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Cheryl Long
Colgate University

Xiaobo Zhang
International Food Policy Research Institute

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Using firm-level data from China's two recent censuses (Industry Census 1995 and Economic Census 2004) and a new measure of clustering (industry proximity), we show that China's rapid industrialization is marked by increased clustering. A higher degree of clustering is further shown to be associated with greater export growth and higher total factor productivity. We also find supporting evidence that clustering helps ease the credit constraints facing many small and medium enterprises through two mechanisms: (1) within a cluster, finer division of labor lowers the capital barriers to entry and (2) closer proximity makes the provision of trade credit among firms easier. Since both mechanisms reduce the need for external financing, a larger number of firms—and thus greater competition—emerge within clusters, which helps explain the higher levels of exports and total factor productivity.

This cluster-based industrialization model fit particularly well with China's comparative advantage during its initial stage of takeoff, which was marked by scarcity of capital and an inefficient financial system. Hence our findings may be helpful to other developing countries with similar factor endowment patterns that are considering cluster-based development strategies.

clustering; industrialization; finance; export; productivity; China

Many have argued that a well-developed financial system is a key prerequisite for industrial development, as it can help pool disparate savings to finance large lump-sum investments in machineries and factory buildings (Goldsmith 1969; McKinnon 1973; King and Levine 1993; Rajan and Zingales 1998; Ayyagari, Demirgüç-Kunt, and Maksimovic 2006). However, China's rapid industrialization in the past three decades seems to defy conventional wisdom. At the incipient stage of reform in the late 1970s, China's financial system was far from developed, by any existing standards (Allen, Qian, and Qian 2005). In particular, the vast number of small and medium enterprises (SMEs) had little access to credit from state-owned banks (Lin and Li 2001; Wang and Zhang 2003; Lin and Sun 2005). Despite the initial lack of financial development, China has achieved the same degree of industrialization in three decades that took two centuries to occur in Europe (Summers 2007). Paradoxically, the SMEs in rural China have grown much faster than the large firms. How was China able to quickly industrialize in such a credit-constrained environment?

Previous research has suggested reliance on informal financing as the main solution (Allen, Qian, and Qian 2006). However, considering that at the onset of China's reform, a large proportion of rural people were poor (Ravallion and Chen 2007), the amount of local savings available for informal financing would have been rather limited. Without denying the importance of formal and informal financing in overcoming credit constraints, we argue herein that the cost of investment in production technologies may not be as prohibitive as suggested in the literature. The presence of credit constraints has the unintended consequence of inducing entrepreneurs to divide seemingly integrated production technologies into incremental steps by adopting the clustering mode of production. Clustering deepens division of labor, hence lowering capital entry barriers and enabling more entrepreneurs to participate in nonfarm production. An additional benefit of clustering is the consequent closer proximity of firms, which allows more inter-firm trade credit and reduces the need for working capital. Both these channels help lower the barriers of entry to industries, which in turn promotes competition and growth.

To establish the link between clustering, financing, and growth, we start by introducing a new measure of clustering to better assess the pattern of industrialization in China during the last decade. Although there are a large number of measures of regional specialization and industry concentration, they do not capture the interconnectedness among firms. For example, in the planned economic era, China concentrated its heavy industries in only a few locations. The existing measures would undoubtedly indicate a high degree of concentration in these industries at the time. However, this artificial industry concentration with little spillover into the local economy is not the same as the emerging patterns of clustering observed in post-reform China.

As has been reported in the media, China's rapid industrialization has been accompanied by the emergence of numerous "specialty cities" of a particular kind.[1] Thousands of firms, large and small, each specialized in a finely defined production step, are lumped together in a densely populated region, where some particular manufactured consumer good is churned out by the millions (if not billions) annually. Many formerly rural towns in the coastal areas have become so specialized that they boast of themselves as the world's Socks City, Sweater City, Kid's Clothing City, Footwear Capital, and so on. Each of the specialty cities described above fits Porter's concept of an industrial cluster, which is "a geographically proximate group of inter-connected companies (and associated institutions) in a particular field" (Porter 2000, page 16).

Despite the numerous popular media reports of this phenomenon, few studies have been performed to rigorously establish patterns using data covering a large sample and a long time period. Toward this end, we use complete firm-level data from the China Industrial Census 1995 and the China Economic Census 2004 to compute measures of clustering. The measure we focus on, industry proximity, allows us for the first time to explore how firms interact with one another, a key feature of clustering as highlighted by Porter (1998, 2000). Our results suggest that China's rapid industrialization during this time period was marked by closer interactions among firms within the same region.

We further examine the role of clustering on firm financing. At the county level, we calculate both clustering measures and the minimum asset level by industry. We find that clustering is associated with lower minimum capital requirements for industrial investment at the county level. With the finer division of labor implied by clustering, a production process is decomposed into small steps and thereby lowers the minimum capital requirement. Next, based on a panel dataset at the firm level from the two censuses, we document that more trade credit is extended among firms within an industrial cluster, thus reducing the reliance on external financing for working capital. In a word, clustering eases both starting and working capital constraints.

The availability of detailed firm-level data also allows us to correlate the observed patterns of clustering with firm performance. We find that firms in more clustered regions experience higher export and total factor productivity (TFP) growth. This provides supporting evidence that an increase in clustering in the past decade has contributed to improved export performance and productivity for firms in China. We view this as evidence that clusters help better align China's growth with its comparative advantage in labor endowment.

Our paper is unique on several fronts. First, we have access to firm-level data from two time periods for China as a whole, which are more disaggregated and updated than data used in previous studies. Second, we have adopted a new industry proximity measure to capture the evolving patterns of clustering, a key feature of China's industrialization. Third, we quantitatively show the positive impact of clustering on firm finance and correlate clustering with firm performance.

[1] For example, see http://www.nytimes.com/2004/12/24/business/worldbusiness/24china.html for a report.

The study of China's industrialization may help shed some light on research on industrialization in general. China's miraculously rapid industrialization provides a unique laboratory enabling us to observe and understand the process of industrialization. While industrialization in Western Europe and North America at the early stages of the Industrial Revolution can now be studied only through the relatively dim mirror of history, industrialization can be viewed directly in the ongoing economic revolution in China. China's experience may be relevant to other developing countries characterized by a high population density and a low capital-to-labor ratio. A clearer understanding of the industrialization processes in China will be of great value in helping propagate these processes to the world's less fortunate regions.

The structure of this paper is as follows: Section 2 reviews the literature on clustering, finance, and industrial development. Section 3 describes the data and the clustering measures, as well as the clustering patterns of China's industrialization. Section 4 examines the role of clustering in firm financing. Section 5 relates the evolving patterns of clustering to firm performance, while Section 6 offers some conclusions.

Industrialization is often accompanied by clustering (or spatial agglomeration) of industrial activities.[2] The literature has highlighted the positive externalities of industrial clusters. Marshall (1920) lists three key externalities: better access to the market and suppliers, labor pooling, and easy flow of technology know-how. Porter (1998) argues that clustering is an important way for firms to fulfill their competitive advantage. Fujita, Krugman, and Venables (2001) view spatial clustering as a key feature of industrialization and highlight many of the positive externalities of spatial agglomeration. Two types of clustering have been observed during the industrialization process of developed countries. In the U.K., the decentralized production system scattered in different family workshops was replaced by a large integrated factory system during the Industrial Revolution (Landes 1998). The trend was similar and more evident in the United States during its industrialization (Chandler 1977). For example, the auto industry is highly concentrated in the Detroit metropolitan area, with several dominant large firms. This type of industrial cluster is generally anchored by a few very large firms while other smaller firms act as suppliers.

Italy, Japan, and other East Asian countries and regions experienced a different path of spatial clustering during the course of industrialization, which was led by small and medium enterprises (SMEs). In this business model, a large number of SMEs often cluster together, with comprehensive vertical division of labor. One noted example is the putting-out system, in which a merchant obtained market orders and subcontracted the production to nearby farmers or skilled workers, who usually finished the work in their

[2] In the literature, various terms for the phenomenon of clustering abound, including , , , , and so on. In this paper, we prefer to use , as it better captures the interconnectedness among firms in a narrowly concentrated location.

homes or family workshops (Hounshell 1984). The putting-out system was popular in the U.K. prior to its Industrial Revolution and was widely observed in nineteenth-century Japan (Nakabayashi 2006). Outsourcing (or subcontracting), the modern variant of the traditional putting-out system, remains a major feature of industrial production organization in contemporary Japan and Taiwan (Sonobe and Otsuka 2006). Industrial districts in which different workshops and factories clustered together were ubiquitous in France and Italy until the mid-twentieth century and are still viable in some regions of Italy (Piore and Sabel 1984; Porter 1998).

One key difference between the two types of clustering is firm size and number of firms. In the second type of clustering, an integrated production process is often disaggregated into many small steps that are performed by a large number of SMEs with dispersed ownership. By dividing a production process into incremental stages, a large lump-sum investment can be transformed into many small steps, thereby lowering the capital entry barriers (Schmitz 1995). Therefore, this mode of industrial organization may fit better in countries or regions with scarce capital and less developed financial sectors. Several in-depth case studies and popular media reports (as mentioned at the beginning of the paper) seem to suggest that China followed the second type of cluster-based industrialization path (Sonobe, Hu, and Otsuka 2002, onon(c)4a.002 Tc -06 a.a(c)-2 Tcehu puzzle either, as most SMEs, the engine of China's industrial growth, do not have access to it. Thus it is hard to resolve the puzzle by looking at only the literature on finance and growth.

An unintended consequence of credit constraints is that they may induce innovations in production organizations, with the cluster-based production structure being one of them. One key feature of clusters in China and other East Asian economies is that production technologies in a cluster are decomposed into many incremental steps that are undertaken by different entrepreneurs. Huang, Zhang, and Zhu (2008) detailed how the footwear cluster in Wenzhou helped overcome financial, institutional, and technological barriers. Ruan and Zhu (2009) in particular demonstrated that clustering lowers capital entry barriers and enables more entrepreneurs to participate in the production process though vertical division of labor.

These case studies provide insight into how clusters work. To generalize these findings, we use firm-level data from China's two censuses to test the hypothesis that the two following mechanisms help firms in clusters overcome financial constraints. First, the inherent finer division of labor in this kind of cluster helps lower the capital barriers to entry and enables a large number of low-wealth entrepreneurs from rural areas to finance profitable projects in a cluster. And second, the greater proximity and repeated transactions among firms in a cluster facilitate interfirm trade credit, thereby reducing working capital constraints.

We utilize firm-level data from the China Industrial Census 1995 and China Economic Census 2004 for analysis in this paper. Tables 1 and 2 present summary statistics of the gross industrial output based on the census data by industry and by region, respectively. Table 3 compares the sample of our datasets with the published national aggregate statistics for China in 1995 and 2004. As shown in the table, our datasets capture the whole universe of Chinese industrial firms in these two years. Compared to the datasets used in previous studies on China's industrialization patterns (Young 2000; Bai et al. 2004; Wen, 2004; Zhang and Tan, 2004), our datasets have more comprehensive coverage and include industrial firms of all sizes (not only those above a certain scale).

Since the data are at the firm level, we can calculate the degree of clustering at any level of our choice, such as township, county, prefecture, or province, for regional aggregation, and two-, three-, or four-digit industry level for sectoral aggregation. For the main part of the analysis, we chose county and four-digit CIC (China Industry Code) as the levels of aggregation. But for robustness tests, we also used prefecture and provincial levels for geographic aggregation, and three-digit and two-digit CICs for industrial aggregation. When constructing the clustering measures, we first determined the level of aggregation to convert firm-level data to cell-level totals, where each cell is a combination of a certain level of region and a certain level of industry. For example, the most detailed cell is the combination of four-digit CIC and county. We then create the clustering measure using the cell-level data.

China modified its industry coding system in 2002 (switching from GB1994 to GB2002). Therefore, when studying changes between 1995 and 2004, we match industry codes that changed from 1994 to 2002 as follows: for industry codes that became more disaggregated in the 2002 coding system, we use the 1994 codes as the standard; for those that became more aggregated, we use the 2002 codes as the standard. In other words, we use the more aggregated codes to group and compare industries between 1995 and 2004. During the period between the two censuses (1995–2004), the territories of some counties were also redrawn and the names of others changed. We have carefully tracked these changes to match the counties throughout the time period.

Conventional measures of industrial agglomeration are based on regional specialization or industrial concentration. The market share of a certain number of the largest, say, three firms, in an industry or region is often used as a concentration measure. The advantage of this measure is that it is easy to calculate and interpret, but when the distribution of firms is relatively spread out, it may miss those firms below the cut-off lines. To overcome this problem, the Gini coefficient is often used to calculate the regional variation of output or employment shares for all the firms in an industry. Krugman (1991) modifies the Gini coefficient by accounting for the discrepancy between a region's share of output/employment in a certain industry and its share in all manufacturing industries in calculating the Gini coefficient.

However, these concentration measures do not distinguish between the following two kinds of "agglomeration": one in which a small number of large firms with minimum interfirm connections are located, versus the other in which a large number of variously sized firms congregate and interact closely with one another. While the first type of agglomeration characterizes cities such as Detroit, the second type of agglomeration seems to better fit the patterns observed in coastal China, where thousands of firms of all sizes are densely populated in a small region, closely intertwined with one another throughout the production processes, all the while churning out thousands of products with breathtaking efficiency.

The second type of agglomeration fits very well into the definition of clusters given by Porter, whose concept of an industrial cluster is summarized as "a geographically proximate group of inter-connected companies (and associated institutions) in a particular field" (Porter 2000, page 16). Although the concept is intuitive and extremely easy to understand, the measurement of interconnectedness seems more elusive. To our knowledge, no previous studies have directly measured it except in case studies in which firms can provide detailed information on how they interact with other firms.

Such detailed information is necessarily absent for large-scale studies like ours. In the absence of the first-best information, we analyze Porter's concept of clustering more carefully to explore alternative ways of measuring the interconnectedness among firms. When delineating the main actors within a cluster, Porter states, "They include, for example,

. Clusters also often extend downstream to channels or customers and laterally to

" (Porter 2000, 16–17, italics added by authors). In addition, Porter emphasizes that one main benefit derived from geographically concentrated clusters is that industries in the same cluster share common technologies, s4( c)4( c)420 u cdgenzed iizend dobeneddie.(f)3(i)-(t)-2wnsiu(i)-2(20 u(i)-2k r)3( e)4(m1 0 T

to the cell level, where the cell is defined as a combination of county and a four-digit CIC industry. (2) Convert the CIC first to ISIC and then to SITC based on the manuals obtained from China's National Bureau of Statistics as well as correspondence tables from Eurostat and the United Nations. (3) For each industry in a cell, calculate its average proximity to all industries located in the same region, using the Hausmann-Klinger product proximity matrix, which gives the proximity (or the inverse distance) between each pair of products (and between each pair of industries through the conversion procedures above). The average proximity for each industry (for a certain region) is computed as a weighted average using the size of the other industry in each pair as the weight. (4) Finally, the average industry proximity for each region is computed as the average of the proximities of all the industries in that region, weighted by the size of each industry.

The proximity measure can be based on assets, employment, or output. In other words, the weights discussed above that are used to adjust for the size of each industry can be assets, employment, or output. We use all these measures, as they may provide different angles of clustering. An illustration follows. Consider a region with three industries: steel, automobiles, and rubber. Intuitively, the automobile industry has a high proximity to both the steel and rubber industries, while the proximity between the other two is low. Now suppose that the region has experienced faster growth in the auto industry than in the other industries. Following the procedures describe above, we see that the average proximity of the auto industry has not changed, since the relative weights of the other two industries have not changed. But the average industry proximity of the whole region has increased, because the industry that is closer to the others, the auto industry in this case, has grown faster. Now consider the role of the weight. If the growth of the auto industry is in its output relative to those of the other industries, then the greater interconnectedness among industries in the region will be reflected in a greater proximity using output as the weight. Proximity measures weighted by asset or employment can be understood accordingly.

These three proximities may therefore measure different kinds of interconnectedness, which in turn imply different kinds of cluster effects. Marshall (1920) outlined three types of advantages from agglomeration or clusters: labor market pooling, specialized supplies, and technological spillovers. Large populations of skilled laborers enter the area and are able to exchange knowledge, ideas, and information. In addition, there is increased access to the specialized goods and services provided for the clustering firms, which provides increasing returns to scale for each of the firms located within that area because of the proximity to the available sources needed for production. Finally, clustering in specific fields leads to quicker diffusion of ideas and adoption of ideas.

Although likely to contribute to all three of these advantages, output-weighted proximity is probably more conducive to technological spillovers, since the output can be used as input in the production of other industries in the same region, while employment-weighted proximity implies more labor-market pooling, and asset-weighted proximity implies more specialized supplies, especially in capital goods. All these effects of agglomeration will lead to higher productivity at the firm level.

In addition, we emphasize in this paper another effect of agglomeration that has not drawn enough attention previously, namely, its impact on firm finances. We argue that industrial clusters help alleviate firms' financial constraints through two channels: (1) the finer division of labor among firms within an industrial cluster lowers capital requirements for these firms and (2) trade credit extended among firms within an industrial cluster helps diminish the need for external financing. As financial transactions permeate the whole production process, including labor hiring, asset purchasing, and product sales, we expect all three measures of proximity to play a role in helping overcome firms' financial constraints.

Using the proximity measures described above, we found that within each region, the proximity among industries increased significantly between 1995 and 2004.[3] Table 4 presents the industry proximity measure for each of the Chinese provinces in 1995 and 2004, based on output. The measures constructed at the prefecture and the county levels give the same pattern of higher industry proximity in each region in the latter year, as shown in Figures 1 and 2.

In addition, we find that the degree of clustering is correlated with firm size distribution in some interesting ways. At the county level, a higher degree of clustering is correlated with larger average firm size. But counties with a greater degree of clustering also tend to have more evenly distributed firm sizes among different industrial sectors as well as more evenly distributed numbers of firms among sectors.[4] Appendix Tables 1 and 2 show how the degree of clustering affects the distribution of firm size and number of firms, using firm-level panel data. In other words, the type of clustering measured by the proximity index is different from the Detroit type, in which a small number of very large firms emerge as the dominant players. Rather, it portrays a pattern similar to the East Asian cluster-based industrialization model, in which a large number of firms are present, often of small and medium size.

We now turn to explore the effects of such increased industry proximity in a geographical location, with our first focus on firm finances. Table 5 provides summary statistics of variables used in the analysis in this and the next sections. As discussed previously, there are two potential mechanisms through which clusters may help alleviate financial constraints for firms located in the clusters. First, because firms are more interconnected, finer division of labor becomes feasible, which reduces the capital requirement for firms on average. Second, the interconnectedness among firms in a narrow location may facilitate inter-firm financing through trade credit.

[3] Interestingly, we find similar results using other ci-8( f)-Tm( ( i)-2(de)8( ).7s(e)-6(s)-3(ul)g m( )TjET44 Tm( a0 109Tc 0.009 T

To explore the effect of clustering on firms' capital requirements, we look at the minimum level of assets among firms within a certain region. It is thus crucial that our sample does not exclude firms due to their small size. The 1995 and 2004 censuses that include all industrial firms provide the ideal data for computing for each county the minimum level of assets and testing the hypothesis. Table 6 shows results from the following regression:

$$= \qquad (1)$$

where indicates county, is the minimum level of assets in 2004, is the minimum level of assets in 1995, is the industry proximity in 1995, and is the random error term. Therefore, the coefficient shows the effect of industry proximity in a region on the minimum requirement of capital for firms located in that region.

As shown in Table 6, higher proximity, measured in both assets and employment, is correlated to a lower level of minimum assets, consistent with the argument that clustering facilitates a finer division of labor and thus reduces the capital requirement for firms. The proximity in output is also negatively related to minimum assets at the county level, but the effect is insignificant. The effects of proximity in assets and employment are economically important as well. In particular, a standard-error increase in industry proximity (0.03) will lead to a reduction in the minimum capital requirement of RMB 50,000 for a typical county, which accounts for about 39% of the average minimum capital requirement. As expected, the minimum capital requirement in 1995 is positively correlated with that in 2004. Column 4 shows that when industry proximity is dropped from the regression, the 1995 minimum capital requirement remains significant but the R-square drops by 2%, which is the additional explanatory power of industry proximity.

To study the effects of industry proximity on trade credit, we use firm-level data from 1995 and 2004. Since detailed accounting information is provided for only a subsample of firms even in the census years of 1995 and 2004, we cannot aggregate the data into county level as for the minimum-asset data. Instead, we construct a balanced panel of firms for which information is available.[5] The estimation regression is as follows:

$$= \qquad (2)$$

where , , and indicate firm, county, and year, respectively; is the proximity measure at the county level by year; is a vector of firm characteristics; and ε is the random error term. Therefore, the coefficient shows the effect of industry proximity in a region on the provision of trade credit among firms located in that region. We use two measures for trade credit: accounts payable / total debt, and accounts receivable / revenue. While the former measures the proportion of the firm's debt that is financed by its trading partners, the latter indicates the degree to which the firm provides credit to its business partners.

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[5] Given that the panel covers only two years, the singletons in the unbalanced panel are dropped out in the fixed effect estimation due to the demeaning process. Thus the results based on the unbalanced panel give the same results as the balanced panel.

Table 7 shows that all three proximity measures are positively correlated with both measures of trade credit.[6] Specifically, for accounts payable as a percentage of total debt, proximity measures weighted by assets, employment, and output all have positive and significant effects. For a standard-error increase in industry proximity (about 0.025), the ratio of accounts payable to total debt increases by about 0.7 percentage point, which amounts to about 3% of the average ratio of accounts payable to total debt. If proximity increases from the lowest to the highest level, then the ratio of accounts payable to total debt increases by about 8 percentage point, which amounts to almost 40% of the average ratio of accounts payable to total debt. Therefore, these effects are of non-negligible magnitude.

The coefficient for the asset variable is significantly positive for firms extending trade credit and negative for firms receiving trade credit. This is consistent with the lending policies of state banks and the findings in the literature (Cull, Xu, and Zhu 2009). In China, the state banks are more likely to extend credit to larger firms, in particular state-owned enterprises, for two reasons. First, because of their multifunctional role in providing many social services, the large state-owned enterprises received preferential treatment in accessing state bank credit. Second, large firms can use their fixed assets as collateral to secure bank loans, while SMEs often lack collateral. In large part because of their difficulty in accessing formal credit, SMEs rely more on trade credit from larger firms. Through trade credit, SMEs can indirectly gain access to state credit to help alleviate the constraints of insufficient working capital.

Our next analysis addresses firm exports and TFP growth. As discussed above, increased proximity may lead to productivity improvements due to increased pooling of labor, easier access to specialized inputs, and technological spillovers. In addition, as shown in the previous section, by lowering the capital barriers, clustering enables more potential entrepreneurs scattered in rural areas to engage in more productive industrial production. The wide availability of trade credit inherent in clusters also eases firms' working capital constraints and boosts output. Thus, we will look at the effects of the proximity measures on firm performance.

We first examine the impact of proximity and geographical concentration on export growth, using the following estimation specification:

[6] Based on the investment climate survey conducted by the World Bank, Cull, Xu, and Zhu (2009) find that trade credit does not play a significant role in firm performance among Chinese firms. There are two possible reasons for the difference between their findings and ours. First, the firm size in their sample is larger than that in the industrial and economic censuses used in this paper. Because large firms are more likely to access formal bank credit, their demand for trade credit is lower than that of smaller firms. Second, they do not relate trade credit with cluster development. Our point is that clustering facilitates the extension of trade credit. Therefore, trade credit is more likely to be observed in areas with industrial clusters than in those without clusters.

= (3)

where , , and indicate firm, county, and year, respectively; is share of export value in total sales or a dummy variable indicating whether a firm exported in a certain year; is the clustering measure at the county level by year; is a vector of firm characteristics including firm age, firm scale (measured by the ratio between firm revenue and the industry average revenue), and firm ownership types; and is the random error term. Therefore, the coefficient shows the effect of industry proximity in a region on the labor productivity of firms located in that region.

We next study the relationship between clustering and TFP based on the following estimation[7]:

= (4)

where , , and denote firm, county, and year, respectively; is value added; and refer to assets and labor; is a clustering measure at the county level by year; is a vector of firm characteristics (including firm age and firm ownership type); and is the random error term. The coefficient measures the effect of industry proximity in a region on the TFP of firms located in that region. To allow the possibility that the production function may have changed between 1995 and 2004, we also include the year 2004 dummy as well as its interaction terms with the logs of and .[8]

Tables 8 and 9 present results from the above estimation. All three proximity measures are found to have positive effects on both the export and total factor productivity of the firms, and the effects are also economically important. Specifically, an increase in industry proximity of a standard deviation (0.03) will lead to a 0.65 percentage point increase in the export-to-sales ratio, amounting to about 12% of the average export-to-sales ratio. The corresponding effect on the likelihood of the firm being an exporter is 0.3 percentage point, which is about 4% of the firms that are exporters. In terms of the effect on TFP, a standard-deviation increase in industry proximity leads to a 1.8 percentage point increase in TFP. In summary, even after controlling for capital intensity and other firm characteristics, we still find evidence showing the positive and non-negligible effects of greater industry proximity on firm performance. Firms in clusters are more productive and more competitive in the international market. As the results are obtained after controlling for firm fixed effects in a balanced panel, they reflect effects of clustering on firms that existed in both years, instead of those on firms that are new entrants.[9]

[7] Truncation of the negative values of value added may be a concern. But by comparing the sample sizes in column 1 and column 4, the reduction in sample size is only 3,500 out of 69,000 (about 5%), which does not seem a major concern to us.
[8] Estimation without the interaction terms obtains similar effects of proximity on TFP.
[9] We thank our referee for pointing this out to us.

Using census data at the firm level from 1995 and 2004, we have shown in this paper that China's industrialization has been accompanied by increasing interactions among industries within regions. The pattern of industrial clustering to a large degree resembles the industrialization path in some European countries and other East Asian economies.

In addition, our results indicate that the number of firms is growing faster and firm size is not significantly larger in clustered areas than in nonclustered regions, while at the same time there is a finer division of labor and closer technological affinity among firms. This pattern is similar to the East Asian cluster-based industrialization model led by numerous SMEs but differs from the observed patterns in the United States, where regional agglomeration and industrial districts were mainly driven by the presence of large firms.

This cluster-based industrialization dominated by SMEs may have fit well with China's comparative advantage. This business model makes more use of entrepreneurs and labor, and less of capital, compared to nonclustered large factories, and thus may have emerged as the choice of Chinese firms over time, leading to more clustered industries in China.

One key benefit of cluster-based industrialization in China is that it helps lessen the credit constraints facing the vast number of SMEs. With lower minimum capital requirements, many low-wealth entrepreneurs can start businesses despite the constrained credit environment. Close proximity and intense competition among firms within a cluster may also reduce the temptation to act dishonestly, making frequent trade credit among firms within a cluster possible. All these factors help ease the reliance on external financing.

It is worth emphasizing, however, that the results obtained do not necessarily indicate that financial-sector development is less important. Rather, clustering may be a second-best solution to the financing problem when the local conditions do not permit easy access to regular financing. One potentially fruitful line of research would be to study whether financial constraints indeed have induced the emergence of industrial clusters in China. A related issue is whether the substitution of clustering as an alternative mechanism for formal financing has affected the formation and growth of firms. For example, do firms tend to be larger in the absence of financial constraints as compared to those in industrial clusters? And do these differences in firm size distribution cause any efficiency loss? These topics are beyond the scope of the current paper, but are subjects we plan to research in the near future.

Nonetheless, given that the ideal conditions for economic development are rarely in existence, the organization innovations embodied in clustering are essential, especial0 Tc 0 Tw 5z

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concentrated capital-intensive industries, in contrast, may not experience the same rate of growth and exports. We leave a more in-depth study of this topic for future investigation.

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Table 1. Summary statistics of gross industrial output by two-digit industry

| | 1995 | | | 2004 | | |
|---|---|---|---|---|---|---|
| Industry | Mean | SD | No. of firms | Mean | SD | No. of firms |
| Coal Mining & Dressing | 9,664 | 96,605 | 11,953 | 17,643 | 224,515 | 26,822 |
| Petroleum & Natural Gas Extraction | 1,066,011 | 4,254,463 | 134 | 962,613 | 5,758,893 | 481 |
| Ferrous Metals Mining & Dressing | 5,228 | 25,019 | 2,141 | 9,554 | 46,737 | 10,256 |
| Nonferrous Metals Mining & Dressing | 8,554 | 36,978 | 3,766 | 14,919 | 104,298 | 6,075 |
| Non-Metallic Minerals Mining & Dressing | 3,087 | 11,114 | 11,820 | 3,293 | 19,150 | 34,945 |
| Other Minerals Mining & Dressing | 2,515 | 4,604 | 149 | 3,948 | 23,920 | 263 |

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Table 2. Summary statistics of gross industrial output by province

| | | 1995 | | | 2004 | | |
|---|---|---|---|---|---|---|---|
| Province | Province code | Mean | SD | No. of firms | Mean | SD | No. of firms |
| Beijing | BJ | 15,067 | 256,247 | 9,623 | 18,926 | 418,528 | 31,364 |
| Tianjin | TJ | 13,638 | 155,565 | 10,735 | 23,949 | 500,129 | 25,432 |
| Hebei | HEB | 9,216 | 80,343 | 23,592 | 15,789 | 201,284 | 64,062 |
| Shanxi | SX | 8,538 | 91,723 | 11,416 | 14,490 | 216,240 | 28,641 |
| Neimeng | NM | 5,559 | 83,740 | 9,432 | 19,689 | 223,747 | 11,759 |
| Liaoning | LN | 10,184 | 171,331 | 29,435 | 16,844 | 365,899 | 54,115 |
| Jilin | JL | 7,751 | 167,292 | 13,100 | 22,085 | 542,689 | 16,037 |
| Heilongjiang | HLJ | 8,524 | 308,216 | 18,745 | 19,613 | 738,370 | 20,101 |
| Shanghai | SH | 23,260 | 273,997 | 16,690 | 26,263 | 499,886 | 55,315 |
| Jiangsu | JS | 15,815 | 106,861 | 41,582 | 15,618 | 262,800 | 187,212 |
| Zhejiang | ZJ | 10,363 | 58,130 | 32,725 | 11,236 | 173,580 | 187,588 |
| Anhui | AH | 6,912 | 64,940 | 23,474 | 10,808 | 189,114 | 38,827 |
| Fujian | FJ | 8,080 | 47,063 | 19,038 | 15,126 | 225,394 | 49,532 |
| Jiangxi | JX | 4,528 | 45,443 | 18,253 | 9,331 | 146,981 | 29,144 |
| Shandong | SD | 17,466 | 179,590 | 26,980 | 20,477 | 303,314 | 119,699 |
| Henan | HEN | 9,703 | 75,318 | 23,119 | 12,065 | 164,347 | 76,292 |
| Hubei | HUB | 10,432 | 139,562 | 20,881 | 18,191 | 359,619 | 28,937 |
| Hunan | HUN | 5,738 | 66,417 | 23,720 | 9,668 | 145,047 | 43,529 |
| Gongdong | GD | 17,715 | 114,052 | 34,536 | 22,969 | 473,908 | 136,606 |
| Gongxi | GX | 7,719 | 42,786 | 12,312 | 11,870 | 155,918 | 18,753 |
| Hainan | HAIN | 9,932 | 52,781 | 1,278 | 21,086 | 198,547 | 2,025 |
| Chongqing | CQ | 6,676 | 82,141 | 11,456 | 12,677 | 149,313 | 20,359 |
| Sichuan | SC | 6,675 | 74,866 | 26,380 | 12,137 | 168,971 | 43,325 |
| Guizhou | GZ | 5,500 | 48,962 | 7,450 | 13,831 | 178,497 | 10,996 |
| Yunnan | YN | 13,970 | 223,904 | 6,267 | 16,157 | 239,845 | 14,271 |
| Tiebet | TB | 2,343 | 6,554 | 295 | 7,004 | 22,096 | 354 |
| Shaanxi | SAX | 6,182 | 60,000 | 12,950 | 12,251 | 209,434 | 25,573 |
| Gansu | GS | 8,260 | 109,848 | 7,140 | 14,648 | 305,597 | 11,549 |
| Qinghai | QH | 8,193 | 77,821 | 1,446 | 17,524 | 218,482 | 2,168 |
| Ningxia | NX | 9,011 | 56,606 | 1,706 | 15,132 | 151,483 | 3,984 |
| Xinjiang | XJ | 9,990 | 187,435 | 5,077 | 28,813 | 441,176 | 5,735 |
| Total | | 10,725 | 134,909 | 500,833 | 16,198 | 310,686 | 1,363,284 |

Note: The gross industrial output is reported in thousands of RMB at current prices.

Table 3. Comparing sample with aggregate data

| | Gross Industrial Output (trillions of RMB, at current prices) | | |
|---|---|---|---|
| | Sample (1) | Statistical Yearbook (2) | (1)/(2)*100% |
| 1995 | 5.495 | 5.526 | 99.438 |
| 2004 | 20.174 | 18.722 | 107.754 |

Note: The official figures for gross industrial output and industrial value added are from the for 1996 and 2005. However, the official figures in the 2005 do not include non-state-owned small enterprises below a certain scale. Therefore, the ratio of the tabulated to official figures exceeds one in 2004.

Table 4. Regional specialization and proximity (output)

| Province | 1995 | 2004 |
|---|---|---|
| Beijing | 0.206 | 0.220 |
| Tianjin | 0.194 | 0.208 |
| Hebei | 0.212 | 0.219 |
| Shanxi | 0.207 | 0.208 |
| Neimeng | 0.198 | 0.214 |
| Liaoning | 0.204 | 0.205 |
| Jilin | 0.206 | 0.220 |
| Heilongjiang | 0.186 | 0.197 |
| Shanghai | 0.222 | 0.219 |
| Jiangsu | 0.210 | 0.210 |
| Zhejiang | 0.211 | 0.220 |
| Anhui | 0.204 | 0.211 |
| Fujian | 0.208 | 0.202 |
| Jiangxi | 0.200 | 0.206 |
| Shandong | 0.200 | 0.205 |
| Henan | 0.201 | 0.209 |
| Hubei | 0.207 | 0.216 |
| Hunan | 0.201 | 0.210 |
| Guangdong | 0.209 | 0.215 |
| Guangxi | 0.208 | 0.214 |
| Hainan | 0.201 | 0.207 |
| Chongqing | 0.206 | 0.197 |
| Sichuan | 0.198 | 0.202 |
| Guizhou | 0.188 | 0.196 |
| Yunnan | 0.187 | 0.197 |
| Tibet | 0.223 | 0.238 |
| Shaanxi | 0.191 | 0.192 |
| Gansu | 0.199 | 0.205 |
| Qinghai | 0.197 | 0.217 |
| Ningxia | 0.215 | 0.22 |
| Xinjiang | 0.190 | 0.199 |
| Weighted sample average | 0.206 | 0.211 |
| Difference | 0.005 (0.001)*** | |

Table 5. Summary statistics of variables used in regressions

| Variable | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| Proximity 2004 (w=output) | 0.226 | 0.038 | 0.000 | 0.631 | 2,833 |
| Proximity 2004 (w=employment) | 0.220 | 0.032 | 0.000 | 0.403 | 2,834 |
| Proximity 2004 (w=asset) | 0.226 | 0.035 | 0.091 | 0.397 | 2,833 |
| Proximity 1995 (w=output) | 0.217 | 0.030 | 0.000 | 0.495 | 2,764 |
| Proximity 1995 (w=employment) | 0.222 | 0.037 | 0.000 | 0.495 | 2,756 |
| Proximity 1995 (w=asset) | 0.218 | 0.031 | 0.000 | 0.495 | 2,765 |
| Minimum asset 2004 (in millions) | 0.178 | 1.536 | 0.000 | 33.001 | 2,860 |
| Minimum asset 1995 (in millions) | 0.101 | 1.454 | 0.000 | 57.603 | 2,791 |
| Firm age | 17.601 | 14.358 | 0.000 | 99.000 | 104,324 |
| Private% | 0.146 | 0.340 | 0.000 | 1.000 | 104,324 |
| HMT% | 0.062 | 0.216 | 0.000 | 1.000 | 104,324 |
| Other foreign% | 0.025 | 0.139 | 0.000 | 1.000 | 104,324 |
| Log(value added) | 7.357 | 1.973 | -2.591 | 17.253 | 104,324 |
| Log(value added1) | 7.396 | 1.992 | -2.461 | 17.309 | 103,016 |
| Log(asset) | 8.933 | 1.941 | 0.693 | 18.235 | 104,324 |
| Log(labor) | 4.339 | 1.791 | 0.000 | 13.317 | 104,324 |
| Export/sales | 0.060 | 0.203 | 0.000 | 1.000 | 152,122 |
| Exporter | 0.118 | 0.322 | 0.000 | 1.000 | 152,260 |
| Accounts receivable/revenue | 0.257 | 0.287 | 0.000 | 1.999 | 93,792 |
| Accounts payable/total debt | 0.204 | 0.247 | 0.000 | 1.187 | 112,321 |
| Debt/asset | 0.639 | 0.316 | 0.000 | 2.997 | 112,321 |
| Fixed asset/asset | 0.383 | 0.222 | 0.000 | 1.000 | 112,321 |

Note: stands for firms owned by Hong Kong, Marco, and Taiwan. is a dummy variable for 2004.

Table 7. Trade credit and proximity at firm level

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variable=accounts receivable/revenue | | | Dependent variable=accounts payable/total debt | | |
| Proximity_asset | 0.165** | | | 0.222*** | | |
| | (0.066) | | | (0.083) | | |
| Proximity_labor | | 0.297*** | | | 0.244*** | |
| | | (0.060) | | | (0.073) | |
| Proximity_output | | | 0.192*** | | | 0.165** |
| | | | (0.064) | | | (0.081) |
| Firm age | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Log(sales) | -0.007*** | -0.007*** | -0.007*** | -0.096*** | -0.096*** | -0.095*** |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| Debt/asset | -0.098*** | -0.097*** | -0.098*** | | | |
| | (0.005) | (0.005) | (0.005) | | | |
| Fixed asset/total asset | -0.148*** | -0.148*** | -0.148*** | | | |
| | (0.007) | (0.007) | (0.007) | | | |
| Private share% | 0.067*** | 0.069*** | 0.067*** | 0.065*** | 0.067*** | 0.065*** |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) |
| HMT share% | -0.035*** | -0.035*** | -0.035*** | 0.015*** | 0.015*** | 0.015*** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) |
| Other foreign share% | 0.230*** | 0.229*** | 0.230*** | 0.018 | 0.017 | 0.018 |
| | (0.008) | (0.008) | (0.008) | (0.046) | (0.046) | (0.046) |
| Year04 | 0.422*** | 0.420*** | 0.422*** | 0.012 | 0.012 | 0.012 |
| | (0.008) | (0.008) | (0.008) | (0.036) | (0.036) | (0.036) |
| Constant | 0.292*** | 0.262*** | 0.286*** | 1.004*** | 0.998*** | 1.016*** |
| | (0.019) | (0.018) | (0.019) | (0.023) | (0.022) | (0.023) |
| Observations | 112,324 | 112,321 | 112,324 | 93,793 | 93,792 | 93,793 |
| R-squared | 0.80 | 0.80 | 0.80 | 0.87 | 0.87 | 0.87 |

Note: Sample includes only firms that are surveyed in both censuses. and are used as two different measures of trade credit among firms. stands for firms owned by Hong Kong, Marco, and Taiwan. The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively. Robust standard errors are in parentheses.

Table 8. Proximity and export

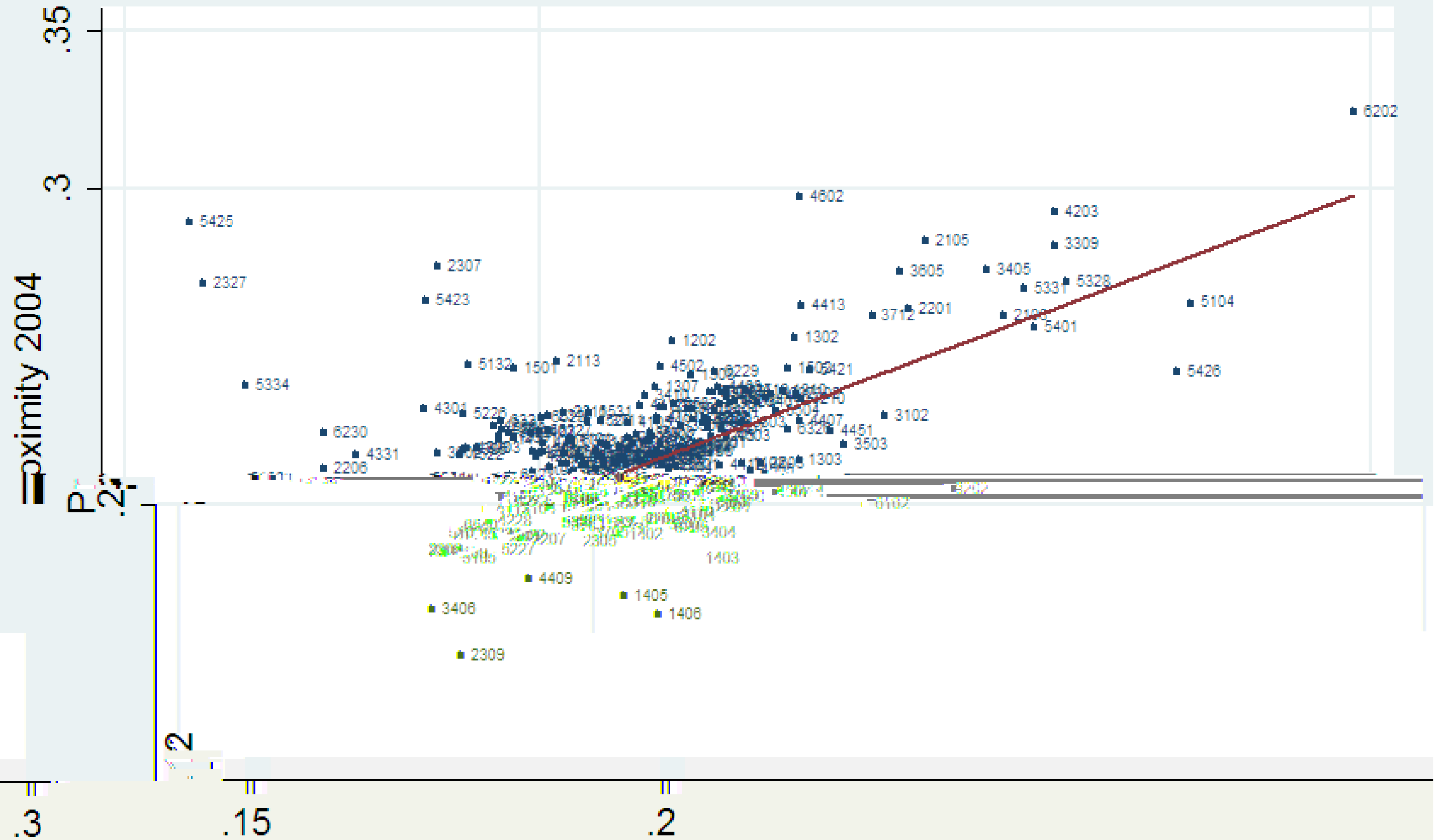
| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | Dependent variable=export/sales | | | Dependent variable=exporter | |
| Proximity_asset | 0.215*** | | | 0.140*** | | |

Table 9. Proximity and total factor productivity

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variable=log(value added1) | | | Dependent variable=log(value added2) | | |
| Proximity_asset | 0.618** | | | 0.553** | | |
| | (0.250) | | | (0.268) | | |
| Proximity_labor | | 0.536** | | | 0.384 | |
| | | (0.229) | | | (0.245) | |
| Proximity_output | | | 0.564** | | | 0.598** |
| | | | (0.250) | | | (0.268) |
| Log(labor) | 0.068*** | 0.068*** | 0.068*** | 0.066*** | 0.065*** | 0.065*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Log(asset) | 0.800*** | 0.801*** | 0.801*** | 0.804*** | 0.804*** | 0.804*** |
| | (0.007) | (0.007) | (0.007) | (0.008) | (0.008) | (0.008) |
| Log(labor)*year04 | 0.262*** | 0.262*** | 0.262*** | 0.239*** | 0.240*** | 0.239*** |
| | (0.008) | (0.008) | (0.008) | (0.009) | (0.009) | (0.009) |
| Log(asset)*year04 | -0.179*** | -0.179*** | -0.179*** | -0.155*** | -0.155*** | -0.155*** |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) |
| Firm age | 0.001** | 0.001** | 0.001** | 0.001** | 0.001** | 0.001** |
| | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) |
| Private share% | 0.083*** | 0.083*** | 0.084*** | 0.074*** | 0.074*** | 0.075*** |
| | (0.015) | (0.015) | (0.015) | (0.016) | (0.016) | (0.016) |
| HMT share% | 0.303*** | 0.302*** | 0.303*** | 0.277*** | 0.276*** | 0.277*** |
| | (0.030) | (0.030) | (0.030) | (0.032) | (0.032) | (0.032) |
| Other foreign share% | 0.683*** | 0.682*** | 0.683*** | 0.660*** | 0.660*** | 0.660*** |
| | (0.029) | (0.029) | (0.029) | (0.031) | (0.031) | (0.031) |
| Year04 | 0.545*** | 0.551*** | 0.546*** | 0.415*** | 0.420*** | 0.415*** |
| | (0.038) | (0.038) | (0.038) | (0.041) | (0.041) | (0.041) |
| | -0.059 | -0.043 | -0.047 | -0.011 | 0.025 | -0.021 |
| | (0.084) | (0.081) | (0.084) | (0.090) | (0.087) | (0.090) |
| Observations | 104,437 | 104,437 | 104,437 | 103,128 | 103,128 | 103,128 |
| R-squared | 0.95 | 0.95 | 0.95 | 0.94 | 0.94 | 0.94 |

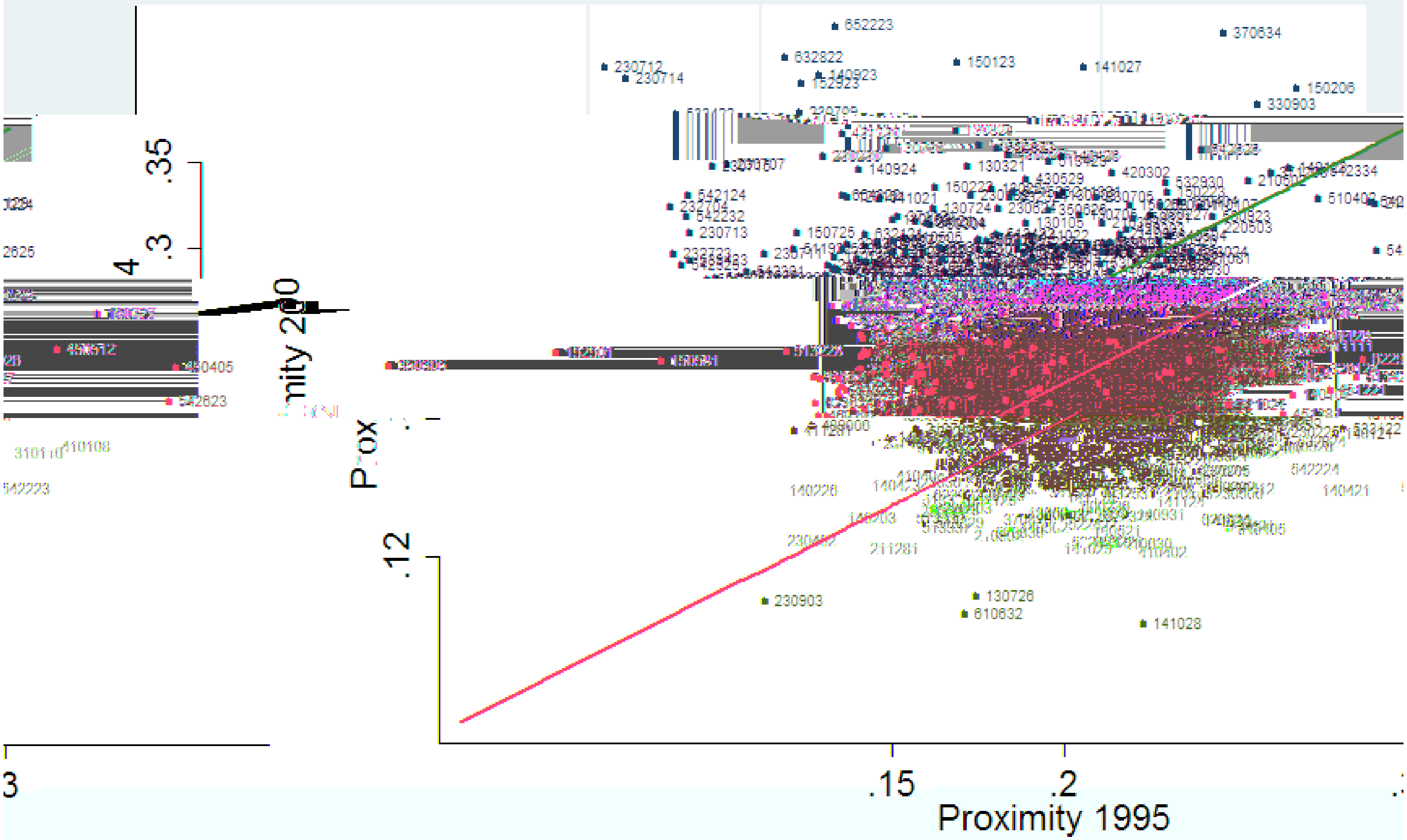
Note: Sample includes only firms that are surveyed in both censuses. is computed as a weighted average of value added constructed from the output approach and value added computed from the income approach; is computed based only on the output approach. stands for firms owned by Hong Kong, Marco, and Taiwan. is a dummy variable for 2004. The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively. Robust standard errors are in parentheses.

# Figure 1: Industry Proximity within Prefecture (1995 vs. 2004)




Data source: Authors' calculation based on CIC 1995 and CEC 2004

# Figure 2: Industry Proximity within County (1995 vs. 2004)




Data source: Authors' calculation based on CIC 1995 and CEC 2004

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Avg firm size_output | Avg firm size_labor | Avg firm size_asset | Firm size Gini_output | Firm size Gini_labor | Firm size Gini_asset |
| Proximity_ output | 13,838.610** | | | -0.209*** | | |
| | (6,492.289) | | | (0.051) | | |
| Proximity_labor | | 322.774*** | | | -0.316*** | |
| | | (61.811) | | | (0.051) | |
| Proximity_ asset | | | 12,097.348 | | | -0.368*** |
| | | | (11,206.631) | | | (0.050) |
| Yr2004 | 2,729.672*** | -49.390*** | 3,075.987*** | 0.043*** | -0.072*** | 0.047*** |
| | (244.740) | (2.418) | (398.439) | (0.002) | (0.002) | (0.002) |
| Constant | 1,773.701 | 17.436 | 4,464.986* | 0.825*** | 0.893*** | 0.855*** |
| | (1,416.099) | (13.822) | (2,460.894) | (0.011) | (0.011) | (0.011) |
| Observations | 5,499 | 5,495 | 5,500 | 5,464 | 5,495 | 5,500 |
| R-squared | 0.71 | 0.58 | 0.68 | 0.76 | 0.72 | 0.81 |

Note: The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively. Robust standard errors are in parentheses.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Avg firm number_output | Avg firm number_labor | Avg firm number_asset | Firm number Gini_output | Firm number Gini_labor | Firm number Gini_asset |
| Proximity_ output | -278.058 | | | -0.345*** | | |
| | (428.162) | | | (0.062) | | |
| Proximity_labor | | 281.563 | | | -0.268*** | |
| | | (400.453) | | | (0.058) | |
| Proximity_ asset | | | -66.682 | | | -0.368*** |
| | | | (450.255) | | | (0.065) |
| Yr2004 | 304.859*** | 303.502*** | 302.955*** | 0.144*** | 0.140*** | 0.143*** |
| | (16.140) | (15.668) | (16.008) | (0.002) | (0.002) | (0.002) |
| Constant | 243.717*** | 120.951 | 198.066** | 0.465*** | 0.450*** | 0.471*** |
| | (93.391) | (89.545) | (98.873) | (0.014) | (0.013) | (0.014) |
| Observations | 5,499 | 5,495 | 5,500 | 5,499 | 5,495 | 5,500 |
| R-squared | 0.65 | 0.65 | 0.65 | 0.86 | 0.86 | 0.86 |

Note: The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively. Robust standard errors are in parentheses.