METROPOLITAN INDUSTRIAL CLUSTERS: PATTERNS AND PROCESSES *

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Abstract

Where do industries locate within a metropolitan area? Do different industrial sectors have different patterns of location/clustering? Can these patterns be understood with reference to industry characteristics? What is the geographical relationship between clusters of different types of industry? To what extent do localization economies influence the clustering process? These questions are investigated with geographically disaggregated industry location and size data from Mumbai, Kolkata, and Chennai. We analyze eight industrial sectors (food/beverages, textiles, leather, printing/publishing, chemicals, metals, machinery, electrical/electronics) for evidence of global and local clustering, and distinguish between and test for co-clustering and co-location of industries. The results suggest an evolutionary model of industry location in mixed rather than specialized industrial districts. There is little evidence of localization economies from labor markets or buyer-supplier networks. We suggest that land use policy is the key variable influencing the intra-metropolitan spatial distribution of industry.

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Metropolitan Industrial Clusters: Patterns and Processes

Industrial clusters have reemerged as important objects of research and policy analysis. The benefits of industry clustering were identified early by Alfred Marshall (1919) who suggested that these arise from localization economies: namely, the availability of common buyers and suppliers, the formation of a specialized/skilled labor pool, and the informal transfer of knowledge (on trade secrets, production processes, market agents etc.). Krugman's work in economic geography (Krugman, 1991, 1996) and Porter's work in business economics (Porter, 1990, 1996) have drawn the interest of economists to the idea of "increasing returns" to proximity in the form of clusters (see Fujita, Krugman, and Venables, 1999). Meanwhile, geographers have long been interested in industrial location and clustering, and theories of globalization and flexible accumulation using clusters of small, networked firms have been widely discussed following the pioneering work of Piore and Sabel (1984).[1] This journal participated in this discourse by publishing a special issue containing a number of narratives on individual clusters (see Nadvi and Schmitz, 1999).

This paper contributes to this growing literature on industrial clustering in developing countries. We focus on one geographical scale—the metropolis—and identify patterns and discuss processes of industrial clustering at that scale. The symbiotic relations between industrialization and metropolitanization are known well enough to be in the realm of common knowledge. It is understood that industrialization takes place in cities, some of which, usually important cities from the pre-industrial or colonial periods,

[1] Note that the questions on industry location and their implications are not new. Examining the locational aspects of economic activity has been of interest to geographers, planners, and regional scientists for some

become so successful at attracting industry and migrants that they become very large cities or metropolitan regions. It is also understood that industrial success in these cities is a cumulative causation process where increasing returns are derived from industrial clustering. However, there are several specific questions that remain unanswered. Where do industries locate within a metropolitan area? Do different industrial sectors have different patterns of location/clustering? Can these patterns be understood with reference to industry characteristics? What is the geographical relationship between clusters of different types of industry? To what extent do localization economies influence the clustering process?

In this paper, we present the first estimates of industrial clustering within metropolitan regions in developing countries using data from three Indian metropolises—Mumbai, Kolkata, and Chennai. We first provide the necessary background – the theory of industrial clustering, cluster measurement methods, the data used for the analysis, and a brief introduction to the study areas. Next, we test eight industrial sectors (food/beverages, textiles, leather, printing/publishing, chemicals, metals, machinery, electrical/electronics) for evidence of global and local clustering, and distinguish between and test for co-clustering and co-location of industries. The results suggest an evolutionary model of industry location in mixed rather than specialized industrial districts. There is little evidence of localization economies from labor markets or buyer-supplier networks. We suggest that the key variable influencing the intra-metropolitan spatial distribution of industry is land use policy.

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time (Weber, 1929; Lösch, 1956; Hotelling, 1929; Greenhut and Greenhut, 1975, Isard 1956). The more

BACKGROUND

Why do industries cluster?

Clustering is a term describing a phenomenon in which events or artifacts are not randomly distributed over space, but tend to be organized into proximate groups. Industrial clustering is a process that has been observed from the beginning of industrialization. From the cotton mills of Lancashire and automobile manufacturing in Detroit, to the textile mills of Ahmadabad and Bombay and the tanneries of Calcutta and Arcot, even even the casual observer can visually discern the evidence on industrial clustering by industry type. Why should this happen? It seems obvious that competing firms in the same industry derive some benefit from locating in proximity to each other. The benefits that are external to the firm and accruing to similar firms in proximity are called the *economies of localization*. Now, these typically are not the only firms in the immediate region. There are usually other factories, producing other goods, distributed through other channels, sometimes for different markets. These other firms, and their employees, and the service workers who provide food, education, and health care for all these employees and their families, comprise, typically an urban area. All the firms that benefit from being in the urban area, regardless of whether or not there are other similar firms in the area, derive *economies of urbanization* from their location choice. In other words, there are productivity gains from industrial clustering.

To put it in another way, at the *firm level*, it is expected that the size and number of firms (i.e., the competitive structure) will influence internal returns to scale. In particular, as demand for a firm's goods and services increases (say, due to improved access to consumer markets), the entrepreneur has an incentive to increase scale of production by restructuring the production process through the use of specialized workers

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recent geographical approaches are summarized in Walker (2000).

and investing in cost reducing technologies (Lall et al., forthcoming). At the *industry level*, we expect to see quantifiable localized benefits of clustering which accrue to all firms in a given industry or in a set of inter-related industries. Productivity is likely to be higher in regions where an industry is more spatially concentrated due to increased potential of knowledge spillovers and buyer-supplier networks, access to a specialized labor pool and opportunities for efficient subcontracting. Finally at the *metropolitan area level*, economies of scale result not from the size of a specific industry or market but from the overall size, diversity, and spatial configuration of the metropolitan area. These economies of urbanization include access to specialized financial and professional services, availability of a large labor pool with multiple specializations, inter-industry information transfers, and the availability of less costly general infrastructure. At the interregional scale these gains are expected to lead to industry concentration in metropolitan and other leading urban regions (as a result of urbanization economies); at the metropolitan scale the gains from localization economies are expected to lead to the creation of local industrial clusters.

These typically un-quantified agglomeration economies are one set of inputs into the location decision of a firm. There are other significant factors that a firm facing a location decision must consider. The two most important of these additional factors (especially in developing countries) are the availability of infrastructure, and the regulatory framework, both arenas where the state is the key player. The state not only sets the rules of market entry and participation, but is also the primary, often the sole provider of physical and social infrastructure (highways, airports, ports, export processing zones, etc. are examples of the former, while schools and hospitals are examples of the latter), and is often directly active in the production process.[2] The state's regulatory role at the local level goes beyond setting the rules of market participation; by being the single largest owner of land, by having the police and taking powers to acquire necessary land, and by being the final arbitrator on land use decisions, the state, as we shall show later, has a very strong influence on industrial location decisions within metropolitan areas.

The measurement of clustering

The ability to describe spatial patterns is the first step to understand spatial processes. Spatial statistics are the most widely used tools for describing and analyzing spatial patterns (see Getis and Ord, 1992 and Anselin, 1995 for excellent discussions on the subject). In classifying spatial patterns, researchers are often interested in determining whether the distribution of economic activity is clustered, dispersed, or random. Such spatial association of distribution patterns is also called spatial autocorrelation meaning that the attribute values being studied are correlated according to the geographic ordering of the objects. When the location of firms is spatially autocorrelated, that implies the geographic distribution of economic activity is not random and is likely to be determined by some underlying political and economic factors attributable to each geographical unit.

Spatial associations are often measured for their strength. Strong spatial autocorrelations mean that the attribute values of adjacent geographical units are closely related (either positively or negatively). One of the most popular measures for spatial autocorrelation is Moran's I. There are two types of Moran's I depending upon geographic scales. The Global Moran is a measure describing overall spatial relationship across all geographical units. Therefore, only one value is derived for the entire study area. On the

[2] In India, in its efforts to capture the "commanding heights of the economy," the state has invested heavily in capital-intensive industry, e.g., integrated steel and power plants. It was so successful in its efforts that as recently as the late 1990's, nine of the top ten and twenty of the top twenty-five corporations in India were public sector units (Nayar 1998).

other hand, The Local Moran (often called Local Indicator of Spatial Association or LISA) is a measure that is designed to describe the heterogeneity of spatial association across different geographical units.

Global Moran's I can be defined as

$$I = \frac{n \sum \sum w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{W \sum (x_i - \bar{x})^2} \tag{1}$$

where x_i is the value of a variable of interest in areal unit i, w_{ij} is a weight derived from a spatial weight matrix, and W is the sum of all cell values of the weight matrix. For the calculation of Moran's I, both a binary and a stochastic weight matrix can be used. A binary weight matrix defines the connectivity of pairs of regions with 0's and 1's. When two regions are adjacent, the corresponding cell value is 1, but otherwise, it is 0. On the other hand, a stochastic weight matrix takes into account the number of immediate neighbors. Rather than assigning 1 to every neighbor, '1/total number of neighbor' is used as a weight for areal unit i.

Equation (1) suggests that the calculation of global Moran's I is based on a comparison of values in neighboring geographical units. Note that the numerator is basically the covariance of neighbors, and the denominator is the sum of the squared deviation scaled by the total weight of the matrix. Therefore, if neighboring units have similar values over the entire study area, the statistic will show a strong positive spatial association. However, if dissimilar values are observed among neighboring units, the statistic should indicate a strong negative spatial association. The value of Global Moran ranges from –1 (negative spatial autocorrelation) to 1 (positive spatial autocorrelation). The statistical significance of Moran's I, which can be an important basis to determine whether the observed spatial association pattern arises from a random or from a systematic process, can be tested by comparing calculated Moran's I from equation (1) and the expected value of Moran's I from $E(I) = -1/(n-1)$.

The magnitude of spatial association is not necessarily uniform over the space. It is more likely to be heterogeneous according to local characteristics that influence the formation of spatial structure. Local Moran's I can be used as an indicator of heterogeneity in spatial association over geographical units and is defined as

$$I_i = z_i \sum_i w_{ij} z_j \text{, where } z_i = (x_i - \bar{x}) / \delta$$

where, z_i is deviations from mean, and δ is the standard deviation of x_i. Similar to global Moran, a high value of local Moran means the association of similar values whereas a low value means the association of dissimilar values. Deriving local Moran statistics does not mean much unless one can determine observed spatial associations occur by chance or by a systematic process. By comparing calculated local Moran with its expected value based on $E(I_i) = -w_i /(n-1)$, the significance of local Moran statistics can be tested.

Data issues

In order to undertake sub-metropolitan level analysis it is necessary to have spatially disaggregated data. In India industrial data are collected by the Central Statistical Organization (CSO) and disseminated as the Annual Survey of Industries (ASI). In the late 1990s the ASI data were first released at the district level and then at the firm level. These data are based on a survey carried out by CSO on a sample taken from an industry sampling frame which includes every registered (or legal) industrial unit with at least ten workers. This sampling frame contains one record for each industrial unit and includes three critical pieces of information: the National Industrial Classification (NIC) code, the number of workers in the unit, and the street address, with, sometimes, a pin code (equivalent to U.S. zip codes).

The last piece of information is the key to disaggregating the district data down to smaller enumeration units. We are fortunate to have access to the sampling frame for the whole country for the enumeration period 1998-99. On further examination we found that while street addresses were generally available for all metropolitan areas, there were no base maps of streets to which these addresses could be matched. Hence we had to rely on the pin code information, which, however, turned out to be erratically available. For some cities the pin codes were generally available or imputable, for other cities they simply were not available. We identified Mumbai, Kolkata, and Chennai as the three metropolises with enough information to begin geocoding the industry location data to the pin code level.

The pin code maps were acquired from a private sector firm in New Delhi (ML Infomap, 1998). These maps have somewhat variable coverage. For Kolkata and Chennai the pin code maps cover the largest definition of their metropolitan areas. For Mumbai the pin codes cover the district of Greater Bombay only; that is, the far northern and eastern suburban reaches of the Mumbai metropolitan area (in Thane and Raigad districts) are not covered. Even in the covered area there appear to be some situations where adjoining pin codes have been merged. As a result some data that are known to be in the metropolitan area could not be geocoded to pin codes. We have been able to achieve the following "hit" rates, that is successfully geocoded factory records: In Mumbai 99.9 percent, in Kolkata 97.1 percent, in Chennai 97.5 percent. Following Ratcliffe (2002), who argues that a "hit rate" of 85 percent is acceptable for most map-based analysis, we believe that these are acceptable levels of address matching.

Finally we aggregated the firms into eight distinct and internally consistent sectors. These are (with NIC codes in parenthesis):

1. Food Processing (151, 152, 153, 154, 155)
2. Textiles and Textile products, including wearing apparel (171, 172, 173, 181)

3. Leather and leather products (191, 192)
4. Paper products, printing and publishing (210, 221, 222)
5. Chemical, chemical products, rubber and plastic products (241, 242, 243, 251, 252)
6. Basic Metals and Metal Products (271, 272, 273, 281, 289)
7. Mechanical Machinery and Equipment (291, 292)
8. Electrical and Electronics (including computer) Equipment (292, 300, 31, 32)

The study areas

Mumbai (Bombay), Kolkata (Calcutta), and Chennai (Madras) are three of India's big four metropolitan areas. All are colonial cities, created by the British primarily for administrative purposes (see Kosambi and Brush, 1988 on their structure and morphology). Our study areas cover the city of Mumbai (with 94 pin codes), metropolitan Kolkata (with 133 pin codes), and metropolitan Chennai (with 108 pin codes).

Mumbai is the sub-continental leviathan. The population of the metropolitan area is estimated to be over 18 million, making it, with Mexico City, the second largest urban agglomeration in the world. The metropolitan population has grown by around 50 percent in each of the two preceding decades. Mumbai is the center of the financial sector in India, home of the Reserve Bank and the majority of the state-owned and international banks and financial institutions. It is a major industrial hub, one end of India's most dominant industrial region stretching north up to Ahmedabad in Gujarat state; this region has done particularly well in attracting new industrial investments after the 1991 structural reforms (Chakravorty 2000).

Kolkata was the most important colonial city in India, the seat of the British empire and its political center till 1911, and the industrial center of the nation till the early 1960s.

The Kolkata metropolitan region is the second largest in the country, after Mumbai, with around 12.5 million people; till the 1991 census it had been India's largest metropolis. The city and the region have seen a dramatic decline in industry in general; its specializations are in "sunset" industries, specifically jute (textiles) and iron and steel. The incomes of the city and the state have declined from an all-India high in 1960 to around the national average now. The state of West Bengal has been ruled by the Communist Party of India (Marxist), popularly known as the CPM, which resisted the 1991 structural reforms and continues to be seen to be deeply suspicious of capitalism and globalization.

Chennai is the fourth largest metropolitan area in India (behind the other two and Delhi). It was the preeminent city of south India for most of the twentieth century, till Bangalore, in the neighboring state of Karnataka, emerged as a serious regional rival, primarily as a result of the growth of the information technology sector. Chennai continues to be a stronger industrial center than Bangalore. It is also part of a large industrial region in the state of Tamil Nadu with the cities of Madurai and Coimbatore.

ANALYSIS

Global clustering

The measures of global clustering for the eight industry sectors for the three metropolises are reported in Table 1. The results are reported separately for number of factories and number of workers. This method of presentation, which is used throughout this paper, is based on the assumption that factory size has some bearing on the location decision. Large factories can be expected to rely more on internal economies of scale; small factories may rely on external or localization economies. Here the variable "factories" suggests small-scale units; when factories are clustered it suggests that a large number of small firms are clustered. Conversely, when workers are clustered we can assume that a small number of large firms are clustered.

In general, clustering is most consistent in Kolkata (other than textile factories and metals and electrical/electronic workers everything else is clustered); Chennai and Mumbai show inconsistent evidence of clustering with more consistent clustering in factories than workers. Let us discuss the results by industry sector.

In the food/beverages sector, factories are clustered in all three metropolises (most weakly in Chennai), and workers are clustered in Kolkata and Mumbai, but not in Chennai. The textiles sector, which is by far the largest in terms of both factories and workers, has strongly clustered factories only in Chennai; there is evidence of weak clustering in Mumbai and no clustering in Kolkata. Textile sector workers, however, are strongly clustered in Kolkata and Mumbai, but not clustered in Chennai. In the leather sector, in Kolkata both factories and workers are strongly clustered, whereas in Chennai and Mumbai neither factories nor workers are clustered. In the printing/publishing sector, both factories and workers are very strongly clustered in Kolkata, strongly clustered in Chennai, and not clustered in Mumbai. Factories in the chemicals sector are clustered in all three metropolises, while workers are clustered only in Kolkata and Chennai. Factories, but not workers, are clustered in Kolkata and Chennai; in Mumbai neither factories nor workers are clustered. Factories in the Machinery sector are clustered in all three metropolises (weakly in Mumbai and strongly in the other two); workers are very strongly clustered in Kolkata, but not clustered in Mumbai or Chennai. Finally, in the appliances sector, factories are clustered in all three metropolises, but workers are clustered only in Mumbai.

In summary, three possible combinations are seen. As expected, clustering among factories and workers in the same industry and city is the most common pattern. However, combinations with only one of them (factories or workers) being clustered are also common. Only factories are clustered in metals and electrical/electronics (in both Kolkata and Chennai). Only workers are clustered in the textiles sector in Kolkata. At this point in the analysis the picture is unclear.

Local clustering

Next we take the analysis one step beyond the simple confirmation of the existence of clusters. In this section we identify the locations and other characteristics of the clusters. Recall from our earlier discussion on the measurement of clustering that local clusters may exist even when the system as a whole is not clustered (hence the distinction between "global" and "local" Moran indices). These results are reported in Table 2 and in a series of maps (Figures 1, 2, and 3).

It is useful to explain what is reported in these figures and the table. We began the analysis by calculating local Morans for each of our eight industry categories, for each of our three cities, for factories and workers separately. We used two methods to calculate local Morans: first, neighbors were identified on the basis of contiguity, and then on the basis of a distance cut-off. Only the contiguity-based local Morans are reported here, in the table and in the figures. The distance based measures yield about the same results. Now, consider Figure 1. The first pair of figures from the top left shows the distribution of local Morans for the Food and Beverage sector in Mumbai; the map on the left shows the local Morans for factories, the map on the right shows the distribution for workers in that industry. The strength of the clusters are determined by the statistical significance of each pin code's local Moran calculation.[3] Next, the numbers of pin codes forming clusters and the numbers of

[3] Z-values for local Morans are mapped. A negative cluster has Z values less than –1.65 (this is not shown). Z values between –1.65 and 1.65 are not clustered. Values of Z between 1.65 and 1.95 are weakly clustered, and values greater than 1.95 are strongly clustered. Pin codes that show weak and strong

factories and workers in their respective clusters were summed. These data are also reported in Table 2. Note the great variation in the results between cities, between industries, and within cities and within industries. Let us identify some of the observed patterns.

First, factories and workers in the same industry do not necessarily cluster in the same pin codes. In the general case there are some common pin codes and some unique pin codes for each industry. There are two types of exceptional cases: one where there is perfect overlap between factory and worker clusters (such as Printing/Publishing in Mumbai and Machinery in Chennai); the other in situations where there are no common pin codes (such as Food and Beverages in Mumbai, where there are five unique clustered pin codes each for factories and for workers) or few common pin codes (such as Textiles or Machinery in Kolkata). This variation is seen in every city, with perhaps Chennai showing less evidence of the extreme situations. This is an important finding. It suggests that within the same industry small-scale operations tend to cluster together (this is where the factories are seen to cluster), often, but not always at separate locations from large-scale operations (where workers are seen to cluster). Later we discuss the implications of this finding.

Second, and related to the first point, it is difficult to discern whether factories are more clustered or workers in specific industries. Recall the argument that large factories rely on internal economies of scale for productivity gains, whereas smaller factories rely on external economies, at least some of which are derived from localization or clustering. Hence, in our data, we can expect factories (small scale units) to cluster more and workers (large scale units) to cluster less. If we use the percentage of factories or workers within clusters as a measure of the extent of clustering, this expectation is correct across cities in only the Printing/Publishing and Metals sectors. The opposite is true in the Food/Beverages

evidence of positive clustering are shown in the maps using different shades. In general, where local clustering does exist it does so at Z values greater than 1.95.

sector, and with the exception of Chennai (where the numbers are close) in the Textiles sector. This may not be a significant issue as it is unclear that the measure used here is an appropriate measure for comparing two very different types of units (factories and workers).

Third, each city has one or two industries that appear to be more clustered than others—for instance, the Textiles and Electrical/Electronic sectors in Mumbai, Leather and Food and Beverages in Kolkata, and Leather in Mumbai. These are also the industries that generally have a significant overlap in terms of the locations of factory and workers clusters (with the exception of Textiles in Mumbai). Moreover, these are also the industries for which these cities have high location quotients (LQs) at the national level.[4] The Electrical/Electronic sector in Mumbai has a LQ of 3.0, the Textiles sector's LQ is 1.7. The Leather sector's LQ in Chennai is 4.0, in Kolkata it is 1.5. Food and Beverages in Kolkata is an exception to this pattern. Another exception is the Machinery sector in Mumbai; its LQ is 2.5, yet it is the only industry in any of our study cities to have absolutely no local clustering among workers (and one of the lowest levels of clustering among factories in all cities). Therefore, though this pattern cannot be generalized, there may be a causal relationship between very high levels of clustering and industry dominance at the regional/national level. At this point, however, it is difficult to determine the direction of the causal arrow.

Fourth, the location of industry clusters generally appears to follow some widely held principles: one, polluting industries are located in fringe areas, and two, many industries are co-located in industrial districts. Consider the first principle. It seems obvious that any local regulatory agency will direct the location of polluting industry toward the urban fringe. The two most polluting industries considered here are Chemicals and Leather. In all three cities these industries are located in the fringe areas, and it appears from the maps that in the cases

[4] The location quotient (LQ) is simple measure of regional concentration used in regional science. It calculates the ratio of the share of a given variable to the share of population. Here, LQ = 1 indicates that the region's share of a particular sector is equal to its share of all industry. If LQ = 3 it indicates that the region's share of that sector is three times its share of all industry.

of Mumbai and Kolkata, there is some degree of co-location of these two industries. The Chennai case is particularly interesting for the Chemicals sector. Chemical factories are clustered in the southern extremity and in the far west, whereas workers (or large scale factories) are located in the northern fringes of the metropolitan area.

Co-clustering or co-location

The idea of the industrial district goes back to Marshall (1919) who suggested that small specialized firms would tend to cluster in space to derive external economies to offset the internal scale economies of large factories. Piore and Sabel (1984) argued that the late twentieth century had seen the arrival of a "second industrial divide" where the vertically integrated organization of production characterized by Fordist manufacturing was giving way to regional specialization organized around networks of small scale producers. Geographers see this in terms of the need for flexible specialization in globalized production systems geared toward rapid changes in technology and the need to respond to shifting patterns of demand (see Amin 2002). Economists have focused on the specific productivity advantages provided by proximity. In the simplest terms, these localization economies (to be distinguished from urbanization economies that accrue to all firms in an urban area) arise from two sources: local labor markets and knowledge spillovers.

Labor markets: Do thick local labor markets create localization economies? We need to distinguish between industries based on unskilled labor (e.g., leather) from those based on skilled labor (printing/publishing). Consider labor markets with unlimited supplies of unskilled labor operating in land markets with minimal land use / zoning regulations but where land rents decline with proximity to industry. In other words, unskilled labor is available in plenty and can locate anywhere, but is likely to locate near factories where rents are lowest. Therefore, unskilled labor is likely to co-locate with industrial clusters. Does this generate localization economies for those industries that are reliant on unskilled labor? If it does we are likely to see unskilled labor-based industries more oriented toward locating in industrial clusters with other unskilled labor-based industry that do not share buyer-supplier networks. These clusters will not include industries based on skilled labor. If these latter (skill-based) industries do cluster, they do not do so for labor market localization economies, as their critical workers, the high-skill high-wage labor, will not co-locate with industry. They do so for other reasons (discussed below). In summary, labor market localization economies, if any exist, are likely to be industry specific and inversely related to the proportion of skilled labor in a given industry.

Knowledge spillovers: These are of two kinds: technology spillovers through informal interaction and information spillovers on market agents. Technology spillovers are irrelevant in low technology firms and industries in mature stages of the product cycle. The vast majority of manufacturing industry in India belongs in this category. Hence, for these industries we can argue that there are negligible localization economies from technology spillovers. Information spillovers on market agents such buyers and suppliers, however, are more likely to provide localization economies. Firms of all sizes (except perhaps the very largest vertically integrated firms) rely on dense buyer-supplier networks. Firms benefit from having to access to local buyers and suppliers, and knowledge pooling on buyer-supplier behavior is likely to eliminate inefficient agents.

Hence, theory suggests the existence of two types of industrial districts: labor-sharing industrial districts that depend on the availability of low skill labor, and buyer-supplier-linked industrial districts where industries that have market interactions with each other benefit from co-location. We do not have spatially disaggregated wage data to test explicitly for the existence of labor-sharing districts. We are, however, able to establish what the expected buyer-supplier links are between our industry groups by assuming that the input-output links at the national level are replicated at the local level. The national input-output tables are available. We assume that similar input-output linkages exist at the level of the metropolis and argue that industries with strong input-output linkages are likely to co-locate.

It is useful at this point to distinguish between co-location and co-clustering. Co-location occurs when industries from two sectors are present in the same small region. Co-clustering occurs if both industries that are co-located are linked through input-output, innovation or labor market linkages. Before we examine the evidence on buyer-supplier linkages, let us first examine the data on co-location by industry for all sectors. The correlation coefficients for factories and workers for all eight industry groups are reported in Table 3. The data in this table are quite remarkable. There is strong evidence that industry groups co-locate at the pin code level, especially in the case of factories, or small scale units. In Mumbai, for instance, factories for every industry group are seen to have a statistically significant correlation with every other industry group. In general the correlation coefficients are very high: 0.93 between Machinery and Chemicals, 0.91 between Machinery and Metals, etc. In the case of workers, however, the correlations are not as high, and fewer are statistically significant. In Chennai, the pattern is even more pronounced. With the exception of the Leather sector (which has a moderate but significant correlation with only the Textiles sector) the correlation coefficients of every other pair of industries is significant, and as in the case of Mumbai, often very high. The Leather sector is anomalous in Kolkata as well. It's only significant correlation in that metropolis, is with the Chemicals sector. But Kolkata itself is somewhat of an anomaly compared to Mumbai and Chennai, at least in terms of the co-location of workers. Factories in Kolkata, with the exception of the Leather sector, are generally co-located; however, workers in at least four industries—Food/Beverages, Textiles, Leather, and Printing/Publishing—are generally not correlated with workers in other industries. This is an intriguing finding whose implications we will discuss later.

It is one thing for industries to be co-located, it is another for them to be co-clustered. If the reasoning on buyer-supplier clusters outlined above is correct we can expect: (a) that industries that have strong input-output links will co-cluster; that is, they will form clusters in the same or proximate pin codes, and (b) industries that do not share buyer-supplier linkages will not co-cluster; if they do it will be for labor-sharing, and therefore they will share similar labor profiles (low-skill with low-skill, or high-skill with high-skill). In order to test this hypothesis we conducted co-clustering tests on four industry pairs; two of these pairs have strong input-output linkages (the two highest among our eight industry groups); Metals and Machinery with an I-O factor of 34.95, and Metals and Electrical/Electronic with an I-O factor of 25.75. The two other pairs have virtually no input-output linkages; Food/Beverages and Electrical/Electronic have an I-O factor of 0.07 and very different labor profiles (the former is low skill, the latter is high skill); Textiles and Metals have an I-O factor of 0.41 and potentially similar labor profiles. We combine the proportion (rather than raw)[5] data on factories and workers for these four industry pairs by pairs, and conduct tests of global clustering (Moran's I) and local clustering.

The results are mixed. Consider the results of the global clustering test first (in Table 4). In Mumbai, among the strong I-O pairs, only factories in the Metals-Electrical combination are clustered, whereas the Food-Electrical combination, which shares neither I-O links nor similar labor profiles, shows clustering for factories and workers. In Kolkata, all four pairs are clustered, for factories and workers (more for the former than the latter). In Chennai, as in Mumbai, factories in the Metals-Electrical combination are clustered; but factories in both weak I-O combinations are clustered. The strongest I-O pair—Metals and

[5] If raw data are used, the dominant industry determines the outcome of paired calculations.

Machinery—is not only not clustered in Mumbai and Chennai, but the value of Moran's I is negative half the time.

Next we look at a final set of data: the share of industry in the top pin codes. Table 5 lists these data by metropolis, for all industry and by sector. (Note that in a given metropolis the top 10 or top 20 pin codes are not separately identified for each sector. What is reported is the share of each sector in the top overall pin codes.) The results are not surprising in the context of what we have presented earlier, but they are quite effective in making the point that industry is concentrated in a handful of pin codes in all three cities, and that all sectors are heavily represented in these top pin codes. In Mumbai the top ten pin codes include close to 55 percent of all factories and workers, and the top 20 pin codes include over 76 percent of all factories and about 80 percent of all workers. In Chennai and Kolkata the proportions are progressively smaller. This decline is probably a function of the fact that the total number pin codes in Kolkata (133) and Chennai (108) are higher than in Mumbai (94). In general, regardless of the number of pin codes in a metropolis, the top ten percent of the pin codes include close to 50 percent of all factories and workers.

Summary of the findings

(1) In Indian metropolises industry is generally clustered—the evidence for clustering is found at level of the metropolis (using the global Moran statistic), and certainly at the level of the pin code (using local Moran statistics and maps). On average about 50 percent of all workers and factory units are concentrated within ten percent of the most industrialized pin codes. At the sectoral level there are extremes: in one case there are no clusters at all; at the other end there are instances where 70 percent or more of workers/factories are concentrated within six to eight pin codes (see Table 2).

(2) The clusters are of two types: first, where factories and workers are both clustered in the same region within a metropolis; second, where factories are clustered at locations separate from where workers are clustered (i.e., separate clusters of small scale operations and large scale operations). The second pattern is more common.

(3) A small number of pin codes account for a very large proportion of all industry, both factories and workers. As a result the extent of industry co-location is very high. However, the expected relationships between industrial sectors—whereby industries with strong input-output linkages are expected to co-locate, and industries using similar labor profiles are expected to co-locate—are not found. On the contrary, we see several examples of counterintuitive co-locations.

(4) Some industries have distinct locational properties. For example, where the Leather industry is significant (as in Kolkata and Chennai) it is located on the urban fringe and is not co-located with other industries except Chemicals. The Printing/Publishing industry is located near the urban core in all three cities. Both industries are highly clustered, and are also examples of cases where workers and factories are clustered in the same pin codes. The Textile industry, on the other hand, the largest industry, is marked by separate factory and worker clusters, where the former is closer to the city center than the latter (except in Mumbai).

(5) The extent of clustering is highest in Kolkata and lowest in Chennai. However, the extent of co-location follows the reverse pattern: highest in Chennai and lowest in Kolkata. This is indicative of the existence of different types of industrial districts, where the ones in Chennai have a greater mix of industries than the ones in Kolkata. These industrial districts appear as spatially separate bands or sectors.

An Explanatory Framework

How can these patterns be explained? To begin with, we suggest that the default approach outlined earlier—whereby localization economies drive cluster formation—may be limited in its explanatory power. There is little evidence in support of the processes of localization, either via local labor markets or via buyer-supplier networks. It is possible to argue that these findings are artifacts of the method of local cluster identification. That is, had we used other methods that would have enlarged the definition of "local" beyond the one used here (a pin code and its contiguous neighbors), there would have been stronger evidence in support of localization economies. That, however, is unlikely. First, at a preliminary stage in our investigations we did indeed use larger definitions of "local", with virtually indistinguishable results. Second, it may be possible to enlarge the definition of local till it is meaningless or large enough to encompass a significant portion of the metropolitan area. At that point it becomes difficult to distinguish localization economies from urbanization economies. Perhaps localization economies arise as a result only of inter-firm technological interaction within an industrial sector (because following the national input-output data, inter-firm trade in most of these sectors is not very high). It is difficult to make that case for many of these sectors, which are dominated by old firms that are not close to the technological frontier (Lall and Rodrigo, 2001). Therefore, it is possible that the debate on the relative strength of localization and urbanization economies should be resolved firmly in favor of the latter.

Looking beyond localization economies, we suggest that firm locations are guided by a complex set of factors which often rule out most spaces within metropolitan areas. These factors include the accidents of history, metropolitan expansion, state regulations (especially ones that affect the land market), and industry characteristics. As a result we see the usually unplanned evolution of *mixed industrial districts,* which include a variety of related and unrelated industry sectors, at leap-frogging locations within metropolitan areas. We suggest that an evolutionary framework may explain the observed patterns of industry location in Indian metropolises. This framework is speculative (we do not have the temporal information needed to make a stronger claim), but it is able to account for many of the expected and unexpected findings.

First, at some specific historic point the pioneer industrial unit in a specific industrial sector makes a location decision within the metropolis. The driving force behind that decision (not the location decision, but the decision to start a new industry) may have one or several motivations: nationalism (as in the case of the first textile mill in 1854 in Mumbai), war (as in the case of the first leather units in Kolkata, created to outfit saddles for the Imperial army during the first world war), bureaucratization and the spread of literacy (creating the need for printed matter), etc. This first factory did not rely on localization economies to boost productivity, but probably relied on urbanization economies, at least in terms of providing market access and pool of labor. This unit located in what was then the urban fringe, beyond dense population settlements, but close enough and connected enough for workers to reach the plant. Following the convention of the time, this unit was large, relying on internal economies of scale to reduce costs.

A cluster of firms in the same industry began forming around this original location. It is difficult to determine whether these subsequent location decisions were the result of localization advantages arising from labor pooling, advantages derived from shared infrastructure such as railheads, or state regulations that directed new firms to this location. It will be necessary to conduct archival research for more concrete judgments. It is very likely that at some point industries in this cluster began to derive benefits from labor pooling. Two factors should be considered here: First, these were not high technology industries of the time; they were industries in the late stages of the product cycle (Vernon, 1966), reliant on unskilled and semi skilled labor. Second, the location of these industries began influencing the land market around them; because of the local environmental impacts of these industries, the only bidders for the proximate land were other industries or low wage labor. In other words, this sub-region became an industrial district, with large-scale factories and slums/tenements for unskilled workers. As the city continued to grow beyond this industrial district most new industry was directed to this district by state regulations. The single purpose industrial district became a mixed industrial district.

Where was even newer industry to locate? With all the land in the original industrial district in use, and with state regulations that forbade the conversion of any land with housing (slums, tenements, or middle class residences) to industrial use, new industries now sought new locations on what was then the urban fringe. The role of the state in discouraging land use change turns out to be a critical influence on industrial location (as we shall see below). The cycle of industrial district formation began again, this time with more active involvement of the post-colonial state which assisted with land acquisition (often the most difficult part of urban industrial location) and provided physical infrastructure.

When this cycle was complete (i.e., the point was reached where there was no more land for new factories) new industrial units leap-frogged over the residential communities that had grown in the interim to new locations at the urban fringe. This is the current stage. Now there is even more active involvement of the state, which sets up export processing zones, free trade zones, technology parks, industrial parks etc. to entice new industrial units. (Consider the names of some of the most active pin codes: in Mumbai, Chakala and SEEPZ, both Maharashtra Industrial Development Corporation centers; in Chennai, Ambattur Industrial Estate and SIDCO Industrial Estate, both set up by the state of Tamil Nadu.)

This stylized framework explains a number of observations—some regularities, some irregularities—listed in the preceding section. In this framework, the exact location of specific industries has to be understood in terms of the functions of these industries. For instance, the Printing/Publishing industry remains located close to the CBD, which is its principal market area. The Leather industry, which pollutes both the air (with the smell of animal hides) and the groundwater, and therefore cannot even co-locate with other industries (not to mention residential areas), remains at the urban fringe—when the fringe moves beyond or envelopes the Leather cluster, the state compels the cluster to move further out. This is exactly what has happened in Chennai and is happening in Kolkata. This framework also explains some anomalies, such as the location of a large textile cluster near Mumbai CBD. This cluster should not exist, for the land there is too valuable to remain devoted to an industry with outmoded technology and very low value addition. Yet it remains a textile cluster, with virtually closed factories, state take-over (or nationalizing) of "sick" units, and job losses that mount by the year, because the state will not permit the conversion of this industrial land to commercial or residential use (D'Monte, 2000). The other significant anomaly comes from the relative locations of factory and worker clusters. It is not unusual to see these clusters form separately, but the expectation is that worker clusters (which are clusters of large factories), which require more undivided land, will locate on the least expensive land, furthest from the center. Yet when there is no exit policy, i.e., factories are not allowed to close and factory land cannot easily be transferred, it is possible to see clusters of large scale units near the center of the city. And most important, this framework explains why co-location is so common, but theoretical expectations on co-clustering are not realized in practice.

We conclude by highlighting two implications of these findings. First, mixed industrial districts are the norm in Indian (and perhaps most developing nation) metropolises. This study is unable to determine whether the past industrial successes of these metropolises arose from this fact; but it suggests that single sector industrial districts, especially ones that cannot benefit from urbanization economies, are unlikely to succeed. Second, land use policies deeply influence industry location. A policy regime that does not allow land use change creates significant inefficiencies in industrial location and, by extension, commercial and residential location. We recognize that land is the most precious and emotive commodity in urban areas, and the political economy of land ownership involves every metropolitan resident. However, the distributional and welfare implications of current policies are unclear. A careful analysis of the issue would be very useful to metropolitan governments in developing nations.

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Table 1. Indices of global clustering

	Total Factories	Moran's I for factories	Z of I	Total Workers	Moran's I for workers	Z of I
Mumbai						
Food/Beverages	274	0.172	2.951	16,992	0.156	2.699
Textiles	1,988	0.100	1.797	131,318	0.191	3.259
Leather	115	0.074	1.374	2,629	0.018	0.474
Printing/Publishing	882	0.060	1.139	17,001	0.048	0.959
Chemicals	1,146	0.149	2.591	41,470	0.008	0.031
Metals	894	0.069	1.290	25,056	-0.019	0.145
Machinery	767	0.104	1.867	40,808	-0.045	0.560
Electrical/Electronic	802	0.244	4.133	58,871	0.141	2.455
Kolkata						
Food/Beverages	355	0.165	3.332	9,573	0.170	3.429
Textiles	355	0.063	1.354	90,621	0.168	3.380
Leather	283	0.211	4.216	6,149	0.316	6.229
Printing/Publishing	428	0.366	7.203	10,574	0.255	5.071
Chemicals	671	0.214	4.274	24,871	0.147	2.992
Metals	1,023	0.178	3.582	38,440	0.047	1.067
Machinery	451	0.130	2.655	13,322	0.459	9.003
Electrical/Electronic	511	0.168	3.400	18,320	0.051	1.129
Chennai						
Food/Beverages	166	0.094	1.798	8,459	0.069	1.353
Textiles	1,446	0.135	2.495	107,266	0.039	0.694
Leather	406	0.058	1.161	17,919	0.087	1.666
Printing/Publishing	402	0.230	4.135	9,361	0.141	2.595
Chemicals	512	0.126	2.329	17,920	0.132	2.443
Metals	695	0.184	3.337	29,076	0.006	0.266
Machinery	416	0.153	2.799	18,772	0.039	0.829
Electrical/Electronic	359	0.127	2.361	21,018	-0.003	0.098

Data Source: CSO Government of India, ASI sampling frame, 1998-99

Table 2. Concentration in clusters

	Total Factories	Factories in Clusters	Percent factories in Clusters	Total Workers	Workers in Clusters	Percent workers in Clusters	# of Pin codes in factory clusters	# of Pin codes in worker clusters	Common Pin codes
Mumbai									
Food/Beverages	274	79	28.8%	16,992	7,791	45.9%	5	5	0
Textiles	1,988	703	35.4%	131,318	62,649	47.7%	5	6	2
Leather	115	45	39.1%	2,629	691	26.3%	4	3	1
Printing/Publishing	882	203	23.0%	17,001	3,567	21.0%	2	2	2
Chemicals	1,146	508	44.3%	41,470	5,623	13.6%	7	3	2
Metals	894	307	34.3%	25,056	1,347	5.4%	4	1	1
Machinery	767	185	24.1%	40,808	0	0.0%	3	0	0
Electrical/Electronic	802	318	39.7%	58,871	34,575	58.7%	4	3	3
Kolkata									
Food/Beverages	355	122	34.4%	9,573	6,034	63.0%	5	9	4
Textiles	355	120	33.8%	90,621	38,271	42.2%	6	7	1
Leather	283	209	73.9%	6,149	4,393	71.4%	6	8	6
Printing/Publishing	428	209	48.8%	10,574	4,155	39.3%	10	9	9
Chemicals	671	224	33.4%	24,871	10,053	40.4%	7	9	7
Metals	1,023	357	34.9%	38,440	8,166	21.2%	4	3	2
Machinery	451	101	22.4%	13,322	4,217	31.7%	6	6	1
Electrical/Electronic	511	170	33.3%	18,320	5,283	28.8%	9	6	4
Chennai									
Food/Beverages	166	45	27.1%	8,459	3,065	36.2%	4	4	2
Textiles	1,446	313	21.6%	107,266	22,447	20.9%	7	3	2
Leather	406	204	50.2%	17,919	9,932	55.4%	4	6	4
Printing/Publishing	402	161	40.0%	9,361	2,534	27.1%	8	5	5
Chemicals	512	137	26.8%	17,920	5,333	29.8%	6	5	2
Metals	695	240	34.5%	29,076	5,755	19.8%	4	3	2
Machinery	416	167	40.1%	18,772	5,222	27.8%	2	2	2
Electrical/Electronic	359	157	43.7%	21,018	1,065	5.1%	4	1	1

Data Source: CSO Government of India, ASI sampling frame, 1998-99

Table 3. Correlation coefficients for industry pairs

	Food/ Beverages	Textiles	Leather	Printing/ Publishing	Chemicals	Metals	Machinery	Electrical/ Electronic
MUMBAI								
Food/Beverages	1.00	**0.39**	**0.31**	**0.39**	**0.34**	**0.40**	**0.40**	**0.25**
Textiles	0.10	1.00	**0.58**	**0.79**	**0.77**	**0.73**	**0.77**	**0.63**
Leather	**0.20**	0.23	1.00	**0.43**	**0.77**	**0.63**	**0.75**	**0.63**
Printing/Publishing	0.16	**0.74**	**0.35**	1.00	**0.49**	**0.44**	**0.51**	**0.45**
Chemicals	**0.25**	**0.37**	**0.42**	**0.33**	1.00	**0.91**	**0.93**	**0.81**
Metals	0.16	**0.26**	0.18	**0.25**	**0.56**	1.00	**0.87**	**0.70**
Machinery	0.09	0.17	0.15	0.07	**0.34**	0.15	1.00	**0.78**
Electrical/Electronic	**0.27**	0.07	0.16	0.10	**0.21**	**0.25**	0.06	1.00
KOLKATA								
Food/Beverages	1.00	**0.31**	0.09	**0.46**	**0.43**	**0.33**	**0.46**	**0.40**
Textiles	0.07	1.00	0.04	**0.36**	**0.64**	**0.33**	**0.51**	**0.51**
Leather	0.02	-0.05	1.00	0.03	**0.49**	0.07	0.12	0.10
Printing/Publishing	0.12	0.03	0.08	1.00	**0.34**	0.15	**0.37**	**0.32**
Chemicals	0.17	**0.19**	**0.33**	0.10	1.00	**0.36**	**0.60**	**0.72**
Metals	0.14	0.09	0.14	0.07	**0.25**	1.00	**0.76**	**0.33**
Machinery	**0.21**	-0.03	0.04	**0.26**	**0.22**	**0.41**	1.00	**0.68**
Electrical/Electronic	**0.25**	0.06	0.02	0.08	**0.37**	0.08	**0.30**	1.00
CHENNAI								
Food/Beverages	1.00	**0.30**	0.02	**0.47**	**0.69**	**0.59**	**0.52**	**0.62**
Textiles	0.15	1.00	**0.29**	**0.61**	**0.51**	**0.40**	**0.41**	**0.40**
Leather	-0.01	**0.35**	1.00	0.10	0.16	0.11	0.14	0.15
Printing/Publishing	**0.25**	**0.32**	0.17	1.00	**0.58**	**0.56**	**0.57**	**0.46**
Chemicals	**0.27**	**0.34**	**0.23**	**0.33**	1.00	**0.87**	**0.84**	**0.79**
Metals	**0.22**	**0.31**	0.13	**0.63**	**0.33**	1.00	**0.95**	**0.71**
Machinery	**0.41**	**0.39**	0.09	**0.31**	**0.41**	**0.34**	1.00	**0.76**
Electrical/Electronic	**0.23**	**0.50**	**0.27**	**0.26**	**0.40**	**0.23**	**0.27**	1.00

Notes:
Factory data above diagonal, Worker data below diagonal
Figures in bold are significant at 0.01.

Data Source: CSO Government of India, ASI sampling frame, 1998-99

Table 4. Indices of co-clustering in selected industry pairs

	Factories				Workers		
	National I-O factor	Total Factories	Moran's I	Z of I	Total Workers	Moran's I	Z of I
MUMBAI							
Strong I-O links							
Metals and Machinery	34.95	1,661	0.082	1.496	65,864	-0.052	0.668
Metals and Electrical/Electronic	25.75	1,696	0.161	2.774	83,927	0.105	1.876
Weak I-O links							
Food/Beverages and Electrical/Electronic	0.07	1,076	0.184	3.145	75,863	0.294	4.936
Textiles and Metals	0.41	2,882	0.080	1.473	156,374	0.045	0.904
KOLKATA							
Strong I-O links							
Metals and Machinery	34.95	1,474	0.222	4.429	51,762	0.121	2.49
Metals and Electrical/Electronic	25.75	1,534	0.211	4.222	56,760	0.109	2.249
Weak I-O links							
Food/Beverages and Electrical/Electronic	0.07	866	0.178	3.579	27,893	0.185	3.730
Textiles and Metals	0.41	1,378	0.270	5.349	129,061	0.181	3.644
CHENNAI							
Strong I-O links							
Metals and Machinery	34.95	1,111	-0.079	1.060	47,848	0.029	0.673
Metals and Electrical/Electronic	25.75	1,054	0.149	2.738	50,094	-0.004	0.087
Weak I-O links							
Food/Beverages and Electrical/Electronic	0.07	525	0.126	2.332	29,477	0.041	0.873
Textiles and Metals	0.41	2,141	0.161	2.948	136,342	0.026	0.623

Data Source: CSO Government of India, ASI sampling frame, 1998-99

Table 5. Industry concentration in top districts

	Number of units	Share of metropolitan total (%)	Food/ Beverages (%)	Textiles (%)	Leather (%)	Printing/ Publishing (%)	Chemicals (%)	Metals (%)	Machinery (%)	Electrical/ Electronics (%)
Mumbai Factories										
Top 10	3,744	55.20	23.73	57.75	56.52	45.69	57.77	60.40	56.32	53.49
Next 10	1,447	21.34	25.18	22.69	19.13	16.78	21.73	20.69	23.99	17.33
Top 20 Total	5,191	76.54	48.91	80.43	75.65	62.47	79.49	81.10	80.31	70.82
Mumbai Workers										
Top 10	176,701	53.19	28.05	51.18	20.27	35.45	34.17	50.00	62.75	77.91
Next 10	86,411	26.01	15.70	32.58	51.16	23.27	29.80	24.15	25.16	11.85
Top 20 Total	263,112	79.21	43.75	83.76	71.44	58.72	63.97	74.15	87.91	89.76
Kolkata Factories										
Top 10	1,610	36.38	24.35	38.64	59.25	26.44	29.70	46.22	35.54	26.37
Next 10	787	17.79	25.13	13.05	21.57	16.78	18.08	13.72	18.88	22.41
Top 20 Total	2,397	54.17	49.48	51.70	80.82	43.22	47.78	59.93	54.42	48.78
Kolkata Workers										
Top 10	77,588	33.73	11.19	57.66	0.42	7.00	19.81	19.02	9.68	25.57
Next 10	49,117	21.35	30.47	23.14	42.00	15.09	13.98	23.82	13.33	13.40
Top 20 Total	126,705	55.09	41.66	80.80	42.42	22.09	33.79	42.84	23.01	38.97
Chennai Factories										
Top 10	1,872	42.53	33.74	27.25	53.20	28.36	40.62	51.22	69.95	66.02
Next 10	792	17.99	21.08	23.03	6.16	33.83	18.16	17.12	5.53	7.80
Top 20 Total	2,664	60.52	54.82	50.28	59.36	62.19	58.79	68.35	75.48	73.82
Chennai Workers										
Top 10	104,902	45.65	23.34	40.60	53.58	35.54	42.91	51.12	44.82	73.68
Next 10	45,364	19.74	29.32	20.44	14.09	14.56	15.17	16.37	38.04	11.66
Top 20 Total	150,266	65.39	52.66	61.04	67.66	50.10	58.08	67.49	82.85	85.34

Data Source: CSO Government of India, ASI sampling frame, 1998-99

Figure 1. Industrial Clusters in Mumbai

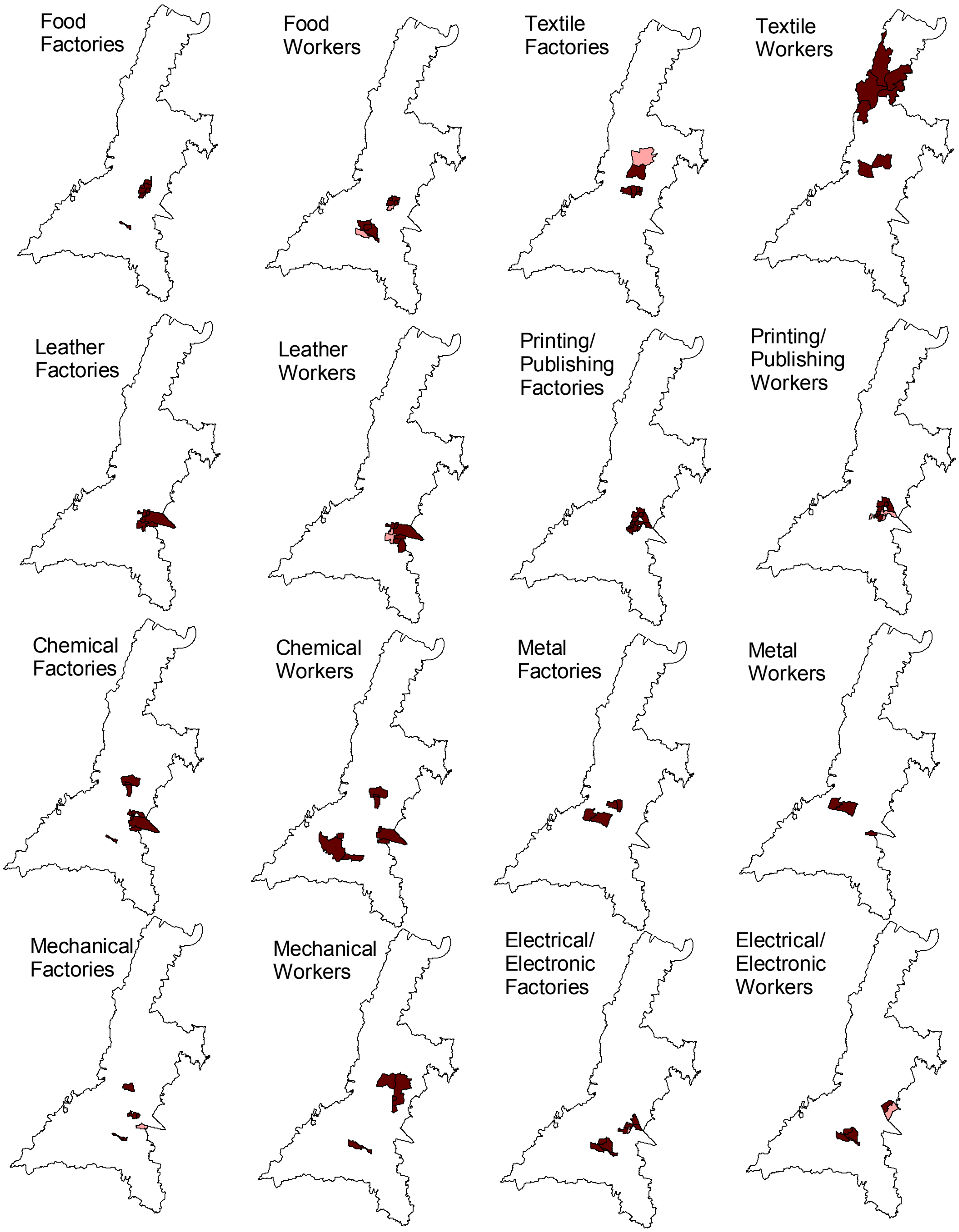

Figure 2. Industrial Clusters in Kolkata

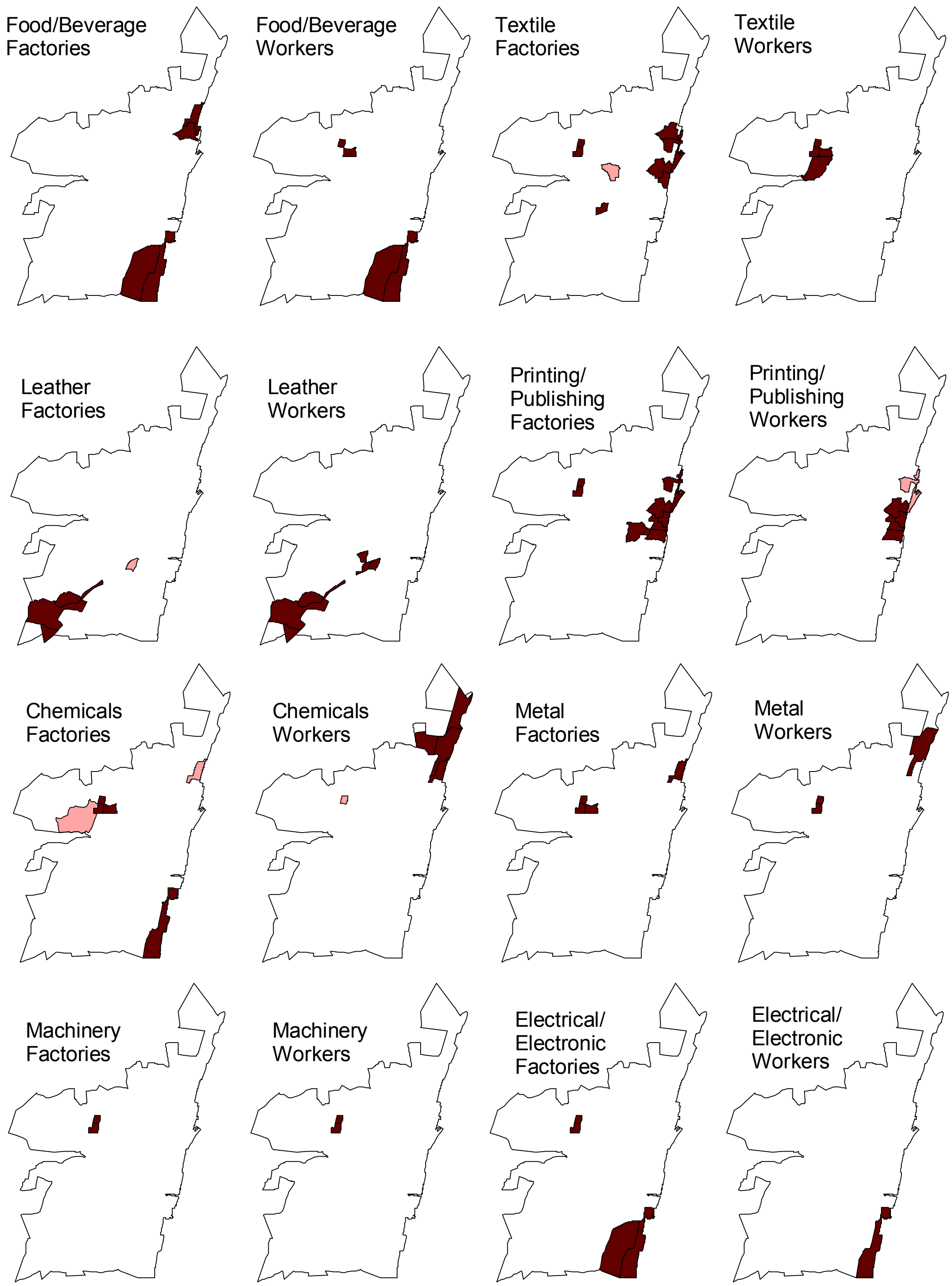

Figure 3. Industrial Clusters in Chennai