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Abstract

Applying the methodology developed by Duranton and Overman (2005, 2008), we analyze localization and dispersion of firms in China. Using a unique and detailed dataset on manufacturing firms in China, we are able to follow the changes in location patterns of firms between 2002 and 2008. Our analysis shows that firms in China are more localized than in the UK or Japan. Localization is comparable to that in the US, and takes place at relative small scales that are consistent with the size of Chinese cities. Localization increases rapidly, even in the relative short period between 2002 and 2008, especially new entrants localize. Private firms, firms from Hong-Kong, Macao and Taiwan, and foreign firms are more localized than state-owned firms. Our findings are consistent with the notion that China is increasingly liberalizing its economy, enabling (profit seeking) manufacturing firms to benefit from agglomeration economies.

JEL-Code: F230, R120, L700.

Keywords: spatial concentration, China, manufacturing firms, localization.

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1. Introduction

Economic activity is unevenly distributed across space. The reason for this is the subject of a large and growing body of literature (see f.i. the surveys of Rosenthal and Strange, 2004, or Brakman, Garretsen, Van Marrewijk, 2009). But before answering the question *why* this is the case, it is important to know *how* economic activity is distributed across space and how strong industries tend to cluster, if at all. Furthermore, if industry tends to cluster it is important to know at what spatial scale this happens. The answers to these questions are important for a number of reasons. Holmes and Stevens (2004, p.2799) f.i. list three problems that are 'at stake' and that require answers to the questions stated above: what is the importance of geography to determine the economic success or failure of a location, can government policy influence location choices, and can regions loose or gain from relocations of core industries? The first step in dealing with these types of problems is to find out where economic activity is located, and that is what we do in this paper. Location studies have by-and-large concentrated on the US, countries of the European Union (EU), and Japan (see f.i. surveys of Holmes and Stevens, 2004, Combes and Overman, 2004, Fujita et al., 2004). In general, the conclusion of these studies is that, indeed, economic activity is unevenly spread across space, but also that many differences between regions and countries exist, that ask for possible explanations. The labour market in the US, f.i. is more integrated than labour market in the EU, which could explain in different spatial patterns of economic activity in these two areas (the US more concentrated than the EU). Comparing the data on location patterns is a first step in explaining these and other differences.

In this paper we concentrate on location patterns in China. China is an interesting case. Historically, concentration of economic activity seems low compared to other countries (see for a long-term historical perspective, Brandt et al. (2013) and for an account on more recent periods, Au and Henderson, 2006a,b). Fujita et al. (2004, p.2955) f.i. note that the Chinese Gini-coefficient in 2000 is 0.43 which is 'way below the world average...Only former Sovjet bloc countries have similarly low Gini's... '. Limited concentration of economic activity is worrying, because it may indicate efficiency losses or the loss of potential agglomeration rents. To a large extent the Chinese Hukou system is held responsible. The Hukou system is a system that limits migration between rural and urban areas and between urban areas. This system is gradually becoming more liberal, but its effects are still visible. A more liberal system most likely results in more concentration, along the Chinese coast but also more in inland China (see Bosker et al., 2012).

Most of the studies dealing with China use regional population/employment data or regional GDP statistics (Bosker et al., 2012). In this paper we employ a detailed dataset on individual manufacturing firms, differentiating between privately owned firms, state and collectively owned firms, firms from Hong Kong, Macao, and Taiwan (HMT), and finally foreign firms. Furthermore, we have sectoral information for these groups of firms. The data allow us to address the question whether there is a ranking of concentration associated with ownership or state control. In the remainder of this paper we will first in section 2 motivate the choice for our measure of spatial concentration. Section 3 then introduces the data set, and section 4 provides the stylized facts on spatial concentration in China. In the remaining sections we differentiate between various types of firms by ownership (section 5), firm size (in section 6), and new firms (section 7). Section 8 concludes. In general, we find that localization is present in China, and seems comparable to that of the US. Evidence that China is in transition is clearly visible from the localization analysis, that indicates that increasingly firms try (and succeed) to benefit from agglomeration economies that go along with increased spatial concentration.

2. Measuring spatial concentration

Measuring spatial concentration remains a challenge despite considerable recent progress (see Combes and Overman, 2004 for an in depth discussion). Measures should ideally be comparable across industries (some industries have many firms, some only a few), across spatial scales (changing spatial scale should not affect conclusions with respect to concentration), have a well-defined null-hypothesis (have a bench-mark), indicate whether findings are significant (confidence intervals), and unbiased with respect to changes in spatial scales (changes in borders of spatial units) or industrial classification (changes in 'borders' of industrial classifications).[2] The ideal index still has to be found but good ones exist. Most notably the Ellison and Glaeser (1997) index and the Duranton-Overman (2005, 2008) index (DO index hereafter). The Ellison and Glaeser (1997) index explicitly deals with the problem of comparing between industries that consist of different number of

[2] See for a detailed discussion of these criteria Combes and Overman (2004), or Combes et al. (2008).

firms (with only a few firms finding concentration might just be spurious). Furthermore it defines a clear benchmark (the dartboard). The index that satisfies most requirements, however, is the DO index, although the index is still susceptible for changes in industrial classification. Results using different indices can be very different. Duranton and Overman (2005) find that the Ellison and Glaeser index indicates that 94% of the UK four digit industries are localized, whereas the DO index shows that only 52% are localized. A disadvantage of both measures is that they require relative detailed location information of (individual) firms.

In this paper we analyze manufacturing concentration in China with the DO index. The main reason is that the DO index is unbiased for changes in spatial scales because it circumvents the use of exogenous spatial units altogether.[3] This is an important advantage of this index. If an industry is concentrated at a specific location it should not matter if an administrative spatial boundary cuts through this agglomeration. Most measures, however, treat neighboring spatial units exactly the same as far away spatial units and dividing an agglomeration over more spatial units affects results. For a large country like China, we especially aim to avoid this potential bias. The DO index calculates the bilateral Euclidian distance between all pairs of firms. Counting the number of firms at a given distance gives the frequency of firms at that distance and allows us to calculate the density of firms at that distance (Duranton and Overman, 2005, p.5). If the distribution of densities has a maximum at a certain distance, this particular distance separates firms the most. Euclidian distance is only a proxy for true distance which can be expected to differ between low-density areas and high-density areas. Kernel-smoothing deals with this problem. Furthermore, Monte Carlo simulations provides confidence intervals.

The empirical analysis proceeds in three steps. We first calculate the pairwise distances between firms. Next, we estimate the kernel density function of the distribution of pairwise distances. Third, we construct (global) confidence interval bands and calculate the index of localization or dispersion of firms in order to assess the spatial pattern of a manufacturing industry.

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[3] Note, that our use of this measure does not fully use this advantage of the DO index, as we allocate firms to the smallest spatial unit that we have, see below.

The Density estimation involves the density of pairwise distances between firms. For each industry A, with n firms, there are $\frac{n(n-1)}{2}$ bilateral distances between firms. The estimator of the density of bilateral distances at distance *d* is given by (Duranton and Overman, 2005, see Silverman, 1986 for a discussion on choosing *h*, and Dinardo and Tobias, 2001 for a discussion of kernel estimates):

$$\widehat{K_A}(d) = \frac{1}{n(n-1)h}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} f\left(\frac{d-d_{ij}}{h}\right), \quad (1)$$

Where d_{ij} is the Euclidean distance between firm *i* and *j*, *h* is the bandwidth, and *f* is the kernel function (we use GIS, to deal with the curvature of the earth which is important for a large country like China).

The counterfactual is a hypothetical industry for which firms are randomly reallocated to possible sites. Assume there are n_M manufacturing firms that define n_M possible sites. Industry A has n_A firms. Following Duranton and Overman (2005, 2008), we randomly select n_A sites from all possible sites n_M and do this 1000 times. This results in 1000 density estimates for each distance as defined in equation (1). Using these estimates we can construct a 90% confidence interval that contains 90% of all values at a particular distance, with the upper bound the 95% percentile, and the lower bound the 5% percentile. If a density exceeds the upper boundary there is *local* concentration at that distance, and if the density is smaller than the lower bound there is *local* dispersion at that distance.

Duranton and Overman (2005) also define *global* concentration and dispersion. Global concentration is the upper limit for which 95% of all draws (over the whole range of distances) is below that upper bound, and vice versa for the lower bound. As Duranton and Overman (2005, 2008) we define a distance threshold, in our case 900km.[4] A sector is defined to be globally concentrated if its density hit the upper limit at least once (over the whole range of distances), and similarly for dispersion (with the added condition that the upper limit is never touched).[5]

[4] Duranton and Overman (2005) chose the range based on the median value of all pairwise distances which is 180 kilometers for UK. In China, the median value of all pairwise distances between manufacturing firms is 952 kilometers in 2002 and 884 kilometers in 2008. Thus, we chose 900 kilometers as the threshold to calculate the confidence intervals.

[5] In principle there are many ways to construct confidence bands such that, say, 5% is globally above or below a band. We follow Duranton and Overman (2005), by using the *local* confidence bands to search for a *global* band. The procedure is as follows. We start by constructing an initial global band by connecting all local 1% confidence intervals (over all distances) and draw the band. Next, we count how many simulations go beyond this band. If this is more than 5% we take something smaller for the local confidence interval, for instance 0.5%, and repeat this until we find a confidence interval that corresponds to 5% of deviations over the entire set of

3 Data Set and Empirical Approach

We use a dataset that is collected via the Annual Survey of Industrial Firms (ASIF). The survey is conducted by the National Bureau of Statistics of China (http://www.stats.gov.cn/tjsj/ndsj); our dataset consists of the years 2002 and 2008 of the ASIF. The micro firm-level data of ASIF are aggregated and published in the China National Statistical Yearbook (CNSY). For our purposes, the disaggregated data of ASIF are essential and enable us to analyze location patterns of various types of firms and also to analyze changes of location patterns over time, that is to say, changes between 2002 and 2008. The published and aggregated data of the CNSY correspond by-and-large to the ASIF. A simple check on consistency between the two sources is to aggregate the micro-level ASIF data and compare the aggregation with the officially published aggregates in the CNSY. This comparison is done in table A1 in the appendix A. Both sources seem consistent, with one exception; Smelting and Pressing of Non-ferrous Metals (Sector 33). In 2002, the firm coverage of Sector 33 in ASIF is only 34% compared to the number of firms in the yearbook (that also has access to other sources). While in 2008, information of Sector 33 is no longer available in the ASIF. We therefore decided to exclude Sector 33 from the analysis.

The ASIF covers all Chinese industrial state-owned enterprises and non-state-owned enterprises with annual sales above RMB five million.[6] The total firm number firms is 176,514 in 2002, and 411,809 in 2008. We exclude the primary sector and the services sector because location decisions are very different from the manufacturing sector. This reduced the number of firms to 157,759 in 2002 and 376,935, in 2008. For the firms in the sample, ASIF gives detailed location information at the county level, industry information at two-, three- and four-digit level, ownership information (state-owned and collectively-owned, private and foreign owned), firm size, the number of employees and other (financial) firm specific indicators.

The precise location of the manufacturing firms is essential in our distance-based analysis. However,

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distances that we consider. This is the global 5% confidence interval.

[6] The threshold implies that small firms are not covered by the survey or that firms enter or exit the survey if the threshold is reached. Note, that we find that small firms are the most active in the dynamics of localization which might imply that we underestimate actual localization (see below). This is also noted by Lu and Tao (2009, p. 169). The survey covers enterprises that conduct only one economic activity (or at least one economic activity which is predominate) at one location. Firms with more establishments in one single location (city) are recorded as a single firm. Firms with more plants at different locations are differentiated in the survey.

restricted by the data, the location information is at the county level.[7] Therefore, bilateral distances between firm pairs are unavailable. Instead, we use the location of counties and assign this location to all firms in that county. The county-level is at a fine geographical scale, compared to China as a whole, and we assume that the aggregation error is small. We use the county-level Administrative Divisions Map (ADM) in 1999 provided by National Geomatics Center of China to construct the geographical information of counties (using the GIS software).[8]

ADM at county level in 1999 has spatial information for 2,367 county spatial units. However, 2,860 county level administrative units are recorded in the Chinese Administrative Divisions System. The reason that the number of county level units in ADM is less than that in the Chinese Administrative Divisions System is that ADM does not have sub-divisions of municipal districts of prefecture-level cities. The Chinese Administrative Divisions System, for example, sub-divides the municipal district of Beijing into six sub-municipal districts (comparable to counties), that are aggregated in our analysis (reducing the number of counties). To make the analysis comparable between 2002 and 2008, we match the location information of the ASIF to the administrative coding system of ADM.[9] The matching process leaves us 2,360 counties which are consistent both 2002, 2008 ASIF and ADM. We then allocate the geo-information on a county to all firms in that county, which might bias results as the size of counties differs (ideally we would like to have individual location information for all firms). An indication of the importance of this bias is to assume that counties are circular and that firms are spread evenly within this circle. The average distance between two points in a circular county equals $D_{ii} = 0.66 * \sqrt{area_i/\pi}$. Such intra-county distances are then used as the distances between firms locating in the same county. County size variation is small, the mean value of the intra-county distances is 19 kilometers, compared to the median value of all pair-wise distances between manufacturing firms in China, which is around 900 kilometers. Figure 1 shows in ascending order intra-county distances, D_{ii}. The largest intra-county distance is around 170 km while the smallest is less than 10 km. Intra-county distances for most counties

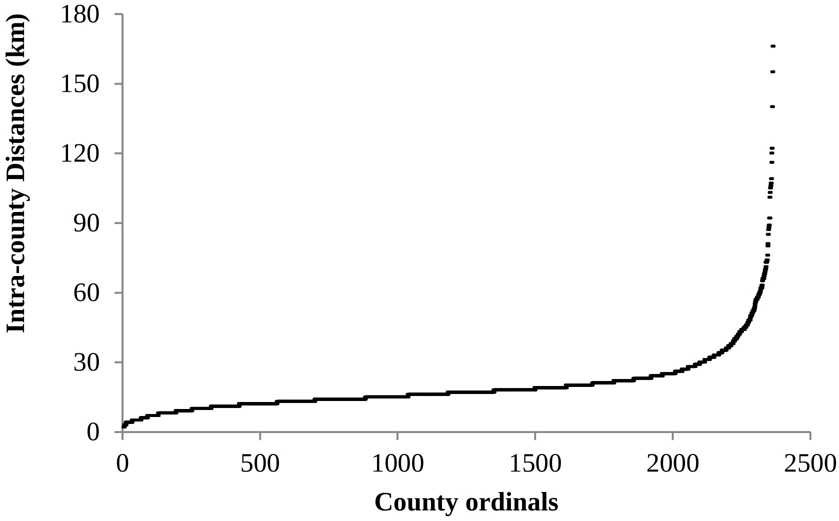
[7] County level is the third level of administrative divisions in Chinese administrative division system which is under the provincial (including municipalities) level and prefecture city level and above township level. County level administrative units include the municipal districts of prefecture-level city, county-level cities, deputy-level cities, forests, etc. In 2002 China had 2860 and in 2008 2859 county level administrative units.

[8] See for National Geomatics Center of China: http://ngcc.sbsm.gov.cn/. ADM at county level definition in 1999 is the closest ADM available for 2002.

[9] In ASIF, location of manufacturing firms includes 2,678 counties and 2,797 counties respectively in 2002 and 2008.

(around 2000 counties) are within 0-20 km range while for the other 300 counties, the intra-county distances range from 20 km to 170 km.

Figure 1 Ascending Order of Intra-county Distances



Source: Authors

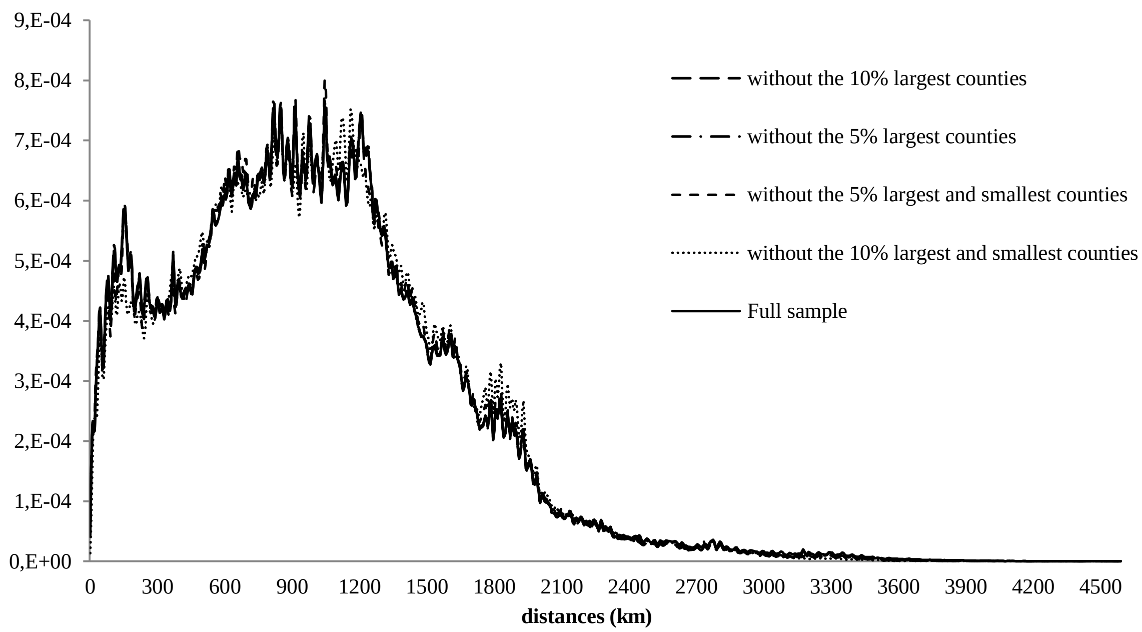
As a sensitivity exercise for the k-densities, we include sub-samples that exclude the largest and smallest counties. Table 1 shows that excluding the 5% or 10% largest counties reduces the number of firms by less than 1%. Excluding the smallest counties, however, does affect firm numbers significantly. The largest counties in China are in the western part of China with very low population and firm densities.

Table 1. Excluding the Largest and Smallest Counties

Sensitivity Analysis		No. manufacturing firms	firm number decreases by:	Bandwidth in calculating K-density	Std. intra-county distances
Full sample with all 2360 counties		157759		5.03	13.4 km
Excluding:	5% largest counties	157189	0.4%	4.99	7.1 km
	5% largest and smallest counties	140841	10.7%	5.21	6.7 km
	10% largest counties	156386	0.9%	4.96	5.6 km
	10% largest and smallest counties	120664	23.5%	5.54	4.8 km

Plotting the k-densities of the four sub-samples and the full sample in figure 2 shows that only for the sub-sample that excludes both the 10% largest and the 10% smallest differences with the full sample are visible. So, inter-county distances dominate the results rather than variation in county size.

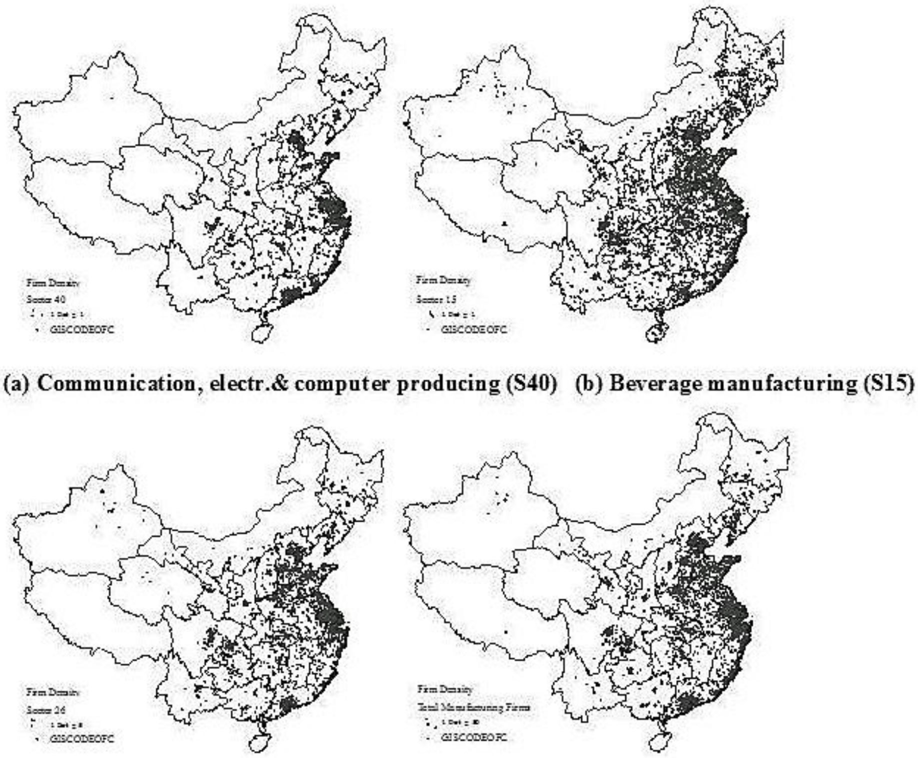
Figure 2. K-densities for sub-samples: excluding largest and smallest Counties



Source: Authors

To illustrate the DO index method, we select three two-digit industries in 2002: Communication, electronic and computer producing (sector 40), Beverage manufacturing (sector 15), and Chemical raw materials and chemical products (sector 26). A look at figure 3 indicates that firms in sector 40 appear to be geographically concentrated, those in sector 15 dispersed, and those in sector 26 have a similar pattern as manufacturing as a whole.

Figure 3. The spatial distribution of selected sectors and total manufacturing



(a) Communication, electr.& computer producing (S40) (b) Beverage manufacturing (S15)

(c) Chemical raw materials and chemical products (S26) (d) Total manufacturing

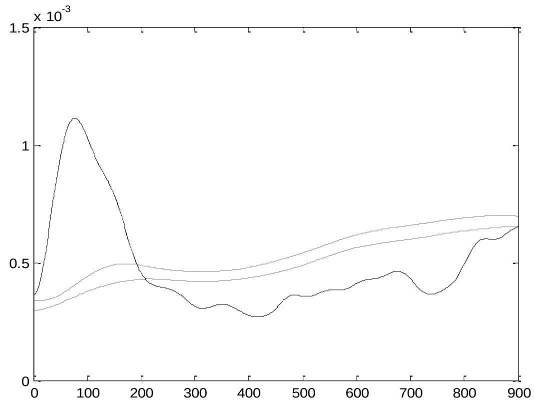
Source: Authors

Figure 4 provides the results of K-densities for these 3 illustrative sample sectors (solid lines). The dashed lines indicate the global upper, and lower 5% confidence bands.

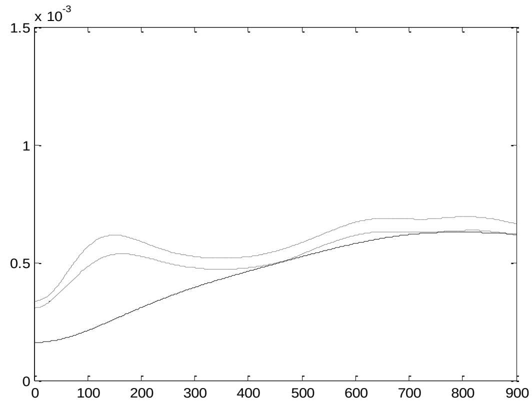
Firms in sector 40 seem to concentrate in three dense clusters: one at the Yangtze river delta, one at the Pearl river delta and one in the Beijing-Tianjin-Hebei area (see figure 3). This spatial pattern is translated into a very high peak around 80 kilometers in figure 4(a).[10] Between distances of 200 – 900 km firms in sector 40 are dispersed.

Figure 4. K-density and 5% global confidence bands for sectors: 40, 15, 26

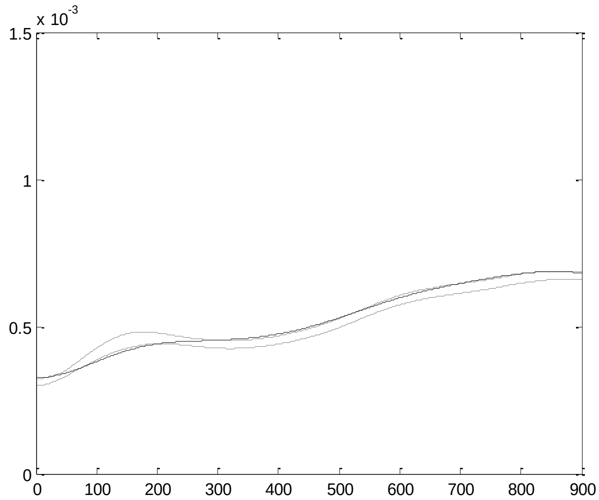
[10] Note, that the clusters are far apart (more than 900 km). If the clusters had been closer to each other they would show up as multiple peaks in graphs like fig.4. Extending the horizontal axis to 1100 km would reveal a second peak. A similar observation holds for the UK, see Duranton and Overman (2005).



(a) Communication, electronic and computer producing (40)



(b) Beverage manufacturing (15)



(c) Chemical raw materials and chemical products (26)

Source: Authors

Figure 4(b) shows that firms within the Beverages sector (15) are evenly distributed and show no tendency to cluster as all observations are below the lower global confidence band. The Chemical raw materials and chemical products sector (26) has a similar geographical pattern as manufacturing as a whole (not shown separately). Neither strong clustering or spreading is observed in figure 4c. Such pattern is then correctly translated from figure 3(c) into figure 4(c). At some distances, the k-density of sector 26 deviate to some extent from randomness, however, over the entire range between 0-900 km it (almost) makes no difference with the distribution of firms in general.

4. Spatial Concentration Analysis

We are interested in the spatial dynamics of manufacturing firms in China. We analyze this by using the DO method described in section 3. Since 1990, China increasingly participated in the global supply chain and increases in productivity of the manufacturing sector might have been stimulated by agglomeration economies, which could be reflected by increased concentration of manufacturing in clusters, stimulated by the Chinese government. We first look at manufacturing industries in general. Next we differentiate between ownership. Finally, we look at firm size differences.

4.1 Localization and Dispersion

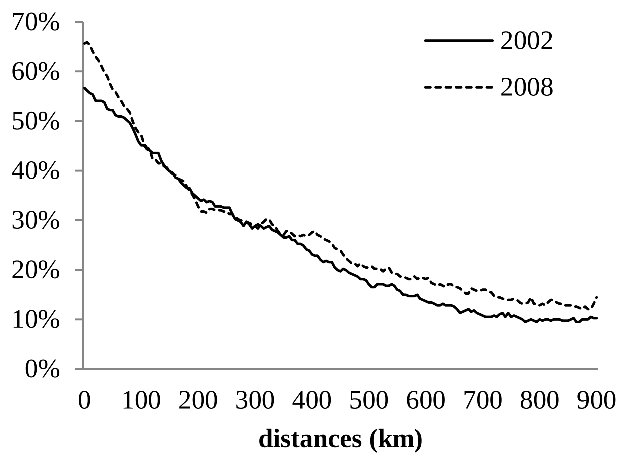
We first sub-divide 2-digit industries into 4-digit industries. We select 381 4-digit code manufacturing industries that have 10 or more firms in *both* 2002 and 2008.[11] Taking the global 5%-global confidence bands as criteria to determine localization or dispersion, we find in 2002 that 73% of the industries are localized (277 industries), and 13% are dispersed (50 industries). The remaining share does not deviate significantly from randomness (54 industries). In 2008, the shares (numbers) change to 81% (309), 14% (52) and 5% (20), respectively.

Figure 5 illustrates the share of localized (panel a) and dispersed (panel b) industries across all distances. Panel 5(a), indicates a steep distance-decline between 0-250 km in the number of industries that are localized. This holds for 2002 as well as for 2008. Comparing 2002, and 2008 more localization takes place at all distances, but more pronounced at smaller distances. Figure 5(b) gives the share of dispersed industries. About 10% industries are dispersed within 50-250 km range, and close to 5% at larger distances. This holds for 2002 as well as for 2008. Note, that the 0-250km range is at the scale of Chinese metropolitan areas. Note, that Lu and Tao (2009, p.173) also using a very detailed firm dataset for China find, using the Ellison and Glaeser index, that only 24% of all industries are somewhat to very concentrated, which is in in contrast to our findings.[12]

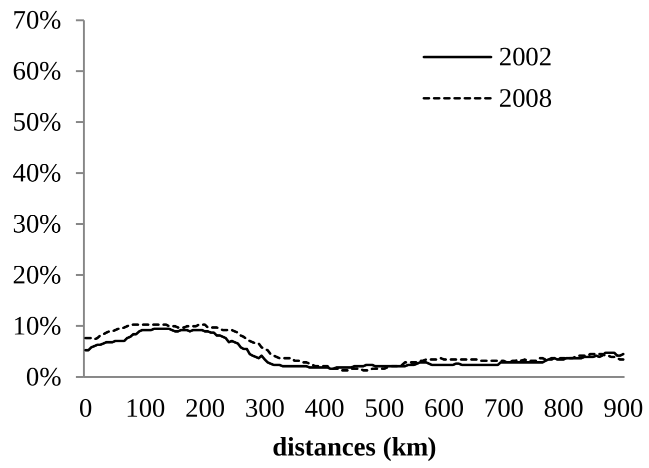
Figure 5. Share of Localized or Dispersed Industries - 2002, 2008

[11] The sample contains of 399 4-digit industries in 2002, and 392 in 2008. Selecting only those industries that have at least 10 firms in both years results in 381 4-digit industries.

[12] This comparison shows the advantages of using the DO index instead of an Ellison and Glaeser (1997) index; border effects tend to bias localization measures downward, see Duranton and Overman (2005, pp 23-24, for a discussion).



(a) Localization



(b) Dispersion

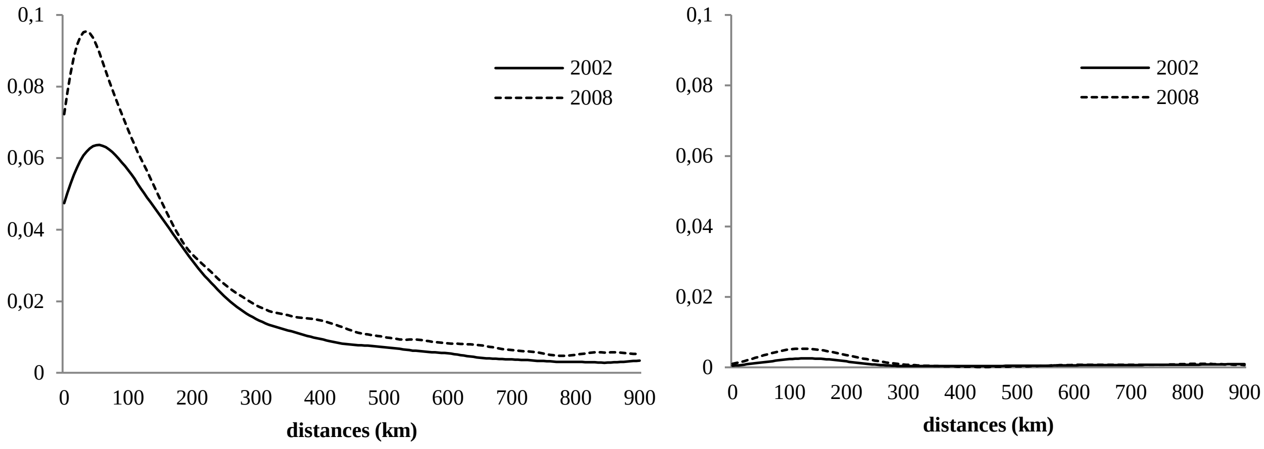
Source: Authors

Figure 5 shows deviations of randomness, but not the extent of these deviations. Duranton and Overman (2005) define indices that allow us to calculate the extent of the deviations (see appendix B for the definitions). Summation over industries gives a measure of the extent of deviations at any given distance: for localization we have $\Gamma\ (d) = \sum_A \Gamma_A(d)$ and similarly for dispersion $\Psi\ (d) = \sum_A \Psi_A(d)$. Figure 6 reports both measures for 381 industries in 2002 and 2008. In a qualitative sense the conclusions with respect to Figures 5 and 6 are the same; the extent of localization and dispersion is greater at smaller distances. However, localization has increased markedly between 2002 and 2008 between distances 0-250km.

Comparing our results to those of Duranton and Overman (2005) for the UK or Nakajima et al. (2012) for Japan we find more localization for China than these studies find for the UK or Japan (around 50% of UK or Japanese industries are localized). Our results for China are more in line with those of Ellison and Glaeser (1997) and Holmes and Stevens (2004) for the USA, or Maurel and Sédillot (1999) for France who find between 75 and 95% of industries to be localized (note, however, that they use employment data).

A common finding in all studies is that localization is more likely to occur at smaller distances. For China this holds for 2002 and for 2008. However, even in this relative short period localization within China has increased markedly. This change could imply some firm relocation that is related to agglomeration economies.

Figure 6. Extent of Localization and dispersion – 2002, 2008



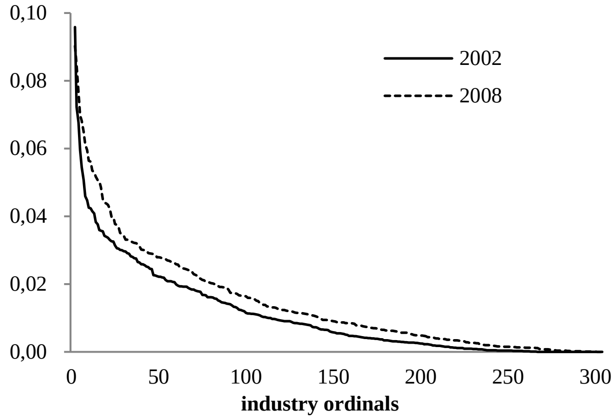
(a) Localization **(b) Dispersion**

Source: Authors

4.2. Spatial structure of 4-digit industries

Instead of summing the localization and dispersion indices over industries, we can sum over distances to give a sector index of both measures: that is, for localization $\Gamma_A = \sum_d \Gamma_A(d)$ and similarly for dispersion $\Psi_A = \sum_d \Psi_A(d)$. Figure 7 shows the result when we rank the sectors in descending order of the indices. As clearly visible in figure 7, the distribution is skewed; around 20 industries (comprising about 5% of all 4-digit industries in our sample) are highly localized compared with other industries. Furthermore, The distribution for 2008 is always above that of 2002, indicating increased localization (mutatis mutandis for dispersion; only a few industries are highly dispersed). Table 2 lists the 30 most localized and dispersed 2-digit industries in 2002 and 2008.

Figure 7. Rank-order distributions of localization indices for four-digit industry



Source: Authors

Table 2 is based on the 30 most localized or dispersed 4-digit industries. In order to avoid too much detail, table 2 lists the names and the codes of the 2-digit industry branches that have the largest number of 4-digit industries (among the 4-digit top 30) in 2002 and 2008. The upper part of table 2 gives the results of localized industries. More than half of the 30 most localized 4-digit industries belong to only three 2-digit industries which are Textile (S17), Electrical machinery and equipment manufacturing (S39) and Special equipment manufacturing (S36). The lower part of table 2 gives the results of dispersed industries. Food manufacturing (S14), Beverage manufacturing (S15), Pharmaceutical manufacturing (S27), Wood processing and products (S20) and Ferrous metal smelting and rolling processing (S32) contain most of the 4-digit dispersed industries.

The results for China are quite similar to those for the UK, the US and Japan. For example, the Textile sector, is highly localized in all these countries and Wood processing is not. These facts hint at common characteristics of these industries that stimulate localization or dispersion in all countries. Textile is an interesting example. China is the world's largest producer and exporter of textile products. Both the historical origin of the sector, along the Yantze River Delta, and the export-orientated sector strategy contribute to the highly localized pattern of Textile in China at Yantze River Delta. Textile is also found among the most localized industries in UK, US and Japan, most likely for the same reasons. Furthermore, even though Textile is among the most localized industry in 2002, the extent of localization still increased; six 4-digit industries in the Textile industry became more localized in 2008. Such change is probably driven by labor market pooling in the coastal areas, because of an increased export orientation of the textile industry.

Table 2. Number of most localized/dispersed industries in two-digit branches (selection out of top-30)

Localized					
2002			2008		
Industry Branch		No. of industries among the most localized 30 industries (No. of total industries in this industry branch)	Industry Branch		No. of industries among the most localized 30 industries (No. of total industries in this industry branch)
S17	Textile	7 (20)	S17	Textile	9 (20)
S39	Electrical machinery and equipment manufacturing	5 (24)	S39	Electrical machinery and equipment manufacturing	5 (24)
S36	Special equipment manufacturing	3 (41)	S36	Special equipment manufacturing	4 (41)
Dispersed					
2002			2008		
Industry Branch		No. of industries among the most dispersed 30 industries (No. of total industries in this industry branch)	Industry Branch		No. of industries among the most dispersed 30 industries (No. of total industries in this industry branch)
S14	Food Manufacturing	5 (9)	S14	Food Manufacturing	7 (9)
S15	Beverage Manufacturing	5 (12)	S15	Beverage Manufacturing	7 (12)
S26	Chemical materials and chemical products manufacturing	3 (31)	S13	Agro-food processing industry	3 (15)
S27	Pharmaceutical Manufacturing	3 (6)	S20	Timber Processing, Bamboo, Cane, Palm Fiber and Straw Products	3 (8)
			S32	Ferrous metal smelting and rolling processing industry	3 (4)

Source: authors

5. Ownership and Spatial Concentration

Ownership might affect the spatial pattern of firms. Governments, for example, might like to stimulate firm spreading instead of clustering to stimulate economic growth in peripheral regions. In China publicly owned firms are still very important and location decisions by these firms might follow government policies. Private firms on the other hand could have different (spatial) objectives.

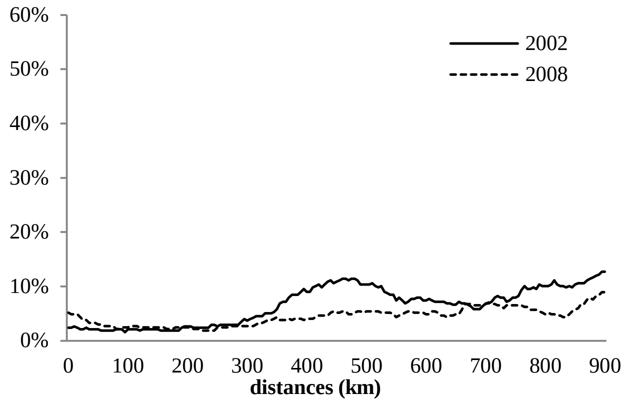
It is well-known that Foreign-owned firms tend to cluster, and this is also the case for China, see e.g. Head and Ries, 1996, Fujita et al. 2004, p. 2967, or Yeaple, 2013 for a general survey). Explicit spatial comparison between firms with *different* ownership has received considerably less attention. For China especially these differences are potentially important as firms with different owners are operated in different institutional environments and could have dissimilar spatial patterns (He and Wang, 2012).

We divide our data into 4 ownership groups: (i) privately owned firms, (ii) firms originating from Hongkong, Macau and Taiwan (HTM) firms, (iii) other foreign firms, and (iv) state and collectively-owned firms (S&C owned) that are controlled and owned by the government or by a (local) community. Appendix C gives more detailed information on these ownership groups. We use essentially the same methodology as in section 4. Excluding industries with less than 10 firms results in 377 industries in which S&C-owned firms are active in 2002, and 368 in 2008; for privately owned firms these numbers are 330 and 380; for HTM firms, 248 and 305; and for foreign firms 249 and 327.

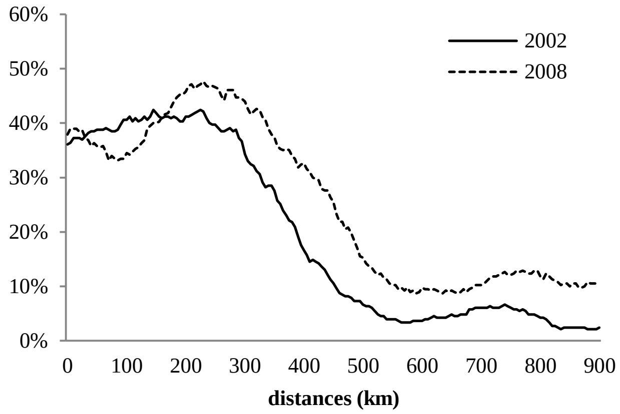
In 2002 31 % of S&C-owned firms are localized while 28% are dispersed; 66% of private firms are localized and 5% are dispersed; 55% of HMT firms are localized and 14% dispersed; finally 45% of foreign firms are localized and 6% are dispersed. Two observations stand out. First, S&C firms are the least localized and most dispersed. Second, although foreign owned firms are more localized and less dispersed than S&C owned firms they are not the most localized firms in China; private firms and firms from HTM show a larger tendency of localization. From 2002 to 2008, the share of dispersed industries in S&C-owned firms increases; in the other three groups the number of localized industries increases considerably.

Figures 8 and figure 9 summarize the findings. The 4 panels in both figures distinguish between ownership and show the changes that took place between 2002 and 2008. Figure 8 shows that S&C owned firms stand out by hardly showing localization at any distance. The other three ownership groups do localize. HMT firms and foreign firms localize at smaller spatial scales, smaller than 200 km, than privately owned firms that localize between roughly 200-400 km.

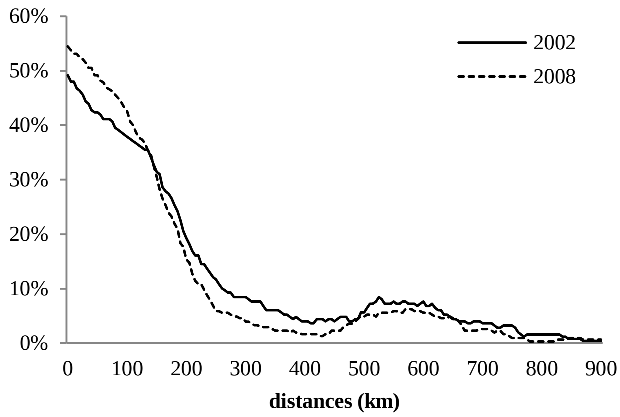
Figure 8. Shares of Localized Industries by Ownership Groups



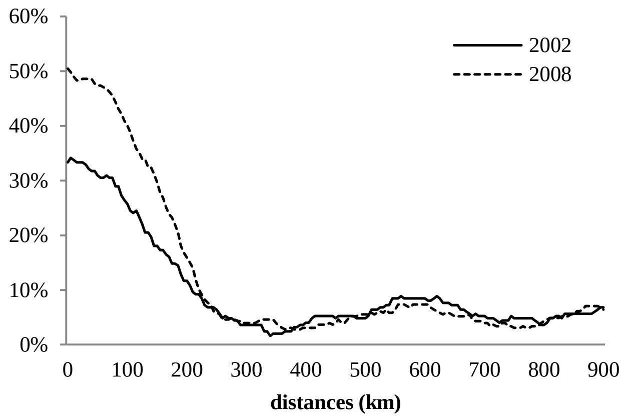
(a) S&C-owned



(b) Privately-owned



(c) HMT



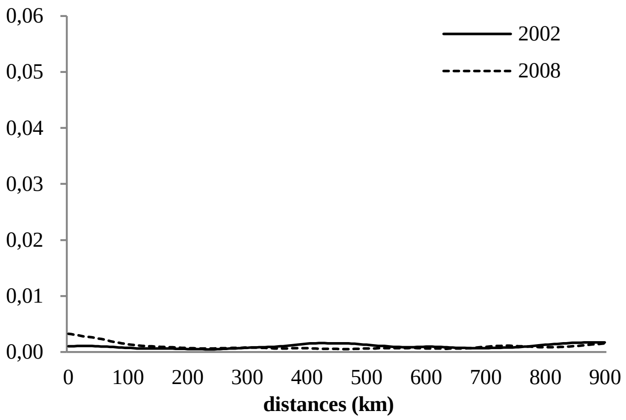
(d) Foreign

Source: Authors

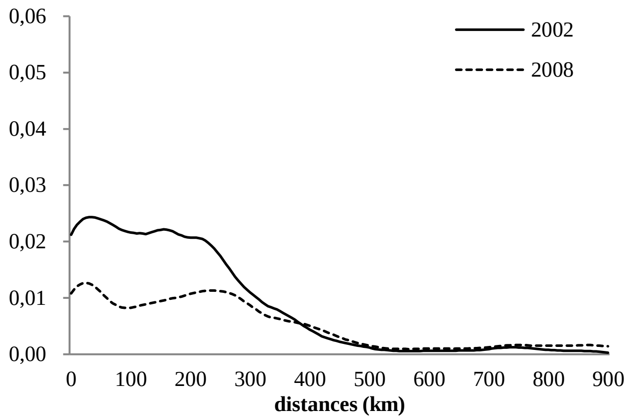
Figure 9 shows the extent of localization, using the localization index. S&C owned firms do not show a tendency to localize, whereas HMT firms form the most localized group at smaller scales, followed by foreign firms. Privately-owned firms do not have peak value and the localization tendency is relatively small, compared to HTM firms and foreign firms, over the 0-400 km range (figure 9).

Both figures 8 and 9 show interesting changes between 2002 and 2008. In Fig 8(b), we see that the numbers of localized private industries decrease noticeably at small scales. At larger scales some increase is visible. In contrast, localization for HMT and foreign owned firms increased remarkably at smaller scales. One can speculate about the causes. Private firms were originally often S&C owned firms and located in cities where congestion rapidly increases, creating an incentive to spread. However, adverse initial conditions and some hysterese is probably active for this group of firms. HTM and foreign firms do not have this unfavorable 'initial condition' effect.

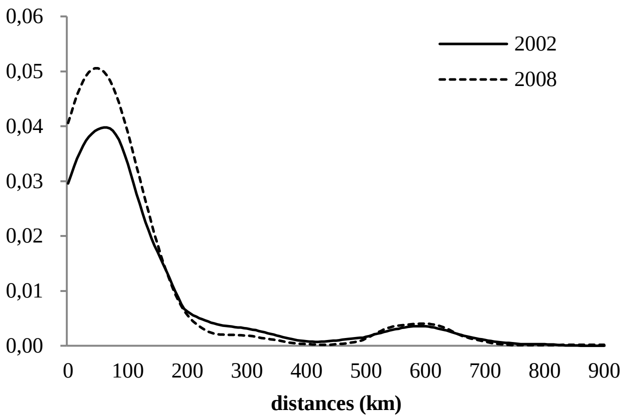
Figure 9. Localization indices by ownership Groups



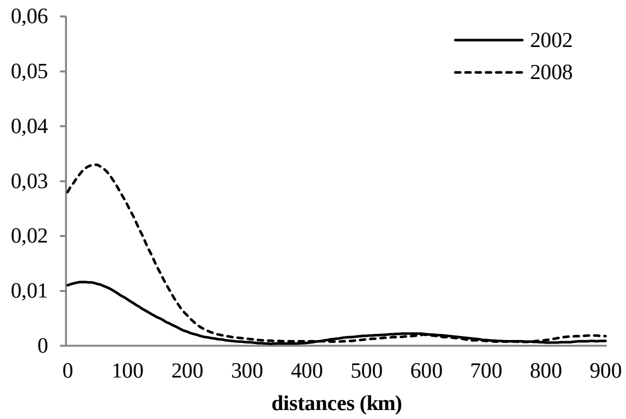
(a) S&C-owned



(b) Privately-owned



(c) HMT

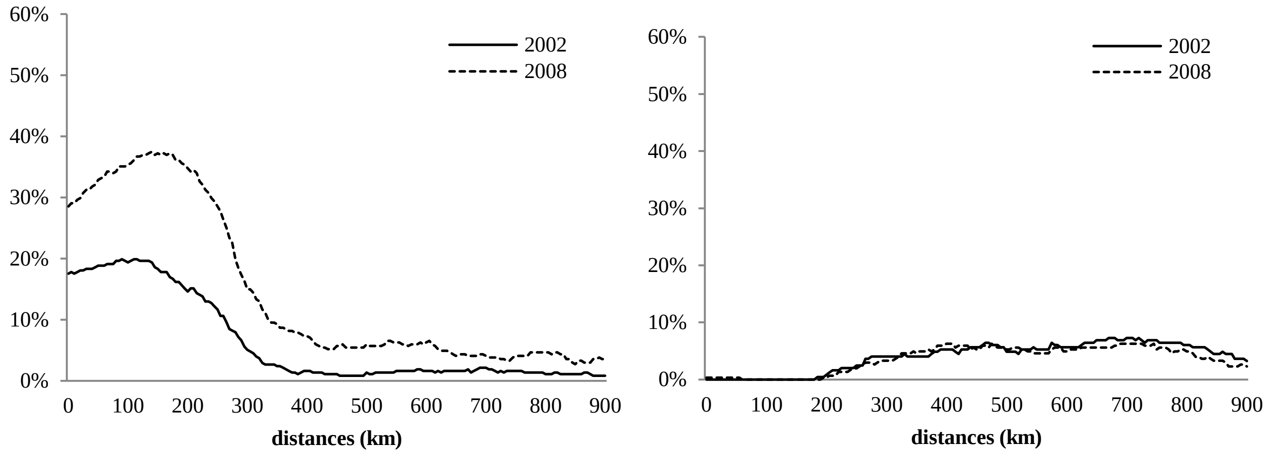


(d) Foreign

Source**:** Authors

Figure 10 shows results for dispersion for only S&C-owned and HMT firms (as privately-owned and foreign firms do not show a clear dispersion pattern). For HMT firms, dispersion is more important for medium and larger spatial scales whereas for S&C-owned firms, around 20% of industries are dispersed in 0-200 km in 2002 and dispersion increases to 30% in 2008.

Figure 10. Shares of Dispersed Industries for S&C-owned and HMT Firms



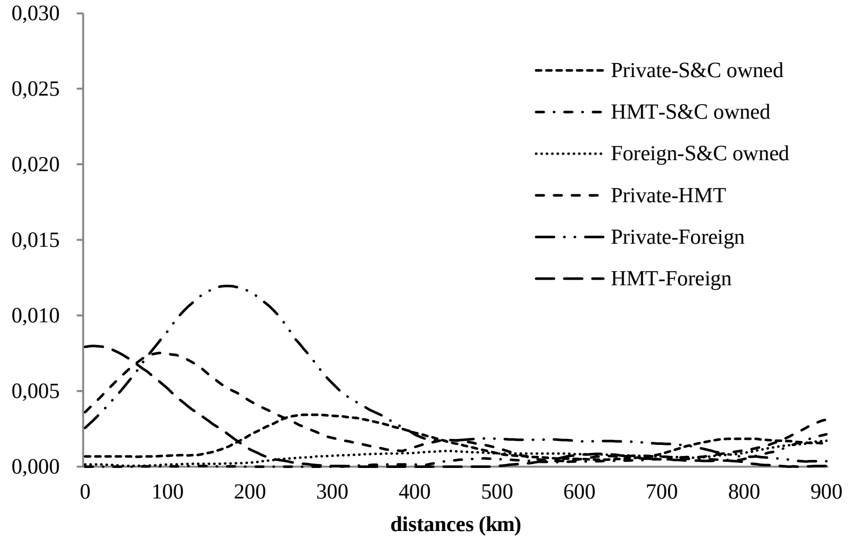
(a) S&C-owned **(b) HMT**

Source: Authors

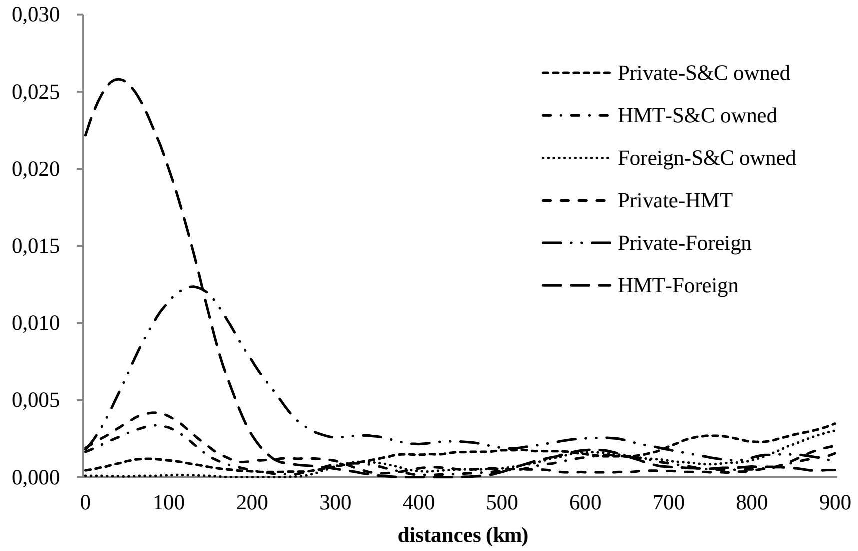
The suggestion of the analysis so far is that S&C owned firms are, from a location perspective, different from firms whose location decision is determined by market forces. Firms that can choose locations without government interference are affected by the same market forces. This could imply that localization clusters for HTM, foreign, and privately owned firms are found at the same places. In order to find out if co-location patterns exist we consider six ownership pairs: S&C owned and private, S&C owned and HMT, S&C owned and Foreign, private and HMT, private and foreign, and the last one is HMT and foreign. We apply the methodology of the previous sections to these ownership pairs (comparing localization patterns of 4 digit industries within an ownership pair).

Figure 11 gives the results for co-location and co-dispersion patterns of the six ownership pairs in 2002 and 2008. In 2002, three group pairs are significantly co-localized: private-foreign, HMT-foreign, and private-HMT. Location decisions for these groups are affected by market forces, and localization is similar. In 2008, HMT-foreign and private-foreign still show co-localization, while private-HMT become less co-localized (which is consistent with the development represented in Fig.9b). Noticeable is the change for HMT - foreign firms between 2002 and 2008. The tendency to co-localize increases remarkably. Turning to co-dispersion; the most noticeable changes are related to S&C owned firms, especially the combination with HTM firms in 2008. S&C owned firms become more co-dispersed. Local protectionism could favor especially the S&C-owned enterprises. The other three ownership groups are more profit oriented, and potentially are interested in benefitting from agglomeration economies.

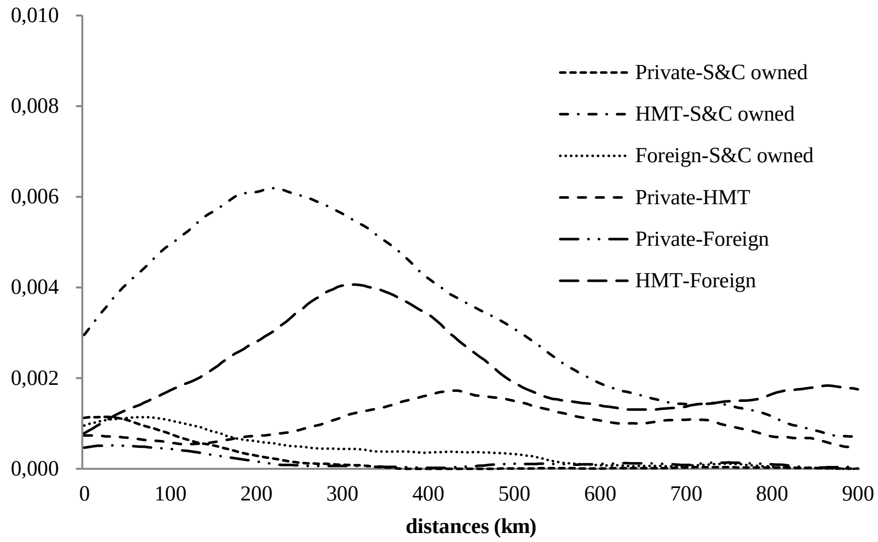
Figure 11. Co-localization and Co-dispersion for Ownership Pairs



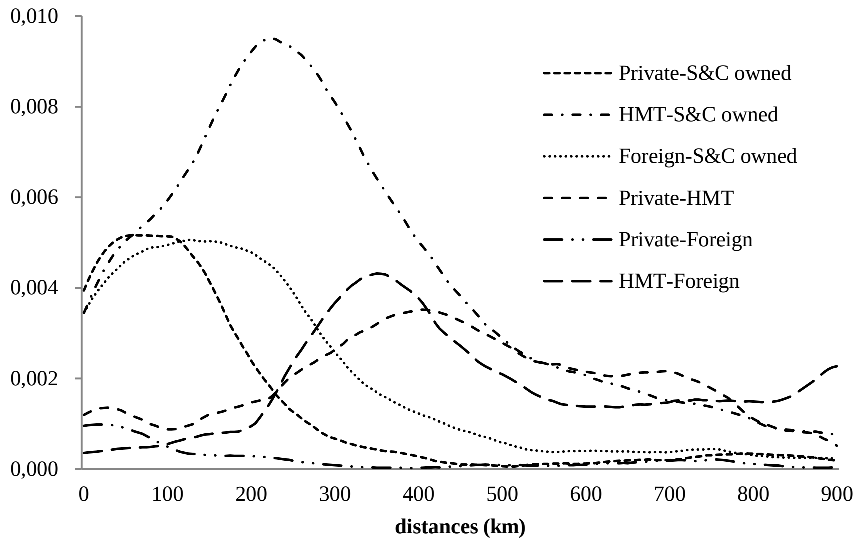
(a) Co-localization in 2002



(b) Co-localization in 2008



(c) Co-dispersion in 2002



(d) Co-dispersion in 2008

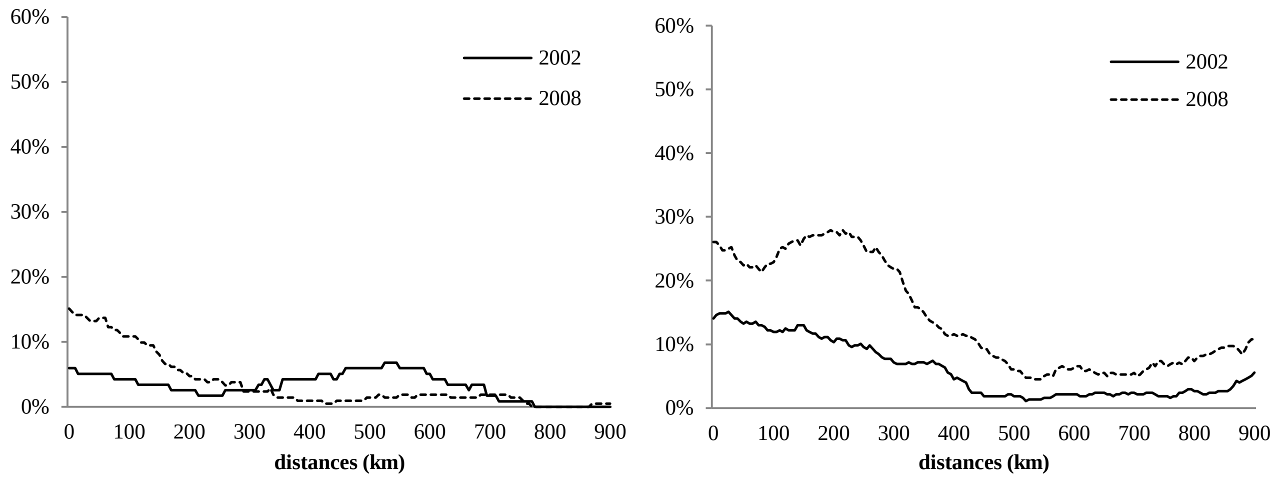
6. Firm Size and Spatial Concentration

In this section, we want to compare the location patterns of small and large firms. Holmes and Stevens (2002, 2004) suggest that clustering in the United States is driven to a large extent by large establishments. Duranton and Overman (2008) revisit this issue and find that large firms affect industry clustering in different ways and they suggest that the role of large establishments are less important than suggested by Holmes and Stevens. In this section we examine the spatial patterns of firms of different sizes.

First, we select the smallest firms in the bottom decile and largest firms in the top quartile with respect to employment in the industry.[13] This gives 118 industries for large firms in 2002 and 212 industries in 2008, and 377 industries for small firms in 2002 and 380 industries in 2008. All industries have at least 10 firms.

For China we find similar results as Duranton and Overman (2008) for the UK; large firms are less important for localization. The share of localized industries for small firms increases from 30% (113 industries) in 2002 to 56% (213 industries) in 2008. Only 14% (51 industries) are dispersed in 2002 and 8% (29 industries) in 2008. For large firms these numbers are: 14% (17 industries) are localized in 2002 and 20% (42 industries) are localized in 2008, 19% (23 industries) are dispersed in 2002 and 23% (48 industries) are dispersed in 2008. Figure 12 gives the detailed information of localization industries at every distance. The share of localized industries is limited for large firms. However, this share has increased in 2008. However, for both large and small firms, localization is less pronounced compared with the baseline estimation of all 4-digit industries (see section 3).

Figure 12. Share of Industries Localized by Size



(a) Large **(b) Small**

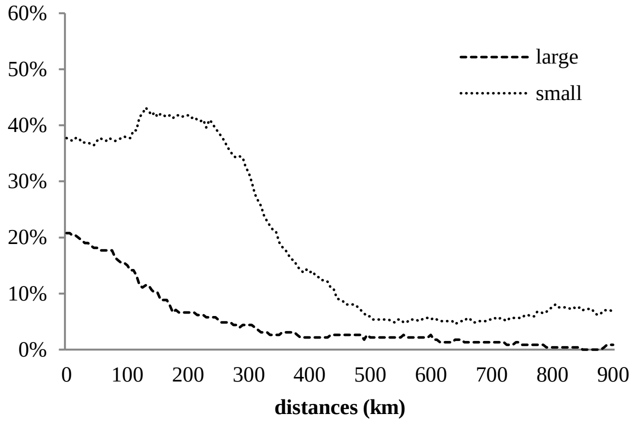
Source: Authors

One possible explanation for the findings in Figure 12 is that S&C-owned are relatively large and we

13 The top decile contains too little firms. Following Duranton and Overman (2008) we choose the top quartile.

already established in the previous section that S&C-owned firms are less localized compared to other firm types. Excluding S&C-owned firms changes the conclusion only marginally.

Figure 13 Share of Localized industries by Size, excluding S&C owned firms, 2008



Source: Authors

Figure 13 shows that excluding S&C firms increase the shares of localized industries for both small and large firms, but the increase seems limited. So, ownership is more important for localization than firm size.[14]

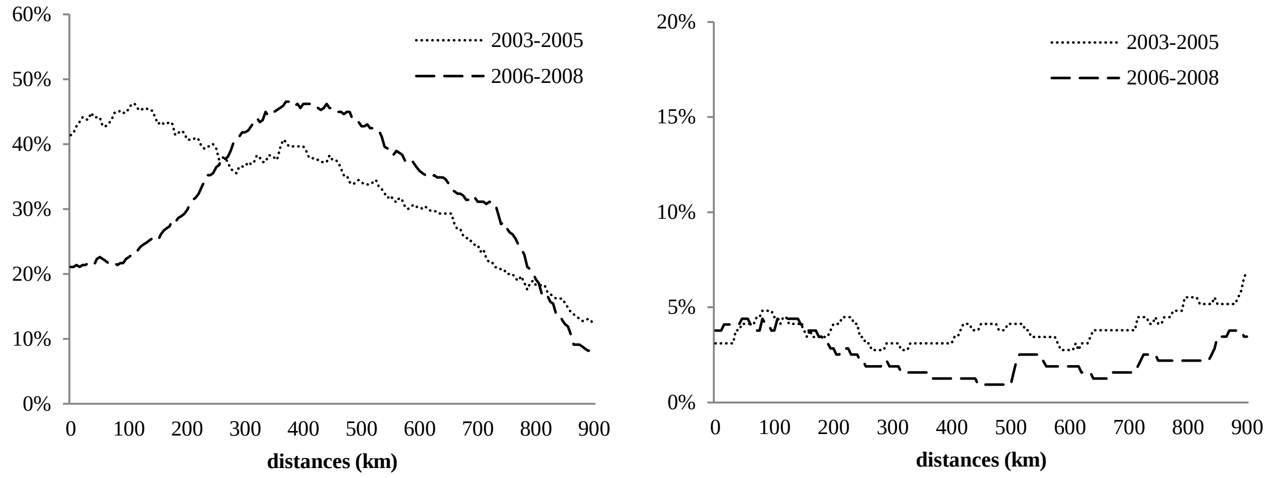
7. New Entrants

If some sort of hysteresis is present in location decisions, new entrants might be more dynamic in finding optimal locations than existing firms. Duranton and Overman (2008) analyze the entry and exit behavior of UK firms and find, that in approximately two thirds of industries, firm entry and exit is not different from permanent establishments. Similarly, Nakajima et al. (2012) find for Japan that the location pattern of firm entry and exit is analogous to permanent firms. China, however, might be different as it more recently liberalized location decisions and became more open to FDI.

In our sample entrants are those firms that start to operate after 2002. Firms that are operating before 2002 are existing firms. To introduce some dynamics we define two sub-periods: 2003-2005 and 2006-2008 and sum the entrants over the (sub-) periods.

[14] Looking at co-location between large and small firms does not change this conclusion.

Figure 14. Share of Localized and Dispersed Entrants



(a) Localization **(b) Dispersion**

Source: Authors

Dropping industries with less than 10 entrants, we are left with entrants in 290 industries in 2003-2005 and 318 industries in 2006-2008. In 80% of the industries entrants are more localized than the existing firms if we compare the entrants in the period 2003-2005 to existing firms in 2002. This number decreases to 74% if we compare entrants in the period 2006-2008 to existing firms before 2002.

Figure 14 shows the share of industries in which entrant firms are localized and dispersed at every distance. Striking is the difference between the two periods. In 2003-2005, entrants are more localized at small scales. While in 2006-2008, the share at medium and large scales increase. A cause might be that formation of new clusters increasingly takes place outside the most agglomerated coastal areas.

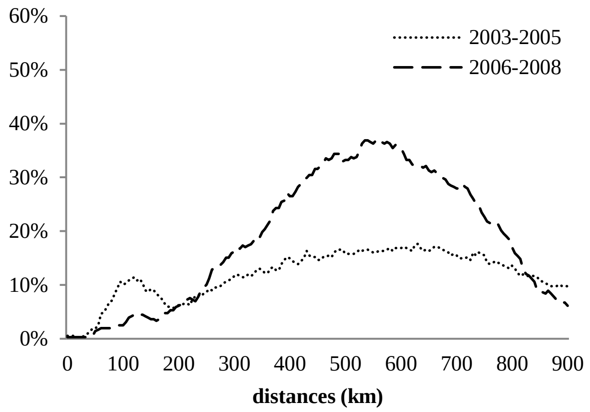
Table 3. Number of the most localized/dispersed industries (for entrants) in two-digit branches

Localized					
2003-2005			2006-2008		
Industry Branch		No. of industries highly localized (for entrants)	Industry Branch		No. of industries highly localized (for entrants)
S31	Non-metallic mineral products industry	5	S17	Textile	3
S17	Textile	4	S26	Chemical materials and chemical products	3
S24	Educational and Sports Goods	3	S31	Non-metallic mineral products	3
S26	Chemical materials and chemical products	3	S39	Electrical machinery and equipment	5
S36	Special equipment manufacturing	3	S41	Instrumentation and culture, office machinery manufacturing	3
Dispersed					
2003-2005			2006-2008		
Industry Branch		No. of industries highly dispersed (for entrants)	Industry Branch		No. of industries highly dispersed (for entrants)
S26	Chemical materials and chemical products	5	S36	Special equipment manufacturing	7
S34	Fabricated Metal Products	3	S13	Agro-food processing industry	6
S36	Special equipment manufacturing	3	S19	Leather, fur, feathers and its products	3
S41	Instrumentation and culture, office machinery manufacturing	3	S41	Instrumentation and culture, office machinery manufacturing	3

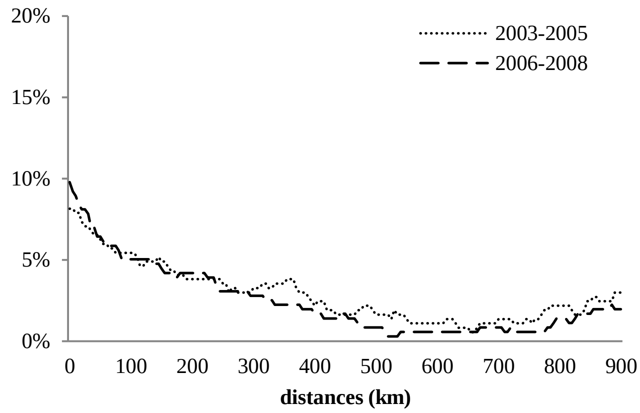
Table 3 indicates in what 2-digit sectors we find the most localized or dispersed 4-digit industries for entrants. Some sectors appear both in the localized and the dispersed group, such as: Chemical materials and chemical products (S26), Special equipment manufacturing (S36) and Instrumentation and culture, office machinery manufacturing (S41). The reason is that 2-digit industries contain 4-digit industries with different location characteristics. An example is S26, that contains for example a basic agriculture inputs industry such as Potash producing (S2623) and a more technological advanced industry S2662 which refers to Special chemicals manufacturing.

Investigating the co-location pattern of entrants with existing firms is again interesting in order to follow the evolution of industrial spatial structures. We use the same co-location methodology as in section 5. Figure 15 gives the co-location results. The number of industries in which the entrants show co-dispersion with existing firms is small. At the range between 0 – 100 km less than 10% of entrants co-disperse with existing firms. Co-localization is clearly visible. It more likely happens at the medium ranges and is more pronounced in the 2006-2008 period than in the 2003-2005 period.

Figure 15. Share of Industries Which the Entrants and the Existing Firms are Co-localized or Co-dispersion



(a) Co-localization



(b) Co-dispersion

Source: Authors

8. Conclusions

The unprecedented growth experience of China is changing location patterns of economic activity. The liberalization of the Chinese Economy allows firms and workers to find more optimal locations. The Hukou system, that restricts internal migration, is increasingly liberalized and China is attracting more and more foreign investors. The question which forces drive these location decisions is subject of a large and growing body of literature, but before one can answer the question what explains location decisions, it is important to know *how* economic activity is distributed over space and how strong industries tend to cluster, if at all. Location studies have by-and-large concentrated on the USA, countries of the European Union (EU), and Japan (see f.i. surveys of Holmes and Stevens, 2004, Combes and Overman, 2004, Fujita et al. 2004). In this paper we concentrate on location patterns of manufacturing firms in China using a very detailed dataset on firm locations. This allows us to use the Duranton and Overman (2005) location index that does not suffer from the disadvantages of other location indices (Combes et al. 2009). Also the dataset allows us to follow location patterns changes between 2002 and 2008. In general we find:

- Strong localization of manufacturing firms in China. The localization pattern in China is stronger than is found for UK or Japan, and comparable to that of the US.
- Localization is strong at relative small scales with a strong distance decay. The scale is

comparable to that of Chinese cities.

- Localization has increased markedly over the period 2002-2008. Dispersion has changed less dramatically.
- Localization tendencies are stronger for private firms, ‘foreign’firms from Hongkong-Macao-Taiwan (HTM), and foreign owned firms. State & Collectively owned manufacturing firms are more dispersed. Private firms are less-localized than HTM and foreign firms, possibly because of an adverse initial condition effect. The more profit oriented firms are found to co-localize.
- Large firms are relatively less important for localization than smaller firms. Most location dynamics take place among smaller firms.
- New firms, that is to say firms that entered our data set between 2002 and 2008, are more localized than incumbents.

Analyzing location patterns of manufacturing firms in China confirms that China is in transition. A more liberalized economy reveals itself by increasing localization, enabling firms to benefit from localization economies. State & Collectively owned firms still have to benefit from the advantages of agglomeration.

Appendix A: Comparison between National Statistical Yearbook (CNSY) and ASIF

Table A1. Comparison between China National Statistical Yearbook (CNSY) and ASIF

	2002			2008		
	Number of firms reported in the CNSY	ASIF	Coverage ASIF	Number of firms reported in the CNSY	ASIF	Coverage ASIF
Logging and Transport of Timber and Bamboo	383	383	100%			
Mining and Washing of Coal	2812	2812	100%	9212	9212	100%
Extraction of Petroleum and Natural Gas	84	84	100%	299	299	100%
Mining and Processing of Ferrous Metal Ores	696	696	100%	3984	3984	100%
Mining and Processing of Nonmetal Ores	1711	1711	100%	3953	3947	100%
Processing of Food from Agricultural Products	10413	10695	103%	22800	22800	100%
Manufacture of Foods	4615	4571	99%	8108	8108	100%
Manufacture of Beverages	3287	3287	100%	5411	5411	100%
Manufacture of Tobacco	287	287	100%	156	156	100%
Manufacture of Textile	13248	12697	96%	33133	33133	100%
Manufacture of Textile Wearing Apparel, footwear and Caps	9061	8711	96%	18237	18236	100%
Manufacture of Leather, Fur, Feather and Related Products	3932	3932	100%	8622	8622	100%
Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products	3033	3033	100%	10314	10314	100%
Manufacture of Furniture	1767	1767	100%	5386	5386	100%
Manufacture of Paper and Paper Products	5285	5285	100%	10011	10011	100%
Printing, Reproduction of Recording Media	3806	3932	103%	6481	6481	100%
Manufacture of Articles For Culture, Education and Sport Activities	2327	2251	97%	4797	4864	101%
Processing of Petroleum, Coking, Processing of Nuclear Fuel	1144	1144	100%	2416	2411	100%
Manufacture of Raw Chemical Materials and Chemical Products	12637	12139	96%	28224	26744	95%
Manufacture of Medicines	3681	3962	108%	6524	6524	100%
Manufacture of Chemical Fibers	909	773	85%	2029	2029	100%
Manufacture of Rubber	1822	1822	100%	4649	4649	100%
Manufacture of Plastics	7665	7665	100%	19484	19484	100%

Manufacture of Non-metallic Mineral Products	15305	15305	100%	30524	30524	100%
Smelting and Pressing of Ferrous Metals	3333	3642	109%	8012	8012	100%
Smelting and Pressing of Non-ferrous Metals	2942	991	34%	8200		
Manufacture of Metal Products	10039	8888	89%	24547	24547	100%
Manufacture of General Purpose Machinery	10767	11074	103%	36919	36919	100%
Manufacture of Special Purpose Machinery	6546	6479	99%	18685	18563	99%
Manufacture of Transport Equipment	7470	7063	95%	18808	18468	98%
Manufacture of Electrical Machinery and Equipment	9385	9433	101%	25727	25727	100%
Manufacture of Communication Equipment, Computers and Other Electronic Equipment	5320	4701	88%	14347	13212	92%
Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work	2146	2230	104%	5620	5600	100%
Manufacture of Artwork and Other Manufacturing		4353		7692	7169	93%
Recycling and Disposal of Waste				1087	1087	100%
Production and Supply of Electric Power and Heat Power	4946	4943	100%	6242	6242	100%
Production and Supply of Gas	329	329	100%	856	856	100%
Production and Supply of Water	2420	2420	100%	2052	2052	100%

Appendix B: Localization and dispersion indices.

The upper and lower global confidence bands of industry A at 5% level are denoted by $\overline{K_A}(d)$ and $\underline{K_A}(d)$ respectively. For industry A, if $\widehat{K_A}(d) > \overline{K_A}(d)$ for at least one *d* between 0-900 km, industry is said to exhibit global localization at the 5% confidence level. If $\widehat{K_A}(d) < \underline{K_A}(d)$ for at least one *d* between 0-900 km and industry A never lie above the upper confidence band, this industry is said to exhibit global dispersion at the 5% confidence level. An index of localization is defined as:

$$\Gamma_A(d) \equiv \max(\widehat{K_A}(d) - \overline{K_A}(d), 0), \tag{2}$$

And an index of dispersion is defined as:

$$\Psi_A(d) \equiv \begin{cases} \max\left(\underline{K_A}(d) - \widehat{K_A}(d), 0\right) & if \sum_{d=0}^{d=900} \Gamma_A(d) = 0 \\ 0 & otherwise \end{cases}, \tag{3}$$

Appendix C: Ownership

Table A2. Statistics of the firm number by 2-digit sectors and by ownership in 2002

Sector		Ownership	No. firms	Sector		Ownership	No. firms	Sector		Ownership	No. firms
13	Agro-food processing industry	State-owned	6109	22	Paper and Paper Products	State-owned	2848	31	Non-metallic mineral products industry	State-owned	9409
		Private	3146			Private	1677			Private	4244
		HMT	601			HMT	492			HMT	942
		Foreign	839			Foreign	268			Foreign	710
14	Food Manufacturing	State-owned	2482	23	Printing and reproduction of recorded media	State-owned	2698	32	Ferrous metal smelting and rolling processing industry	State-owned	2053
		Private	1077			Private	670			Private	1338
		HMT	485			HMT	412			HMT	139
		Foreign	527			Foreign	152			Foreign	112
15	Beverage Manufacturing	State-owned	2077	24	Educational and Sports Goods	State-owned	548	34	Fabricated Metal Products	State-owned	3940
		Private	747			Private	631			Private	3144
		HMT	210			HMT	687			HMT	1057
		Foreign	253			Foreign	385			Foreign	747
16	Tobacco industry	State-owned	280	25	Petroleum processing, coking and nuclear fuel processing industry	State-owned	688	35	General equipment manufacturing	State-owned	6317
		Private	2			Private	348			Private	3361
		HMT	3			HMT	39			HMT	574
		Foreign	2			Foreign	69			Foreign	822
17	Textile industry	State-owned	5206	26	Chemical materials and chemical products manufacturing	State-owned	7199	36	Special equipment manufacturing industry	State-owned	3994
		Private	4778			Private	3152			Private	1583
		HMT	1810			HMT	930			HMT	457
		Foreign	903			Foreign	858			Foreign	445
18	Textile and garment, shoes, hat manufacturing	State-owned	2270	27	Pharmaceutical Manufacturing	State-owned	2560	37	Transportation Equipment Manufacturing	State-owned	4236
		Private	2906			Private	729			Private	1721
		HMT	2087			HMT	311			HMT	527
		Foreign	1448			Foreign	362			Foreign	579
19	Leather, fur,	State-owned	1115	28	Manufacture of	State-owned	378	39	Electrical machinery	State-owned	4665

	feathers (down) and its products	Private	1220		Chemical Fibers	Private	215		and equipment manufacturing	Private	2710
		HMT	1009			HMT	117			HMT	1173
		Foreign	588			Foreign	63			Foreign	885
20	Timber Processing, Bamboo, Cane, Palm Fiber and Straw Products	State-owned	1100	29	Rubber	State-owned	938	40	Communications equipment, computers and other electronic equipment manufacturing	State-owned	1603
		Private	1302			Private	511			Private	784
		HMT	358			HMT	208			HMT	1240
		Foreign	273			Foreign	165			Foreign	1074
21	Furniture Manufacturing	State-owned	568	30	Plastic products industry	State-owned	3033	41	Instrumentation and culture, office machinery manufacturing	State-owned	1080
		Private	666			Private	2387			Private	408
		HMT	326			HMT	1503			HMT	386
		Foreign	207			Foreign	742			Foreign	356

Table A3 Ownership Classification

Ownership type in ASIF	Classification
State-owned enterprises	
Collective enterprises	
Stock cooperative enterprises	
State-owned joint venture	
Collective joint venture Enterprises	State-owned and
State-owned collective Associates	Collectively-owned
Other associates	
State-owned sole proprietorship company	
Other limited liability company	
Inc.	
Private enterprise	
Private partnership	Private
Private limited liability company	

Private Limited	
Other domestic enterprises	
Joint ventures (Hong Kong, Macao and Taiwan)	HMT
Cooperative Enterprises (Hong Kong, Macao and Taiwan)	
Hong Kong, Macao and Taiwan-owned enterprise	
Hong Kong, Macao and Taiwan-invested shares in the company	
China-foreign joint ventures	Foreign
CJV	
Foreign (owned) enterprises	
Foreign Investment Co., Ltd.	

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