Cluster-Based Industrialization in China:
Financing and Performance

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Abstract

China's rapid industrialization despite the lack of a well developed financial system seems to defy the conventional thinking on the role of finance in development. This paper tries to explain the puzzle from the clustering point of view. Based on firm-level data from two recent censuses, we find that within industrial clusters: finer division of labor lowers the capital barriers to entry; closer proximity makes the provision of trade credit among firms easier. With less reliance on external financing, more small firms emerge within clusters, leading to higher levels of export and total factor productivity thanks to the resultant more fierce competition.

Keywords: clustering; industrialization; finance; export; productivity; China

1. Introduction

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 machinery 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 over the past three decades seems to defy the 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 privately-owned small and medium enterprises (SMEs) had little access to formal 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 in three decades the same degree of industrialization that took two centuries to occur in Europe (Summers 2007). How was China able to quickly industrialize in such a credit-constrained environment?

Without denying the importance of formal financing and informal mechanisms of alternative financing (as pointed out in Allen, Qian, and Qian 2005, Fisman and Love 2003) 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 thanks to the clustering mode of production. We hypothesize that by dividing an integrated production process into many incremental steps, clustering can lower capital entry barriers, thereby 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 thus reduces the need for working capital. Both channels help lower the entry barriers to industries, thereby stimulating competition and enhancing productivity.

To establish the link between clustering, financing, and firm performance, we start by introducing a new measure of clustering to better assess the pattern of industrialization in China. 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 economy 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. Yet obviously, this artificial industry concentration with little spillover to 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 in the past several decades has been accompanied by the emergence of numerous "specialty cities" of a particular kind, where thousands of firms, large and small, each specializing in a finely defined production step, are lumped together in a densely populated region to churn out some particular manufactured consumer good by the millions (if not billions) annually.[1]

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.[2] 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, which is 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 increased clustering — closer interactions among firms within the same region.

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

[2] Lu and Tao (2009) found a clear trend of industrial agglomeration during the period of 1998-2005. But their sample includes only large firms and does not capture the large number of small and medium firms prevalent in these "specialty cities".

We then examine the role of clustering on firm financing. At the county level, we calculate both clustering measures and the minimum asset level among all firms and find that clustering is associated with lower minimum capital requirements for industrial investment. Next, based on a panel dataset at the firm level from the two censuses in 1995 and 2004, we document that clustering is accompanied by a more prevalent use of trade credit among firms, thus reducing their reliance on external financing for working capital.

With such positive roles of clustering in reducing firms' need for external financing, we expect that clustering would help create more new establishments and result in extensive industrial growth. To show this point, we relate the number of firms by ownership at the county level in 2004 with the initial degree of clustering in 1995.[3] The emergence of domestic non-state establishments in a location is found to be highly associated with the degree of local industrial clustering. In contrast, the number of state-owned enterprises (SOEs), which are not financially constrained and thus should not be affected by clustering, is not related to the degree of clustering at all.

As more firms operate in a geographically narrow area, clustering will also boost intensive growth —improving firm productivity through increased competition among similar firms. Based on firm-level data, we find that domestic non-state firms in more clustered regions have higher export and total factor productivity (TFP) levels, while clustering has little to do with the performance of SOEs.

These patterns of how differently clustering relates to non-state firms versus SOEs are consistent with our argument that the observed correlations between clustering, firm financing, and firm performance are causal, as the correlations are only significant for non-state firms, which lack access to external finances. In addition, we adopt the Rajan-Zingales approach to

[3] Of course, we control for the initial number of firms at the county level in 1995.

explore how such correlations vary across industries that have different degrees of dependence on external finances, again obtaining results consistent with causality from clustering to firm financing and firm performance. Even if one does not believe these findings can fully establish causal relationships, they could still shed some light on China's growth puzzle and lend support to theoretical works that try to model the recent China growth paradigm (Song, Storesleten, and Zilibotti, 2009).

The study of China's industrialization may also be useful for the 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, the clustering measures, as well as the clustering patterns of China's industrialization. Section 4 examines the role of clustering in firm financing and firm entry using county-level data, while Section 5 uses firm level data to study how the evolving patterns of clustering relate to firm financing and firm performance. Section 6 offers some conclusions.

2. Literature Review on Clustering, Finance, and Industrial Development

Our study is closely related to two threads of literature. The first relevant body of literature is on finance and industrial growth. Because of the high cost to build up a factory and purchase machinery, in the absence of a well developed capital market, it would be hard for many potential entrepreneurs with limited financial resources to start their own businesses (Banerjee and Newman 1993). Therefore, financial development is regarded as having first-order importance in promoting economic growth (King and Levine, 1993).

In an influential empirical paper, Rajan and Zingales (1998) show that firms in industrial sectors relying heavily on external finance grow faster in countries with more developed financial markets, suggesting that financial development can help reduce firms' costs of external finance. However, the lack of a well-functioning capital market is common in developing countries.

Previous research has suggested the reliance on informal financing—such as borrowing from family members, relatives, and friends—as the main solution (Allen, Qian, and Qian 2005). 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. Another alternative is for firms to rely on suppliers in the form of trade credit as an alternative source of funds (Fisman and Love, 2003). Yet despite the positive role of trade credit in easing working capital constraints, it alone does not explain how capital entry barriers can be overcome in the case of China because many entrepreneurs also lack starting capital to set up their businesses. Moreover, it is unclear how trade credit functions in developing countries, including China, that often lack effective formal legal enforcement mechanisms.

Our study is also related to the literature on industrial clustering. Industrialization is often accompanied by clustering (or spatial agglomeration) of industrial activities.[4] Italy, Japan, and other East Asian countries and regions have all experienced a path of spatial clustering during the course of industrialization, which was led by small and medium enterprises (SMEs). One noted example is the popular putting-out system in the U.K. prior to its Industrial Revolution, in which a merchant obtained market orders and subcontracted the production to nearby farmers or skilled workers, who usually finished the work in their homes or family workshops (Hounshell 1984). 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).

The literature on clustering has highlighted at least three key positive externalities of industrial clusters: better access to the market and suppliers, labor pooling, and easy flow of technology know-how (Marshall, 1920). Glaeser and Gottlieb (2009) emphasize the role of agglomeration in speeding the flow of ideas. With these positive externalities, Porter (1998) argues that clustering is an important way for firms to fulfill their competitive advantage. Ciccone and Hall (1998) and Ciccone (2002) have empirically shown that agglomeration is positively associated with productivity at the local geographical level in the US and Europe.

We argue in this paper that another main advantage of clustering in developing countries with limited financial development is in helping firms alleviate financial constraints, a point that has not been previously discussed except in several case studies. One key feature of industrial

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

clustering observed in China is that an integrated production process is disaggregated into many small steps that are performed by a large number of small firms. By dividing a production process into incremental stages, a large lump-sum investment can be transformed into many small steps (Schmitz 1995). Based on a case study on cashmere sweater cluster, Ruan and Zhang (2009) empirically show that clustering enables many farmers with entrepreneurial talents to move into industrial production by lowering capital entry barriers. Furthermore, as an integrated production is split up among many firms in a narrow geographic area, these firms have to interact repeatedly on a regular basis. Over time, firms build up trust with their customers and suppliers within the cluster, which in turn lowers transaction costs of extending and receiving trade credit among firms, easing their burden of financing for working capital. Huang et al. (2008) and Ruan and Zhang (2009) provide supporting evidence that trade credit is indeed prevalent in footwear and cashmere clusters in China.

To test whether the financing effects of clustering described in these case studies still hold up in a broader context, we will resort to a more rigorous analysis using a large sample in this paper. By linking the literature on finance and growth and on clustering, our paper also attempts to offer an explanation to China's growth puzzle.

3. Data, Proximity Measure, and Patterns of China's Industrialization

We utilize firm-level data from the China Industrial Census 1995 and China Economic Census 2004 for analysis in this paper. Compared to datasets used in previous studies on China's industrialization patterns (Young 2000; Bai et al. 2004; Wen, 2004; Zhang and Tan, 2007; Lu and Tao, 2009), our datasets have more comprehensive coverage in both time and the number of firms—spanning a time period of ten years and including industrial firms of all sizes (not only those above a certain scale). In addition to allowing for firm-level analysis, the data also permit us to compute various measures at more aggregated levels, including constructing proximity measures to evaluate the degree of clustering, which we will discuss next.

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 inter-firm 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 interconnectedness among firms. When delineating the main actors within a cluster, Porter states, "They include, for example, *suppliers of specialized inputs such as components, machinery, and services as well as providers of specialized infrastructure*. Clusters also often extend downstream to channels or customers and laterally to *manufacturers of complementary products or companies related by skills, technologies, or common inputs*" (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, skills, knowledge, inputs, and institutions. Previous work has also shown that technology linkages among related industries are an important engine for innovation (Scherer 1982; Feldman and Audresch 1999).

The works cited above suggest one way to measure interconnectedness as envisioned in the cluster concept by Porter. If industries and firms produce similar goods, then they are more likely to use similar combinations of inputs in their production processes, and more likely to rely on the same set of suppliers and clients, and thus are more likely to be interconnected through skills, technologies, and other common inputs. The similarity among products of industries can thus be used as a measure for clustering, as defined by Porter.

New results obtained by Hausmann and Klinger (2006) allow us to implement the above measure of interconnectedness among industries (and participating firms) in a cluster. Hausmann and Klinger (2006) constructed a proximity matrix for all four-digit SITC products, in which the proximity between any two goods captures their similarity in the following sense: If the two goods need the same combination of inputs (or endowments and capabilities) to produce, then there is a higher probability that a country has a comparative advantage in both, and the two products are more likely to be both exported. In other words, the proximity between each pair of goods can be computed as the probability that a country has net exports in both (averaged over all countries in the world).[5]

It follows that firms and industries that produce products with a higher proximity are more likely to interact with one another in various ways, including dependence on similar inputs (be they raw materials, labor, or machinery), reliance on similar technologies and research and development, and even dependence on the same supply or marketing facilities. Thus, those industries producing commodities that are more proximate in the Hausmann-Klinger space are likely to be more interconnected in the Porter sense. As a result, this proximity measure can be used to provide a gauge for how closely interconnected industries and their participating firms are within a specific region.

To implement the idea of measuring interconnectedness among firms using product proximity, we follow the procedures below: [6] (1) Aggregate firm level output, asset, and employment 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

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[5] For a more detailed discussion on how the Hausmann-Klinger proximity matrix is constructed and what advantages it has in measuring industry clustering, see Long and Zhang (2010).

[6] For more details on constructing these measures, see Long and Zhang (2010).

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 in (2) 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, as the weights discussed above that are used to adjust for the size of each industry can be assets, employment, or output.[7] We use all these measures, as they reflect different kinds of interconnectedness and thus measure different effects of clustering. Although likely to contribute to all three of these advantages as outlined by Marshall, 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. 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.

[7] For a more detailed discussion on how these measures with different weights differ, see Long and Zhang (2010).

Using the proximity measures described above, we found that clustering among Chinese industries increased significantly between 1995 and 2004.[8] Table 1 presents the industry proximity measures in 1995 and 2004 weighted by asset, employment and output at the county level, showing that the measures have increased significantly during this period.[9] The measures constructed at the prefecture and the provincial levels give the same pattern of higher average industry proximity in each region in the latter year (Long and Zhang, 2010).

Finally, compared to the conventional measures, the proximity measures fare much better in accurately reflecting the clustering patterns observed in reality. By 2004, the coastal regions were boasting of some well-known industrial clusters in China. Examples include Shanghai (with clusters in refined steel, petroleum, general and special purpose equipment, and automobile), Zhejiang (with clusters in textile, shoes, apparel, electrical appliances, and electronic and telecommunications equipment), and Guangdong (with clusters in textile, apparel, electronics, and computers and related products.)

Consistent with this pattern, Li and Fung (2006) report 23 well known industrial clusters at the prefecture level in China, all located in the Coast. We thus divide Chinese prefectures into two groups—the prefectures with well known industrial clusters reported by Li and Fung (2006) and those without the above mentioned industrial clusters. On average, the proximity measure (be it weighted by output, asset, or employment) is significantly higher for the prefectures with industrial clusters than that for prefectures without clusters. In contrast, when the conventional measures (the concentration ratio, the Gini Coefficient, or the Krugman-Gini-Coefficient) are used, the value for the clustering group is either statistically indifferent from or smaller than that for the non-clustering group. In summary, proximity measures seem superior to the conventional

[8] Interestingly, we find similar results using other conventional concentration measures, including the Hirfendahl index and Gini coefficient. See Long and Zhang (2010) for details.

[9] The exception is employment weighted proximity, which did not change significantly. This most likely reflects the fact that SOEs laid off massive number of workers as part of the restructuring reform in the middle and late 1990s.

measures in evaluating the degree of industrial clusters in China. For detailed results, see Table A in the Appendix.

4. Clustering, Firm Financing, and Number of Firms: County Level Evidence

We now turn to explore the effects of such increased industry clustering within geographical regions. As discussed in the introduction, we believe that clustering plays an important role in China's firm growth and industrial development mainly through its impact on firm financing. Through two channels, the greater degree of clustering has helped alleviate the difficulty in firms' access to external finances: The finer division of labor within industrial clusters reduces the level of capital requirement, and the greater availability of trade credit among firms within the clusters helps satisfy working capital requirement. With financial constraints eased, the number of firms increases, and thus the degree of competition. In turn, we expect to observe better firm performance.

To study the potential effects of clustering on firm finances, firm entry, and firm performance outlined above, we utilize data at two levels of aggregation. County-level data will be used to explore the impact of clustering on the minimal capital requirement and the number of firms; while firm level data will be analyzed to study how clustering relates to the amount of trade credit among firms, the export performance of firms, and their productivity. In this section we first focus on analysis using county-level data, while the firm-level analysis follows in the next section. In particular, between the two potential mechanisms through which clusters help alleviate financial constraints for firms located in the clusters—the reduction in capital requirement for firms on average and the greater inter-firm financing through trade credit—the minimal capital requirement is to be studied at the county level in this section, while trade credit is best studied at the firm level in the next section.

Table 1 provides summary statistics of variables used in the county-level analysis, where two patterns are worth noting. First of all, the minimum level of assets at the county level has dropped between 1995 and 2004, in stark contrast to the tremendous growth in the size of the overall Chinese economy. This result is consistent with the second pattern: The total number of firms has risen substantially from 1995 to 2004, indicating an increase in competition over time. In particular, the number of domestic non-state firms has risen faster than the total number of firms, while the number of state owned enterprises (SOEs) has shrunk over time, consistent with the privatization process in China during this time period. Finally, the level of financial inefficiency has fallen slightly during this time period, although the change is not statistically significant.

To explore the effect of clustering on firms' capital requirements, it is 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 the minimum level of assets for each county and testing the hypothesis. Table 2 shows results from the following regression:

$$log(min(asset_{c,2004})) = \alpha + \beta_1 * log(\, min(asset_{c,1995})) + \beta_2 * P_{c,1995} + \beta_3 * F_{c,1995} + \varepsilon, \qquad (1)$$

where c indicates county, $min(asset_{c,2004})$ is the minimum level of assets among all firms located in the county in 2004, $min(asset_{c,1995})$ is the minimum level of assets in 1995, $P_{c,1995}$ is the industry proximity in 1995, $F_{c,1995}$ measures the degree of financial inefficiency in 1995,[10] and ε

[10] In an ideal world with perfect capital markets, the marginal product of capital should be equal across firms and regions. Based on this insight, Zhang and Tan (2007) and Hsieh and Klenow (2010) propose to use the variation in marginal product of capital to measure the degree of financial inefficiency. For a production function with constant returns to scale, the marginal product of capital is proportional to average product of capital. Therefore, the variation in the log(marginal product of capital) = variation in the log(average product of capital). In this paper, we compute the standard deviation of logarithm of the value added/total asset ratio at the county level as a measure of financial inefficiency.

is the random error term. Therefore, the coefficient β_2 shows the effect of industry proximity in a region on the minimum requirement of capital for firms located in that region.

Columns 1-3 in the top panel of Table 2 suggest that greater financial inefficiency is associated with a higher level of minimum assets in a region, implying higher entry barriers related to finances in regions with less financial development. The finding is consistent with the mainstream literature that finance plays a role in economic development. Yet the magnitude of impact is rather small. A reduction in one standard deviation of financial inefficiency will lower the minimum asset by about 1%.

However, the lack of financial development does not determine a region's destiny. Given the same degree of financial development, a region with higher clustering, regardless of being measured in output, assets, or employment, is correlated with a significantly lower level of minimum assets. In other words, apart from formal financial development, clustering provides an additional channel to facilitate a finer division of labor and thus reduce the capital requirement for firms. The effects of clustering are economically important. A standard-error increase in clustering (0.03) will lead to a reduction in the minimum capital requirement by 12% in a typical county, which amounts to about RMB 21,000 in the average minimum capital requirement in 2004.

To test if clustering substitutes or complements financial development, in Columns 4-6 we add an interaction term between the clustering and the financial inefficiency measures as an explanatory variable. The coefficients for the interaction term are negative but statistically insignificant. If we take the face value trusting the regressions with interaction terms, the results suggest that clustering and financial development do not substitute or complement each other in affecting the minimal asset level in a location. The insignificant results are likely due to high collinearity among the regressors, in particular between the financial inefficiency and the interaction term. The correlation coefficient between these two variables is as high as 0.7, much greater than the R-squared, suggesting some evidence of strong collinearity. In addition, a comparison of the adjusted R-squared and AIC across the columns indicate that the specifications without interaction terms generally perform better than those with interaction.

The middle and bottom panels of Tables 6 repeat the above analysis using alternative measures of minimum asset level in a certain region. Instead of the lowest level of assets among firms in a certain region, the 5th percentile level of assets and the 10th percentile level of assets are used, respectively, yielding qualitatively similar results. When the interaction term is excluded, greater clustering is associated with lower levels of asset requirement. The coefficient for the clustering measure is statistically significant among four out of the six regressions. The magnitude of the effects drops as we move from using the lowest asset level to the 5th percentile asset level, and to the 10th percentile asset level, suggesting that the effects of proximity are felt the most by the smallest firms (with the lowest asset levels).

With lower asset requirements and the consequent lower entry barriers, we expect more firms to emerge. We study this hypothesis based on the following estimation:

$$log(number\ of\ firms_{c,2004}) = \alpha + \beta_1 * log(\ number\ of\ firms_{c,1995}) + \beta_2 * P_{c,1995} + \beta_3 * F_{c,1995} + \varepsilon, \qquad (2)$$

where the coefficients β_2 and β_3 show the effect of clustering and financial development in a region on the number of firms located in that region.

Panel A in Table 3 reports the regressions on the total number of firms in 2004. As shown in Columns 1-3, at the county level, a higher degree of clustering in 1995 is correlated with a larger number of firms in 2004, after controlling for the initial number of firms and financial development in 1995. This finding is robust regardless of how the clustering measure is weighted.

Consistent with expectations, the coefficient for the financial inefficiency variable is negative and significant. These results illustrate that both financial development and clustering are important to the emergence of new firms.

In Columns 4-6, we include the interaction term between financial development and clustering measure. The clustering measure remains significantly positive, while the financial inefficiency measure loses its significance. The coefficient for the interaction term is negative and significant among two of the three cases, suggesting that clustering and financial development reinforce each other in breeding new firms.

As foreign firms have better access to credit and state owned enterprises (SOEs) in China enjoy preferential access to credit from state banks, they may not benefit as much from industrial clustering as domestic non-state firms. We test this possibility in Panels B-D of Table 3, where the numbers of domestic non-state firms, foreign firms, SOEs are used as a dependent variable, respectively. The regressions on the SOEs can be treated as a placebo test on the impact of clustering on the emergence of firms. The results in Panel B for the domestic non-state firms echo those in Panel A for the whole sample, with the number of domestic non-state firms significantly and positively correlated with the degree of clustering and negatively associated the level of financial inefficiency. For foreign firms, financial inefficiency is shown to have negative effects on their numbers, but the degree of clustering does not matter, implying that foreign firms do not benefit from a higher level of clustering, which is consistent with their having better financial access (see Panel C). Similarly, the clustering measure has nothing to do with the number of SOEs no matter whether the interaction term is included or not. Interestingly, the degree of financial inefficiency in 1995 is positively correlated with the number of SOEs in 2004. These results are not surprising given that the returns to capital among SOEs are significantly lower than those among private enterprises as shown in Hsieh and Klenow (2010). When the interaction term is included, none of the coefficients for the clustering measure, the financial inefficiency measure, and the interaction term is significant. Overall, clustering matters greatly to the number of domestic non-state firms but exerts little impact on the number of foreign firms or SOEs.

These findings suggest that 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 domestic non-state firms of small and medium size.[11]

5. Clustering, Firm Financing, and Firm Performance: Firm Level Evidence

The county-level evidence presented so far is consistent with the beneficial effects of industrial clustering on financing. We study in this section the effects of clustering on trade credit and firm performance, using firm-level data from 1995 and 2004. Table 4 provides summary statistics for firm level variables used in the analysis.

5.1 Baseline results

We begin with an analysis of inter-firm trade credit. 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-level data. Instead, we

[11] Lu and Tao (2009) also find that there have been more and smaller firms in China's manufacturing industries between 1998 and 2005.

construct a balanced panel of firms for which information is available.[12] The model estimated is as follows:

$$trade\ credit_{ict} = \alpha_i + \alpha_t + \beta_1{*}P_{ct} + \beta_2{*}F_{ct} + \boldsymbol{\gamma Z} + \varepsilon, \tag{3}$$

where i, c, and t indicate firm, county, and year, respectively; P and F are the clustering and financial development measures at the county level by year; $\boldsymbol{Z}$ is a vector of firm characteristics; and ε is the random error term. Therefore, the coefficient β_1 and β_2 show the effects of industrial clustering and financial development in a region on the provision of trade credit among firms located in the same region. Note that the model controls for firm fixed effects (α_i) and year fixed effects (α_t).

To measure trade credit, we use the following two ratios: accounts payable / short-term debt, and accounts receivable/asset.[13] While the former measures the proportion of the firm's short-term debt that is financed by its trading partners, the latter indicates the degree to which the firm provides credit to its business partners. The basis for trade credit is frequent business transactions among firms. Thus, a larger amount of trade credit indicates a higher degree of inter-firm connectedness. But it is crucial that both types of trade credit are considered together to draw the above conclusion, as accounts payable and accounts receivable considered separately may merely manifest the competitiveness of the market in which the firm is located. A higher level of accounts payable may indicate that the firm is in a buyer's market for its inputs, while a higher level of accounts receivable reflects a buyer's market for the firm's products.

Table 5 reports estimation results from our baseline specifications where robust standard errors clustered at the county and year level are presented. The results indicate that all the three

[12] 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.

[13] Using alternative measures such as accounts payable/total debt and accounts receivable/revenue yield similar results.

clustering measures are positively correlated with both trade credit measures.[14] For a standard-error increase in clustering, the ratio of accounts payable to short-term debt increases by 3.9-6.4% and the ratio of accounts receivable/asset by 1.7-2.7% depending upon which clustering measure is used. It is likely that the nature of repeated transactions in a cluster enables more frequent use of trade credit among firms at a lower transaction cost.

The financial inefficiency variable has a positive and significant effect on extending trade credit but does not reveal a noticeable effect on receiving trade credit. Theoretically, the relationship between financial development and trade credit is ambiguous. On the one hand, financial development provides firms with more credit, enabling them to lend to each other if necessary. On the other hand, when firms have better access to formal credit, they may rely less on trade credit from other firms.

The coefficient for the shares of private ownership is significantly negative in regressions on both extending trade credit and receiving trade credit, implying that private firms enjoy less access to trade credit. Coupled with the lending policies of state banks giving preferences to SOEs and large firms, these results highlight the need for privately-owned SMEs to more actively look for alternative ways to circumvent these constraints. Also consistent with expectations, the coefficient is positive and significant for the share of foreign ownership (whether by Hong Kong, Macao and Taiwan investors or by other foreign investors).

Having shown that clustering enables a greater number of potential entrepreneurs to engage in more productive industrial production by lowering capital barriers and easing firms'

[14] 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 to 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.

working capital constraints through trade credit, we expect a positive association between clustering and firm performance for two reasons. First, easy entry as a result of clustering boosts competition, likely making firms more productive. Second, the easing of firm financial constraints constitutes an additional mechanism through which clustering helps improve firm performance. We now look at the effects of the proximity measures on firm performance — export and TFP.

We first examine the impact of clustering on exports, using the same specification as equation (3) by replacing trade credit with the share of export value in total sales:

$$export_{ict} = \alpha_i + \alpha_t + \beta_1 * P_{ct} + \beta_2 * F_{ct} + \boldsymbol{\gamma Z} + \varepsilon. \tag{4}$$

Next we estimate the relationship between clustering and total factor productivity (TFP) as follows[15]:

$$log(Y_{ict}) = \alpha_i + \alpha_t + \beta_1 * log(K_{ict}) + \beta_2 * log(L_{ict}) + \beta_3 * P_{ct} + \beta_4 * F_{ct} + \boldsymbol{\gamma Z} + \varepsilon, \tag{5}$$

where Y is value added; K and L refer to assets and labor. 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 K and L.

Table 6 present results from the above estimations. All three clustering measures are found to have positive effects on both export and total factor productivity of the firms, and the effects are also economically important. Specifically, an increase in one-standard deviation of clustering will increase the average export-to-sales ratio by 10.9-18.6%, whereas a standard-deviation increase in the degree of clustering improves TFP by 2.0-2.5 percentage points.

The coefficients for the financial inefficiency variable are statistically negative for TFP. However, its magnitude is small. A one-standard deviation reduction in financial inefficiency

[15] 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.

contributes about only 0.06 percentages to TFP. By comparison, clustering plays a greater role in fostering TFP than financial development. Clustering is shown to be effective in promoting export, whereas the level of financial development has little to do with firm export performance. Both private and foreign-owned enterprises are more productive and export more than SOEs. The result is consistent with the findings by Hsieh and Klenow (2010).

In summary, clustering provides firms, in particular private ones, with an additional mechanism to overcome financial constraints. Even after controlling for firm characteristics, we still find positive and non-negligible effects of clustering on firm performance. Firms in clusters are more productive and more competitive in the international market.

5.2 Robustness tests

To further establish the validity of our findings, we conduct a series of robustness tests.[16] Having shown that clustering provides firms with an alternative channel to ease financial constraints, we further investigate whether clustering acts as a substitute or a complement for formal financial development. We repeat the analyses in Tables 5 and 6 by adding an interaction term of financial inefficiency with the clustering measure at the county level and report the estimates for the clustering measure and its interaction with financial development measures in Panel A of Table 7. After including the interaction term, the clustering measure remains significantly positive in three regressions except for TFP. The coefficient for the interaction term is significantly negative in regressions for extending trade credit and exports but insignificant in receiving trade credit and TFP. Thus clustering and financial development could reinforce each other in

[16] To save space, we report only the results based on clustering measure weighted by asset in the robustness checks. The results using clustering measures weighted by output and employment are largely the same. They are available upon request.

providing trade credit provision and promoting exports. The positive impact of clustering on trade credit and export is larger in areas with well developed financial markets.

A vast body of literature on finance and growth shows that there are sizable differences on the dependence on external finance and even trade credit reliance across sectors (Rajan and Zingales, 1998; Fisman and Love, 2003), which provides another potential robustness check for our results. We first consider the measure of reliance on external finance taken from Rajan and Zingales (1998), which has been widely used in the literature. It is constructed as the industry-level median of the ratio of capital expenditures minus cash flow over capital expenditures based on the Unite States data. Panel B in Table 7 reports the estimates for clustering and its interaction with the external finance reliance variable.[17] All the four coefficients for the interaction term are positive and statistically significant. The more an industry relies on external finance, the stronger the correlation between clustering and trade credit and firm performance. This is consistent with the argument that clustering leads to improved credit access and firm performance.

Fisman and Love (2003) show that trade credit provides an alternative source of funds in poorly developed financial markets. By the same token, we would like to investigate the relationship between trade credit and the impact of clustering. Panel C presents the estimates on industry reliance on trade credit and its interaction with clustering, where the reliance on trade credit variable is defined as the median ratio of accounts payable to total assets at the industry level (Fisman and Love, 2003). The coefficient for the interaction term between the industry-wide reliance on trade credit and clustering measures is significant and positive in three of our regressions except for receiving trade credit. In other words, industries that are relatively more in need of trade credit are more productive and export more in areas with higher degree of

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[17] Because the variable is at the industry level and thus invariant over time, we cannot include it as a separate regressor due to perfect collinearity with firm fixed effects. Instead, we add only the interaction term between this variable and the clustering measure.

clustering. Again, this is consistent with clustering causing improvement in credit access and firm performance.

Next, we address the issue that the impact of clustering on firm financing and performance is likely subject to the nature of underlying technologies. In industries with indivisible technologies, such as petroleum refineries, clustering may prove much less effective. To test this idea, we include an interaction of clustering with capital intensity, drawn from Ciccone and Papaioannou (2009) and originally used in Bartelsman and Gary (1996). The physical capital intensity variable is measured as the share of real capital stock to total value added in 1980 from the NBER Manufacturing Database in the US. Thus to a large extent, the capital intensity variable measures technology divisibility. A highly capital intensive sector implies that its technology is likely less divisible. As shown in Panel D, all the four coefficients for the interaction term are negative, three of them are highly significant and the one for value added is marginally significant. The results suggest that clustering is more effective in helping firms mitigate their financing needs and improve their performance in sectors with more divisible technologies, which is consistent with the role of finer division of labor within clusters.

Not only does the impact of clustering differ by industry characteristics, but also it may vary by firm ownership. Because domestic non-state firms have less access to formal credit than SOEs and multinationals, we expect that clustering has a greater impact on firm financing and performance for domestic non-state enterprises than for foreign firms and SOEs. Table 8 repeats the same analyses in Tables 5 and 6 by splitting the sample into domestic non-state, foreign-owned, and state-owned enterprises. Panels A, B and C report the estimates for the two variables of interest — clustering and financial inefficiency measures for the three types of firms, respectively. As shown in Panel A, all the coefficients for the clustering measure are positive and three out of four are statistically significant, indicating that clustering contributes positively to the financing and performance of domestic non-state enterprises. For foreign firms (Panel B), clustering is shown to be effective only for export. In comparison, none of the coefficients for the clustering measure is significant for SOEs as shown in Panel C. Facing more severe credit constraints, the domestic non-state enterprises have made more effective use of clustering as a way to overcome financial constraints than their foreign and state counterparts. This to a large extent helps explain the myth behind China's phenomenal growth in the private sector in the past several decades despite the initial low level of formal financial development.

All these firm-level analyses so far rely on a panel data set. Although the panel enables us to control unobservable firm fixed effects, it is subject to potential selectivity and survivorship bias. To address this concern, we repeat the regressions in Table 8 by using the entire sample of the two censuses and replacing the firm fixed effects with county-sector fixed effects.[18] Using the full sample is a double-edged sword. On the one hand, it attenuates the selectivity bias because all the firms in the two periods are included in the analysis. On the other hand, it fails to provide adequate control for unobservable firm effects as the inclusion of firm fixed effects will give the same results as those from the balanced panel analysis. Nonetheless, the exercise can serve as a robustness check for the main findings of our previous panel analyses. Table 9 presents the estimates for the cluster and financial development measures. The results largely mirror the major findings in Table 6. Clustering is found to strongly influence both financing and performance of domestic non-state firms. It is positively associated with only extending and receiving trade credit among foreign firms. By contrast, for SOEs, none of the four coefficients for the cluster variable is significant, revealing no correlations between clustering and the outcome variables.

[18] The results are largely the same if we use county and sector fixed effects instead of county-sector fixed effects.

Lower financial efficiency has a positive correlation with extending trade credit for all three types of firms. However, the impact of financial development on export is mixed. Financial development promotes the export of foreign firms but inhibits the export of domestic non-state firms and SOEs. Lack of local financial development impedes TFP of domestic non-state firms and SOEs, whereas it does not matter much to the TFP performance of foreign firms. Overall, the results on the financing effect of clustering are robust no matter whether we use county-level data, firm-level panel, or firm-level non-panel data set. However, the findings for the financial development measure are more mixed depending upon the outcome variables and the underlying data used.

6. Conclusions

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. In addition, our results indicate that the number of firms is growing faster in clustered 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.

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 firms, in particular domestic non-state firms, ease the reliance on external financing.

It is worth emphasizing, however, that the results obtained do not necessarily indicate that financial-sector development is not important. Rather, clustering may be a second-best solution to the financing problem when local conditions do not permit easy access to regular financing. Nonetheless, given that the ideal conditions for economic development are rarely in existence, the organization innovations embodied in clustering are essential, especially for developing countries, for which economic growth is particularly important.

The cluster-based industrialization model may apply to other developing countries, but at least two issues need to be taken into account when implementing such a model. First of all, most clusters in China are based on labor-intensive production technologies, which are in line with China's comparative advantage. This business model makes more use of entrepreneurs and labor, and less use of capital, compared to non-clustered large factories, and thus may have emerged as the choice of Chinese firms over time, leading to more clustered industries in China, which tend to be both more productive and more export oriented. Fitting in well with its comparative advantage may have been crucial in explaining the success of cluster-based industrialization dominated by SMEs in China. As a result, governments should be cautious in promoting cluster-based development in industrial sectors that do not make use of the region's comparative advantage (Rodríguez-Clare 2007).

Secondly, even for developing countries with similar endowments, one should be aware of institutional contexts that may affect cluster-based development. With the deepening division of labor inherent in the clustering mechanism, the demand for collective actions and public goods usually goes up. Therefore, local governments often need to play a key role in nurturing clustering development. Under fiscal decentralization, local governments in China are active in promoting cluster-based industrial development (Xu and Zhang, 2009). Yet local governments in many other developing countries are more passive in fostering industrial policy.

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Table 1. Summary statistics of county-level variables used in regressions

Variable	Mean	SD	Min	Max	N
Proximity 2004 (w=asset)	0.226	0.035	0.091	0.397	2,833
Proximity 2004 (w=employment)	0.220	0.032	0.000	0.403	2,834
Proximity 2004 (w=output)	0.226	0.038	0.000	0.631	2,833
Proximity 1995 (w=asset)	0.218	0.031	0.000	0.495	2,765
Proximity 1995 (w=employment)	0.222	0.037	0.000	0.495	2,756
Proximity 1995 (w=output)	0.217	0.030	0.000	0.495	2,764
log(minimum asset 2004) (in millions)	3.061	1.455	0.000	10.404	2,761
log(minimum asset 1995) (in millions)	3.540	1.264	0.000	10.075	2,761
log(5^{th} percentile asset 2004) (in millions)	4.852	0.875	0.000	10.404	2,761
log(5^{th} percentile asset 1995) (in millions)	4.739	0.977	0.000	10.075	2,761
log(10^{th} percentile asset 2004) (in millions)	5.399	0.788	0.000	10.404	2,761
log(10^{th} percentile asset 1995) (in millions)	5.242	0.931	0.000	10.075	2,761
log(total number of firms 2004)	5.289	1.353	0.405	9.835	2,761
log(total number of firms 1995)	4.684	1.040	0.693	7.676	2,761
log(number of non-state firms 2004)	5.180	1.467	0	9.833	2,761
log(number of non-state firms 1995)	4.117	1.357	0	7.628	2,761
log(number of SOEs 2004)	0.294	0.413	0	3.177	2,761
log(number of SOEs 1995)	1.738	0.734	0	4.803	2,761
Financial inefficiency 2004	1.116	0.307	0.023	3.850	2,761
Financial inefficiency 1995	1.145	0.206	0.036	2.576	2,754

Note: Calculated by authors based on China Industrial Census 1995 and China Economic Census 2004.

Table 2. Minimum level of assets and clustering at county level

Panel A:	Clustering measures weighted by Asset	Employment	Output	Clustering measures weighted by Asset	Employment	Output
	Dependent variable= log(minimum asset in 2004)					
Cluster measure	-4.408***	-3.948***	-4.131***	-1.407	0.611	-2.979
	(0.87)	(0.70)	(0.89)	(4.13)	(3.03)	(4.12)
Financial inefficiency	0.433***	0.431***	0.424***	1.008	1.317**	0.644
	(0.13)	(0.13)	(0.13)	(0.79)	(0.59)	(0.78)
Cluster*financial inefficiency				-2.690	-4.040	-1.027
				(3.62)	(2.61)	(3.58)
Minimum asset in 1995 (log)	0.387***	0.390***	0.391***	0.386***	0.389***	0.391***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Adjusted R-squared	0.111	0.112	0.110	0.111	0.113	0.110
AIC	9490.8	9433.4	9487.5	9492.2	9433.0	9489.4
Panel B:	Dependent variable=log(5 percentile level of asset in 2004)					
Cluster measure	-1.037**	-1.230***	-0.673	1.773	3.192*	1.229
	(0.53)	(0.42)	(0.54)	(2.50)	(1.82)	(2.48)
Financial inefficiency	0.131*	0.153*	0.122	0.671	1.014***	0.485
	(0.08)	(0.08)	(0.08)	(0.48)	(0.35)	(0.47)
Cluster*financial inefficiency				-2.518	-3.919**	-1.695
				(2.19)	(1.57)	(2.16)
5 percentile asset in 1995 (log)	0.272***	0.280***	0.273***	0.271***	0.279***	0.273***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Adjusted R-squared	0.088	0.094	0.089	0.088	0.095	0.089
AIC	9490.8	9433.4	9487.5	9492.2	9433.0	9489.4
Panel C:	Dependent variable=log(10 percentile level of asset in 2004)					
Cluster measure	-0.942**	-1.056***	-0.503	1.052	2.572	1.606
	(0.47)	(0.38)	(0.48)	(2.24)	(1.62)	(2.22)
Financial inefficiency	0.118*	0.150**	0.106	0.501	0.857***	0.51
	(0.07)	(0.07)	(0.07)	(0.43)	(0.32)	(0.42)
Cluster*financial inefficiency				-1.787	-3.216**	-1.880
				(1.96)	(1.40)	(1.93)
10 percentile asset in 1995 (log)	0.276***	0.285***	0.275***	0.276***	0.285***	0.275***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Adjusted R-squared	0.102	0.110	0.103	0.102	0.111	0.103
AIC	6120.9	6010.0	6080.6	6122.1	6006.7	6081.6
Number of observations	2754	2747	2753	2754	2747	2753

Note: *Minimum asset* is the lowest amount, the lowest 5 percentile, and the lowest 10 percentile of assets among firms at the county level in 1995 or 2004 (in millions of RMB), respectively, in the three panels. *Cluster measure* refers to the proximity measure. *Financial inefficiency* is measured as the standard deviation of log(value added/asset) at the county level. The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively. Robust standard errors are in parentheses.

Table 3. Firm number and clustering at county level

	Clustering measures weighted by			Clustering measures weighted by		
	Asset	Employment	Output	Asset	Employment	Output
Panel A:	Dependent variable=total number of enterprises in 2004					
Cluster measure	1.697***	1.687***	2.480***	8.713***	3.213**	7.918***
	(0.46)	(0.37)	(0.47)	(2.17)	(1.60)	(2.17)
Financial inefficiency	-0.758***	-0.771***	-0.751***	0.592	-0.473	0.29
	(0.07)	(0.07)	(0.07)	(0.41)	(0.31)	(0.41)
Cluster* financial inefficiency				-6.291***	-1.354	-4.848**
				(1.91)	(1.38)	(1.89)
Total no. of firms in 1995	1.109***	1.113***	1.110***	1.110***	1.113***	1.110***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adjusted R-squared	0.716	0.715	0.716	0.717	0.715	0.717
AIC	5976.1	5925.0	5960.6	5967.2	5926.1	5956.0
Panel B:	Dependent variable=total number of domestic non-state firms in 2004					
Cluster measure	2.065***	2.082***	2.747***	7.017***	2.756	8.767***
	(0.56)	(0.45)	(0.57)	(2.63)	(1.94)	(2.62)
Financial inefficiency	-0.866***	-0.857***	-0.862***	0.0871	-0.725*	0.29
	(0.08)	(0.08)	(0.08)	(0.50)	(0.38)	(0.50)
Cluster* financial inefficiency				-4.440*	-0.598	-5.367**
				(2.31)	(1.67)	(2.28)
Total no. of private firms in 1995	0.857***	0.852***	0.856***	0.857***	0.852***	0.857***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adjusted R-squared	0.626	0.621	0.626	0.626	0.621	0.626
AIC	7019.6	6978.4	7003.5	7017.9	6980.2	6999.9
Panel C:	Dependent variable=total number of foreign-owned enterprises in 2004					
Cluster measure	0.154	0.23	0.259	1.552	0.948	1.88
	(0.30)	(0.24)	(0.31)	(1.43)	(1.05)	(1.42)
Financial inefficiency	-0.153***	-0.154***	-0.152***	0.116	-0.0142	0.158
	(0.04)	(0.04)	(0.04)	(0.27)	(0.21)	(0.27)
Cluster* financial inefficiency				-1.254	-0.637	-1.446
				(1.25)	(0.91)	(1.24)
Total no. of foreign firms in 1995	1.019***	1.019***	1.019***	1.020***	1.020***	1.019***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adjusted R-squared	0.788	0.789	0.788	0.788	0.789	0.788
AIC	3642.8	3633.7	3641.9	3643.7	3635.2	3642.6
Panel D:	Dependent variable=total number of SOEs in 2004					
Cluster measure	0.139	0.134	0.30	0.419	-0.737	-1.233
	(0.24)	(0.20)	(0.25)	(1.15)	(0.85)	(1.15)
Financial inefficiency	0.228***	0.225***	0.232***	0.282	0.0554	-0.0617
	(0.04)	(0.04)	(0.04)	(0.22)	(0.17)	(0.22)
Cluster* financial inefficiency				-0.252	0.772	1.367
				(1.01)	(0.73)	(1.00)
Total no. of SOEs in 1995	0.208***	0.209***	0.209***	0.208***	0.209***	0.209***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adjusted R-squared	0.156	0.158	0.158	0.156	0.158	0.159
AIC	2476.7	2456.5	2459.8	2478.7	2457.4	2459.9
Number of observations	2754	2747	2753	2754	2747	2753

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

Table 4: Summary statistics for firm-level variables used in the regressions

Variable	Mean	SD	Min	Max	N
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(asset)	8.933	1.941	0.693	18.235	104,324
Log(employment)	4.339	1.791	0.000	13.317	104,324
Export/sales	0.060	0.203	0.000	1.000	152,122
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: Calculated by authors based on China Industrial Census 1995 and China Economic Census 2004. *HMT* stands for firms owned by Hong Kong, Marco, and Taiwan. *Year04* is a dummy variable for 2004.

Table 5. Clustering and trade credit: Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable= accounts receivable/asset			Dependent variable= Accounts payable/short-term debt		
Cluster_asset	0.201***			0.243**		
	(0.05)			(0.12)		
Cluster_employment		0.196***			0.378***	
		(0.05)			(0.11)	
Cluster_output			0.132***			0.278**
			(0.05)			(0.12)
Financial inefficiency	0.0106***	0.0109***	0.0104***	0.0125	0.0126	0.0117
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Firm age	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(sales)	-0.0004	-0.0004	-0.0004	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Debt/asset	0.000	0.000	0.000	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed asset/total asset	-0.228***	-0.228***	-0.228***	-0.124***	-0.125***	-0.125***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Private share%	-0.009***	-0.009***	-0.009***	-0.0378***	-0.0379***	-0.0375***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
HMT share%	0.086***	0.086***	0.086***	0.248***	0.247***	0.248***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Other foreign share%	0.180***	0.179***	0.180***	0.456***	0.454***	0.456***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Year04	0.019***	0.021***	0.019***	0.060***	0.062***	0.059***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.161***	0.161***	0.177***	0.282***	0.249***	0.275***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Adjusted R-squared	0.183	0.184	0.183	0.159	0.160	0.159
Number of observations	101322	101318	101322	100127	100124	100127

Note: Sample includes only firms that are surveyed in both censuses. *Accounts receivable/asset* and *accounts payable/short-term debt* are used as two different measures of trade credit among firms. *HMT* stands for firm shares owned by Hong Kong, Marco, and Taiwan. The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively. Standard errors clustered at the county level are in parentheses.

Table 6. Clustering and firm performance (export & TFP): Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable=export/sales			Dependent variable=log(value added)		
Cluster_asset	0.199***			0.636**		
	(0.07)			(0.30)		
Cluster_employment		0.323***			0.575*	
		(0.06)			(0.32)	
Cluster_output			0.210***			0.746**
			(0.07)			(0.31)
Financial inefficiency	0.0004	0.0005	-0.0002	-0.285***	-0.284***	-0.287***
	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.03)
Firm age	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(sales)	0.006***	0.006***	0.006***			
	(0.00)	(0.00)	(0.00)			
Private share%	0.006*	0.006	0.006*	0.084***	0.084***	0.085***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)
HMT share%	0.221***	0.220***	0.221***	0.290***	0.289***	0.290***
	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.05)
Other foreign share%	0.199***	0.198***	0.199***	0.706***	0.704***	0.705***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)
Year04	0.047***	0.049***	0.046***	0.555***	0.562***	0.555***
	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.04)
Log(labor)				0.079***	0.079***	0.079***
				(0.00)	(0.00)	(0.00)
Log(asset)				0.819***	0.819***	0.819***
				(0.01)	(0.01)	(0.01)
Log(labor)*year04				0.267***	0.267***	0.267***
				(0.01)	(0.01)	(0.01)
Log(asset)*year04				-0.181***	-0.181***	-0.181***
				(0.01)	(0.01)	(0.01)
Constant	-0.085***	-0.114***	-0.086***	-0.008	0.002	-0.030
	(0.02)	(0.02)	(0.02)	(0.10)	(0.11)	(0.11)
R-squared	0.117	0.118	0.117	0.470	0.470	0.470
Number of observations	136351	136347	136351	92633	92633	92633

Note: Sample includes only firms that are surveyed in both censuses. *HMT* stands for firm shares owned by Hong Kong, Marco, and Taiwan. *Year04* is a dummy variable for 2004. The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively. Clustered standard errors at the county and year level are in parentheses.

Table 7. Robust check on trade credit and firm performance with industrial controls

	Accounts receivable /asset	Accounts payable /short-term debt	Export /sales	Log(value added)
Panel A:	Variable of interest=regional level financial development			
Cluster measure	0.474***	0.504*	0.890***	-0.521
	(0.14)	(0.30)	(0.19)	(1.21)
Cluster*financial inefficiency	-0.232**	-0.223	-0.588***	0.992
	(0.11)	(0.23)	(0.14)	(1.02)
Panel B:	Variable of interest=reliance on external finance			
Cluster measure	-0.009	-0.121	0.123**	-0.133
	(0.06)	(0.12)	(0.06)	(0.44)
Cluster*external finance	0.733***	1.385***	0.201*	1.544*
	(0.18)	(0.31)	(0.11)	(0.80)
Panel C:	Variable of interest=reliance on trade credit			
Cluster measure	-0.182	0.331	-0.566***	-4.540***
	(0.21)	(0.43)	(0.18)	(1.47)
Cluster*trade credit	4.562**	0.108	8.741***	56.53***
	(2.33)	(4.47)	(2.02)	(16.42)
Panel D:	Variable of interest=capital intensity (divisibility)			
Cluster measure	0.725***	1.606***	0.592***	1.400*
	(0.14)	(0.28)	(0.12)	(0.73)
Cluster*capital intensity	-0.347***	-0.895***	-0.288***	-0.664
	(0.08)	(0.14)	(0.06)	(0.43)

Note: Sample includes only firms that are surveyed in both censuses. *Clustering measure* refers to the proximity measure weighted by asset. The *reliance on external finance* is taken from Rajan and Zingales (1998) and defined as the industry-level median of the ratio of capital expenditures minus cash flow over capital expenditures based on the Unite States data; *reliance on trade credit* comes from Fisman and Love (2003) and is defined as the median ratio of accounts payable to total assets at the industry level in the U.S.; *capital intensity*, defined as the share of real capital stock to total value added in 1980 in the U.S., is obtained from and Ciccone and Papaioannou (2009). The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively. Clustered standard errors at the county and year level are in parentheses.

Table 8. The effect of clustering on firm trade credit and firm performance by ownership

	Accounts receivable/asset	Accounts payable /short-term debt	Export /sales	Log(value added)
Panel A:		Domestic non-state firms		
Cluster measure	0.246***	0.169	0.136**	0.968**
	(0.07)	(0.12)	(0.06)	(0.49)
Financial inefficiency	0.016***	0.044***	0.004	-0.487***
	(0.01)	(0.01)	(0.00)	(0.05)
R-squared	0.114	0.010	0.070	0.472
Number of observations	60548	59758	92892	59196
Panel B:		Foreign-owned enterprises		
Cluster measure	0.105	0.386	0.848***	0.186
	(0.07)	(0.27)	(0.29)	(0.71)
Financial inefficiency	0.023***	-0.014	-0.106***	-0.031
	(0.01)	(0.03)	(0.02)	(0.09)
Adjusted R-squared	0.588	0.629	0.270	0.444
Number of observations	8808	8734	9065	8410
Panel C:		State-owned enterprises		
Cluster measure	0.0387	-0.015	-0.06	-0.161
	(0.04)	(0.09)	(0.04)	(0.64)
Financial inefficiency	0.008**	0.011	0.010***	-0.512***
	(0.00)	(0.01)	(0.00)	(0.06)
Adjusted R-squared	0.073	0.012	0.044	0.352
Number of observations	26498	26264	26967	20448

Note: Sample includes only firms that are surveyed in both censuses. *Cluster measure* refers to the proximity measure weighted by asset. The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively. Clustered standard errors at the county and year level are in parentheses.

Table 9. Robust check on trade credit and firm performance: Unbalanced panel with industry-county fixed effects

	Accounts receivable /asset	Accounts payable /short-term debt	Export /sales	Log(value added)
Panel A:		Domestic non-state firms		
Cluster measure	0.221***	0.254***	0.068*	0.472
	(0.04)	(0.09)	(0.04)	(0.37)
Financial inefficiency	0.034***	0.030***	0.008***	-0.233***
	(0.00)	(0.01)	(0.00)	(0.04)
R-squared	0.133	0.016	0.028	0.671
Number of observations	509084	494880	1485652	941946
Panel B:		Foreign-owned enterprises		
Cluster measure	0.181***	0.532**	0.285	-0.436
	(0.06)	(0.22)	(0.24)	(0.74)
Financial inefficiency	0.028***	0.027	-0.076***	0.074
	(0.01)	(0.02)	(0.02)	(0.07)
Adjusted R-squared	0.329	0.352	0.087	0.662
Number of observations	92466	91368	134569	106374
Panel C:		State-owned enterprises		
Cluster measure	-0.024	0.037	-0.050	0.353
	(0.04)	(0.07)	(0.03)	(0.55)
Financial inefficiency	0.014***	0.004	0.008***	-0.500***
	(0.00)	(0.01)	(0.00)	(0.05)
Adjusted R-squared	0.129	0.02	0.031	0.648
Number of observations	94275	93261	96749	69064

Note: Sample includes all the firms surveyed in the two censuses. *Cluster measure* refers to the proximity measure weighted by asset. Industry-county fixed effects are included but not reported due to page limit. The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively. Clustered standard errors at the county and year level are in parentheses.

Appendix: Table A. Comparing different cluster measures

	Prefectures with known clusters mentioned in Li & Fung (1)	Prefectures without clusters mentioned in Li & Fung (2)	Difference (1)-(2)
proximity (asset)	0.224	0.216	0.009
	(0.002)	(0.001)	(0.005)*
Gini (asset)	0.637	0.743	-0.106
	(0.014)	(0.005)	(0.019)***
Krugman-Gini (asset)	0.485	0.678	-0.192
	(0.020)	(0.006)	(0.025)***
concentration ratio (asset)	0.397	0.578	-0.182
	(0.022)	(0.009)	(0.035)***
proximity (employment)	0.226	0.209	0.017
	(0.002)	(0.001)	(0.004)***
Gini (employment)	0.628	0.678	-0.05
	(0.012)	(0.004)	(0.018)***
Krugman-Gini (employment)	0.478	0.617	-0.139
	(0.020)	(0.007)	(0.025)***
concentration ratio (employment)	0.371	0.489	-0.118
	(0.019)	(0.008)	(0.031)***
proximity (output)	0.223	0.216	0.007
	(0.002)	(0.001)	(0.005)
Gini (output)	0.665	0.737	-0.072
	(0.013)	(0.005)	(0.019)***
Krugman-Gini (output)	0.521	0.680	-0.159
	(0.022)	(0.007)	(0.026)***
concentration ratio (output)	0.429	0.555	-0.126
	(0.022)	(0.010)	(0.036)***

Note: Li and Fung (2006) report 23 well-known clusters across China all at the prefecture level. We compute various cluster measures at the prefecture level based on China Economic Census 2004 and compare them between prefectures with and without the above mentioned clusters. Standard errors are in the parentheses. The symbols *, **, and *** stand for significance level at 10%, 5%, and 1%, respectively.