the value found in the CBSA dataset net of the noise is an unbiased estimation of concentration which satisfies the five benchmark requirements listed in Combes and Overman (2004). A comparison of latter results with the corresponding values of Ellison-Glaser index reveals remarkable differences.

The results obtained from both the counterfactuals (PSAs and Noise) are used to calculate a “Labour Market Determinants Index”, which provides a ranking of industries according to the significance of labour market determinants in explaining their spatial concentration pattern. Both the CBSA – PSA difference and the LMDI provide robust evidence confirming that industries which are dependent to labour market characteristics in choosing their location are highly heterogeneous in skill and labour intensity, which in turn corroborates the advantages of following a non parametric approach. Moreover, the methodology also shows that labour market determinants play a significant role in explaining the overall pattern of concentration, although the effect is more easily recognizable at a wider level of industry classification.

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Figure 1 – A stylized example

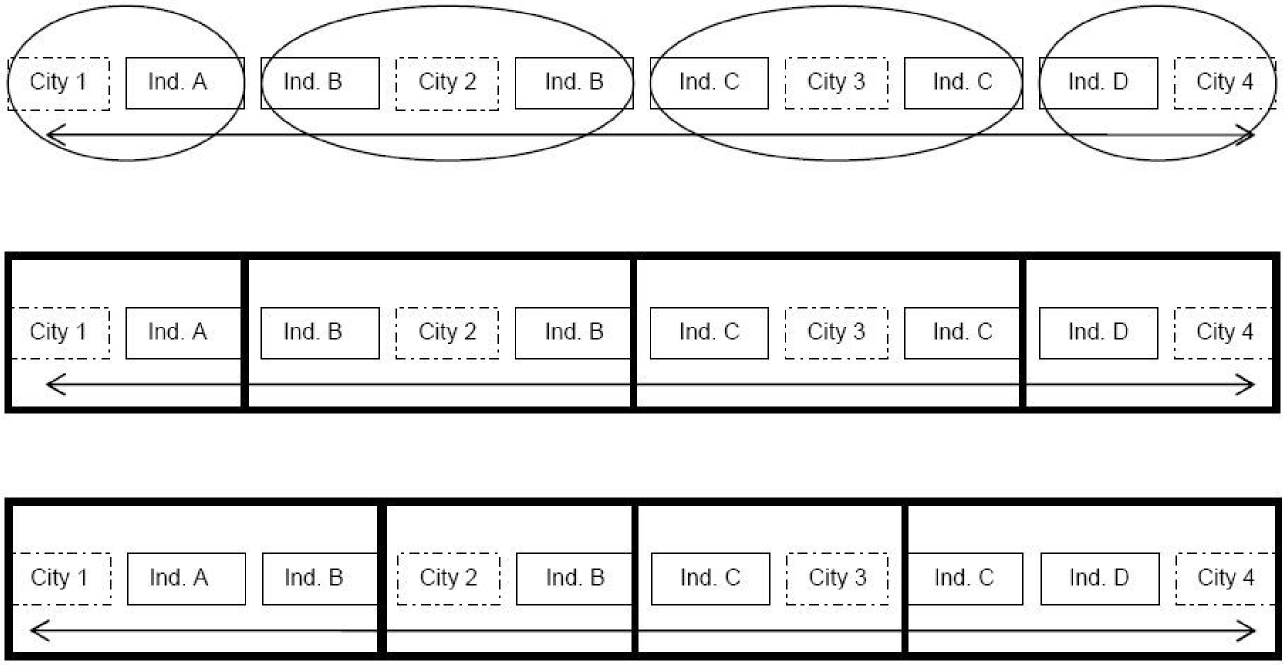
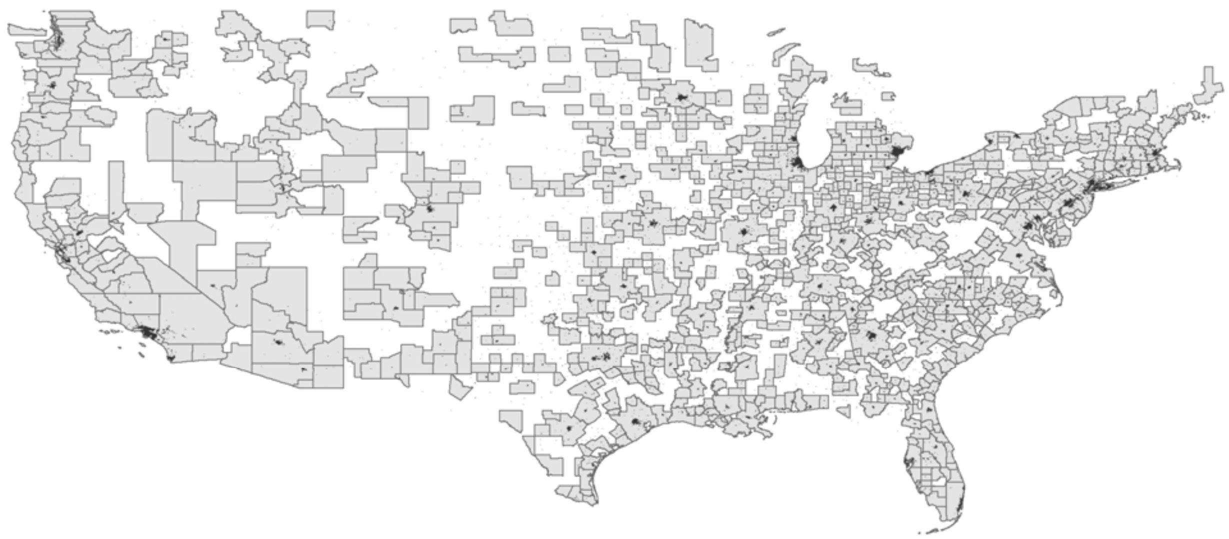
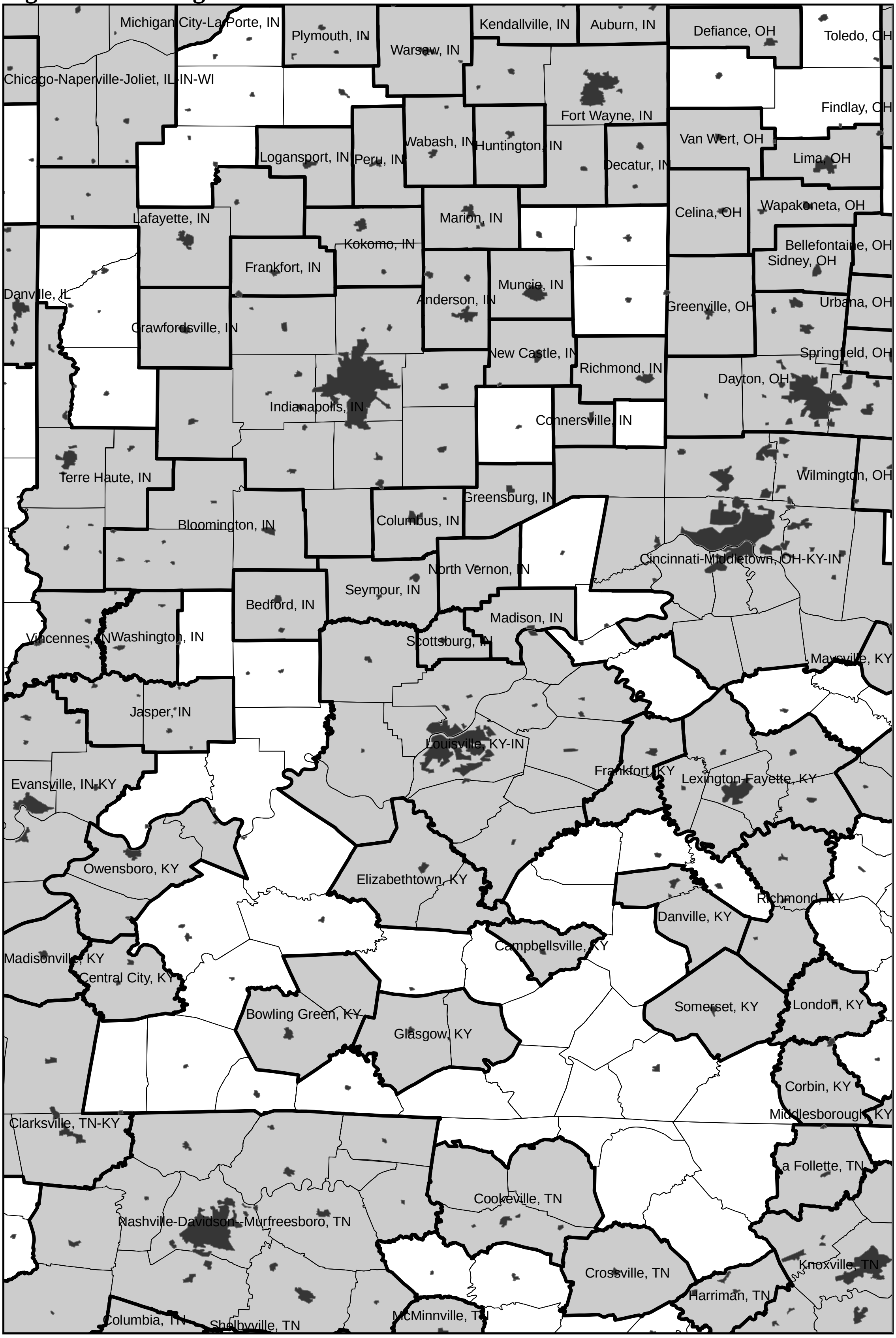


Figure 2 – CBSAs borders and populated places



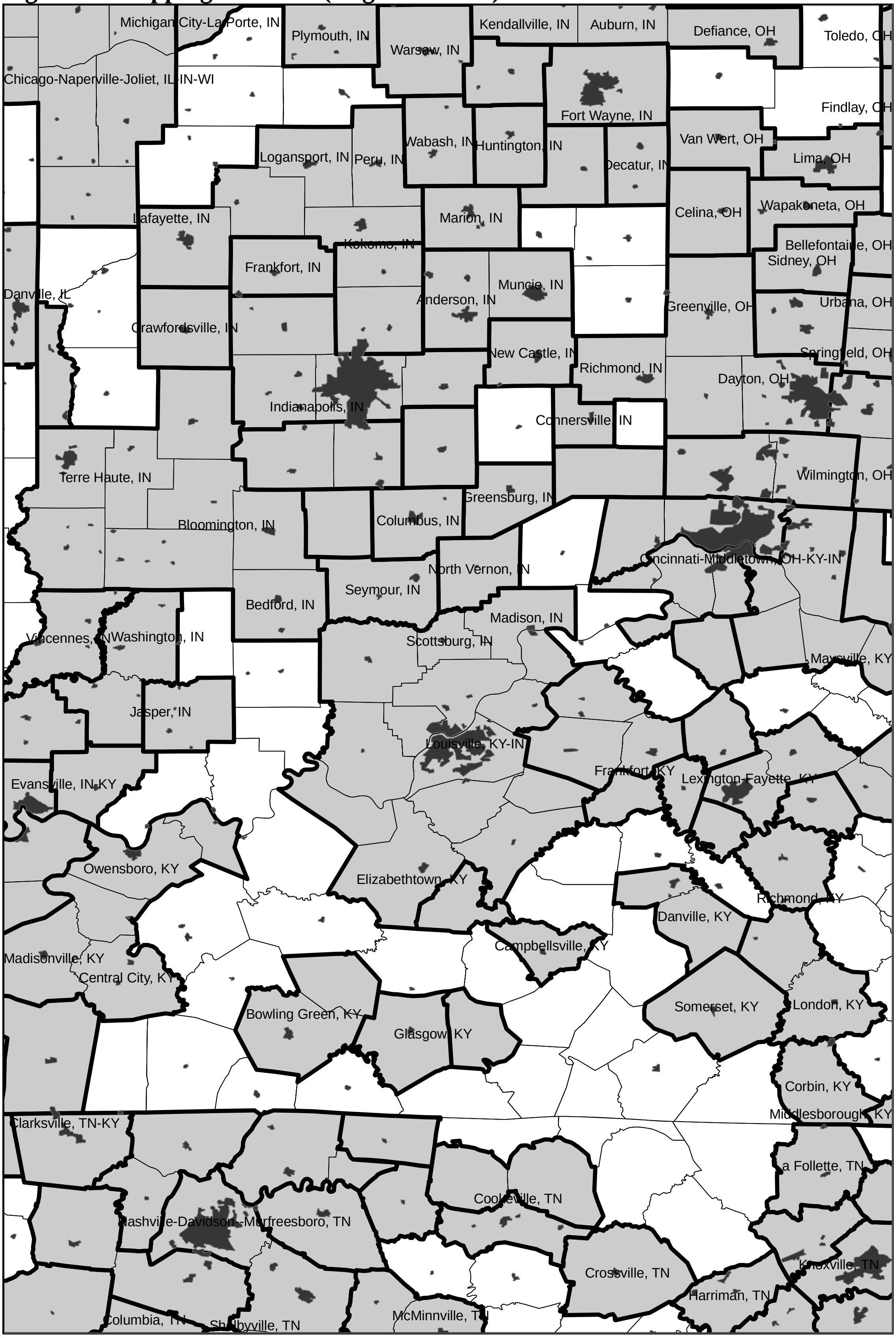
Note: the picture reports the CBSA classification. The empty areas in the map are rural and low populated counties, not comprised in the CBSA classification. The darker polygons report populated places, i.e., urban agglomerations. Source: *US Atlas*

Figure 3 - zooming to CBSAs



Note: this picture is a zoom of picture 2 around the area of Indianapolis. The white areas in the map are rural and low populated counties, not comprised in the CBSA classification. Source: *US Atlas*

Figure 4 - Mapping the PSAs (single iteration)



Note: the picture reports the same area of figure 3, substituting the CBSA borders with the PSA ones.
Source: Author’s elaboration on *US Atlas* shape files.

Table 1 - CBSA and PSA (average across 1000 it.) distributions: moments and percentiles

	Employment		Area	
	CBSA	**PSA**	**CBSA**	**PSA**
St. dev.	421818	400,220	0.61	0.87
Kurtosis	122.6	135	33.55	31.57
Skewness	9.5	10	4.46	4.77
Max	6,996,312	6,648,427	6.98	8.76
Min	1,886	1,840	0.011	0.001
p25	13,052	10,726	0.160	0.129
p50	25,811	24,908	0.255	0.197
p75	60,687	74,837	0.525	0.403

Table 2 – G Employment Concentration Index in the noise counterfactual, top 20 industries

NAME	NR. PLANTS	AV. EMP.	RANK HERF.	G NOISE*	G CBSA - G NOISE*	RANK CBSA-NOISE	EG NOISE*
Primary smelting & refining of copper	13	231.3	6	0.381	-0.114	472	0.299
Engineered wood member (exc truss) mfg	12	72.6	1	0.283	0.064	39	0.023
Roasted nuts & peanut butter mfg	133	73.2	127	0.247	-0.191	473	0.282
Cellulose organic fiber mfg	11	253.9	2	0.233	0.070	34	0.024
Other ordnance & accessories mfg	50	152.3	3	0.227	0.049	61	0.024
Alumina refining	11	189.5	4	0.224	0.057	45	0.023
Other missile, space veh parts & aux equip mfg	45	166.9	7	0.197	0.080	25	0.015
Missile, space veh propulsion unit & parts mfg	20	699.7	13	0.188	-0.047	465	0.103
Women's footwear (exc athletic) mfg	90	65.2	19	0.184	-0.027	464	0.135
Magnetic and optical recording media mfg	242	57.1	120	0.169	-0.098	470	0.183
Gum & wood chemical mfg	48	38.7	11	0.156	0.034	95	0.046
Overhead crane, hoist & monorail system mfg	273	55.4	98	0.149	-0.110	471	0.153
House slipper mfg	16	98.6	9	0.138	0.008	294	0.023
Motor home mfg	79	200.5	57	0.128	0.036	88	0.105
Small arms ammunition mfg	110	65.4	18	0.122	0.009	289	0.035
Cane sugar refining	15	223.5	16	0.115	0.064	40	0.020
Household laundry equipment mfg	20	783.4	10	0.114	0.064	41	-0.012
Household vacuum cleaner mfg	39	285.5	17	0.114	0.052	55	0.019
Guided missile & space vehicle mfg	16	3419.3	12	0.110	0.074	30	-0.009
Cigarette mfg	14	1469.2	5	0.109	0.178	8	-0.164

* Average across 1000 iterations

Table 3- CBSA minus NOISE, top 20 industries

INDUSTRY NAME	TOT. EMP.	NR. PLANTS	AV. EMP.	HERF. INDEX	Rank HERF.	EG CBSA	G CBSA	G NOISE	G CBSA - G NOISE
Jewelers' material & lapidary work mfg	5776	372	15.5	0.034	146	0.304	0.291	0.030	0.261
Sugarcane mills	3433	35	98.1	0.088	34	0.263	0.317	0.076	0.241
Women's, girls' cut & sew dress mfg	21086	756	27.9	0.010	344	0.311	0.239	0.024	0.214
Oil & gas field machinery & equipment mfg	23636	498	47.5	0.010	331	0.228	0.222	0.011	0.211
Petrochemical mfg	10287	50	205.7	0.051	101	0.267	0.288	0.084	0.203
Carpet & rug mills	40839	417	97.9	0.014	282	0.199	0.212	0.012	0.199
Women's, girls' cut & sew blouse mfg	16538	596	27.7	0.010	341	0.256	0.202	0.010	0.191
Cigarette mfg	20569	14	1469.2	0.267	5	0.024	0.288	0.109	0.178
Women's, girls', infants, cut, sew apparel contr	99024	5873	16.9	0.001	469	0.247	0.179	0.003	0.176
Costume jewelry & novelty mfg	10227	828	12.4	0.011	320	0.198	0.180	0.011	0.169
Motor vehicle air-conditioning mfg	24575	65	378.1	0.196	8	0.041	0.230	0.072	0.158
Ethyl alcohol mfg	1107	27	41.0	0.094	32	0.144	0.229	0.083	0.147
Fiber optic cable mfg	11742	74	158.7	0.116	22	0.089	0.182	0.058	0.125
Tobacco stemming & redrying	4976	31	160.5	0.086	39	0.106	0.193	0.073	0.119
Photographic & photocopying equipment mfg	19317	385	50.2	0.068	62	0.097	0.141	0.023	0.118
Sanitary paper product mfg	23799	118	201.7	0.051	102	0.094	0.145	0.037	0.108
Women's, girls' cut & sew other outerwear mfg	38665	1520	25.4	0.008	368	0.158	0.117	0.016	0.100
Choc & confectionery mfg from cacao beans	9628	142	67.8	0.144	14	0.010	0.153	0.053	0.100
Photo film, paper, plate & chemical mfg	26834	323	83.1	0.139	15	0.014	0.141	0.041	0.099
Other hosiery & sock mills	21129	274	77.1	0.017	256	0.091	0.115	0.016	0.099

Table 4 - EG index in the noise conterfactual

Statistics	EG noise
Mean	0.0208
Max	0.2991
P25	0.0177
P50	0.0183
P75	0.0196
P90	0.0288

Table 5 – CBSA - PSA, top 50 industries*, 6-digit

INDUSTRY NAME	TOT. EMP.	NR. PLANTS	G CBSA	G PSA	G CBSA - G NOISE	G CBSA - G PSA	LMDI
Jewelers' material & lapidary work mfg	5776	372	0.2914	0.175	0.261	0.117	1.81
Women's, girls' cut & sew dress mfg	21086	756	0.2385	0.183	0.214	0.055	1.35
Ethyl alcohol mfg	1107	27	0.2293	0.183	0.147	0.047	1.47
Guided missile & space vehicle mfg	54709	16	0.1832	0.142	0.074	0.041	2.24
Men's & boys' neckwear mfg	3781	100	0.1328	0.096	0.084	0.037	1.77
Upholstered household furniture mfg	71978	1443	0.0822	0.052	0.074	0.030	1.69
Women's, girls', infants, cut, sew apparel contr	99024	5873	0.1792	0.149	0.176	0.030	1.20
Jewelry (exc costume) mfg	32813	2114	0.0923	0.063	0.073	0.029	1.65
Fiber optic cable mfg	11742	74	0.1823	0.154	0.125	0.029	1.30
Costume jewelry & novelty mfg	10227	828	0.1798	0.151	0.169	0.028	1.20
Motor vehicle metal stamping	118041	682	0.0762	0.051	0.068	0.026	1.61
Fur & leather apparel mfg	2416	256	0.1186	0.096	0.099	0.023	1.30
Welding & soldering equipment mfg	19687	266	0.0829	0.061	0.054	0.022	1.70
Other hosiery & sock mills	21129	274	0.1151	0.096	0.099	0.020	1.25
Other footwear mfg	1459	70	0.1054	0.089	0.049	0.017	1.51
Women's, girls' cut & sew other outerwear mfg	38665	1520	0.1165	0.102	0.100	0.015	1.17
Other metalworking machinery mfg	17726	433	0.047	0.032	0.037	0.015	1.64
Special die, tool, die set, jig & fixture mfg	74585	4117	0.0357	0.021	0.033	0.014	1.79
Copper wire (except mechanical) drawing	4137	68	0.0753	0.061	0.025	0.014	2.32
Textile machinery mfg	11080	427	0.0573	0.043	0.044	0.014	1.49
Other pressed & blown glass & glassware mfg	34393	475	0.0485	0.036	0.028	0.013	1.84
Cane sugar refining	3352	15	0.1781	0.167	0.064	0.012	1.22
Aircraft engine & engine parts mfg	80072	371	0.066	0.056	0.053	0.010	1.24
Machine tool (metal cutting types) mfg	24054	463	0.0344	0.024	0.017	0.010	2.33
Rolled steel shape mfg	15503	269	0.0488	0.040	0.030	0.009	1.43
Women's, girls' cut & sew blouse mfg	16538	596	0.2015	0.193	0.191	0.009	1.05
Electric lamp bulb & part mfg	13257	87	0.0662	0.058	0.031	0.008	1.38
Other aircraft part & auxiliary equipment mfg	102716	1018	0.0636	0.055	0.035	0.008	1.31
Flat glass mfg	11681	61	0.064	0.056	0.027	0.008	1.44
Nonupholstered wood household furniture mfg	108471	3323	0.031	0.023	0.026	0.008	1.45
Cement mfg	15273	226	0.0234	0.016	0.013	0.008	2.48
Synthetic organic dye & pigment mfg	7496	121	0.0495	0.042	0.027	0.008	1.40
Gasoline engine & engine parts mfg	78943	780	0.0508	0.044	0.037	0.007	1.23
Search, detection & navigation instrument mfg	168093	611	0.0447	0.038	0.029	0.006	1.28
Metal heat treating	21264	754	0.0207	0.014	0.016	0.006	1.70
Women's, girls' cut & sew lingerie mfg	11881	208	0.0398	0.034	0.023	0.006	1.39
Secondary smelting & alloying of aluminium	6200	159	0.0381	0.032	0.021	0.006	1.43
Photographic & photocopying equipment mfg	19317	385	0.1407	0.135	0.118	0.006	1.06
Power boiler & heat exchanger mfg	19986	407	0.0253	0.020	0.017	0.006	1.54
Mineral wool mfg	20031	266	0.0356	0.030	0.019	0.006	1.45
Other apparel accessories & other apparel mfg	23261	1626	0.0418	0.036	0.035	0.006	1.19
Industrial & commercial fan & blower mfg	10224	169	0.0336	0.028	0.014	0.005	1.64
Household vacuum cleaner mfg	11134	39	0.1662	0.161	0.052	0.005	1.11
Coated & lamnd pkg paper & plastics film mfg	5997	98	0.0381	0.033	0.013	0.005	1.57
All other cut & sew apparel mfg	8330	335	0.0194	0.015	0.008	0.005	2.49
Electropl, plating, polish, anodize, coloring	73042	3179	0.0162	0.012	0.013	0.005	1.56
Industrial mold mfg	44980	2193	0.0198	0.015	0.016	0.005	1.39
Industrial pattern mfg	7762	648	0.028	0.024	0.015	0.004	1.43
All other motor vehicle parts mfg	151673	1292	0.0197	0.015	0.013	0.004	1.47
Inorganic dye & pigment mfg	6959	73	0.0545	0.050	0.017	0.004	1.31

* The table reports only values significant at 5% level in both the CBSA-PSA and CBSA-NOISE difference.

Table 6 – CBSA - PSA, 4-digit*, positive values

INDUSTRY NAME	TOT. EMP.	NR. PLANTS	G CBSA	G PSA	G CBSA - G NOISE	G CBSA - G PSA	LMDI
Cut & sew apparel mfg	311677	11789	0.078	0.066	0.072	0.0122	1.19
Metalworking machinery mfg	218427	9260	0.022	0.015	0.020	0.0070	1.52
Aerospace product & parts mfg	412944	1691	0.041	0.035	0.032	0.0063	1.25
Motor vehicle parts mfg	740523	5104	0.025	0.019	0.023	0.0060	1.36
Apparel accessories & other apparel mfg	40112	2163	0.031	0.026	0.026	0.0051	1.28
Motor vehicle mfg	255966	378	0.037	0.032	0.019	0.0049	1.35
HH & institutional furniture & kitchen cabinet mfg	339880	12941	0.016	0.011	0.013	0.0048	1.49
Nav, measuring, medical, control instruments mfg	443652	4934	0.017	0.013	0.012	0.0041	1.57
Motor vehicle body & trailer mfg	125491	1748	0.035	0.031	0.025	0.0036	1.15
Steel product mfg from purchased steel	63958	863	0.014	0.011	0.009	0.0028	1.35
Clay product & refractory mfg	69827	1616	0.011	0.008	0.006	0.0027	1.99
Other transportation equipment mfg	38752	757	0.033	0.030	0.022	0.0027	1.12
Coating, engrave, heat treating & oth activity	150012	5917	0.010	0.007	0.009	0.0026	1.52
Glass & glass product mfg	117749	2124	0.013	0.011	0.008	0.0025	1.35
Mach shops, turn prod, screw, nut, bolt mfg	389848	24141	0.006	0.004	0.005	0.0019	1.65
Other nonmetallic mineral product mfg	68044	2286	0.009	0.007	0.006	0.0019	1.62
Cement & concrete product mfg	196681	7739	0.005	0.003	0.004	0.0017	1.75
Ag, construction & mining machinery mfg	161659	2442	0.017	0.015	0.014	0.0016	1.19
Other wood product mfg	258822	8661	0.009	0.007	0.007	0.0015	1.19
Other electrical equipment & component mfg	202114	2378	0.007	0.005	0.002	0.0015	2.12
Animal food mfg	41536	1314	0.011	0.009	0.007	0.0015	1.25
Boiler, tank & shipping container mfg	86680	1603	0.008	0.006	0.005	0.0015	1.30
Other fabricated metal product mfg	290455	6784	0.005	0.004	0.003	0.0015	1.76
Communications equipment mfg	244061	2165	0.022	0.021	0.012	0.0014	1.10
Other miscellaneous mfg	390362	17629	0.005	0.004	0.003	0.0012	1.46
Foundries	197312	2537	0.011	0.010	0.007	0.0010	1.24
Dairy product mfg	113462	1510	0.007	0.006	0.004	0.0010	1.36
Rubber product mfg	190260	2479	0.010	0.009	0.007	0.0006	1.21
Other general purpose machinery mfg	307881	6209	0.005	0.004	0.003	0.0005	1.38
Plastics product mfg	763061	12501	0.003	0.003	0.002	0.0004	1.37
Architectural & structural metals mfg	369395	10911	0.002	0.002	0.001	-0.0002	0.97

* The table reports only values significant at 5% level in both the CBSA-PSA and CBSA-NOISE difference.