Information and communication technologies and geographic concentration of manufacturing industries: Evidence from China

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Abstract

Using the 2004 China economic census database, this paper examines the impact of information and communication technologies (ICT) on the geographic concentration of manufacturing industries, controlling for other determinants of industrial agglomeration. Higher geographic concentration is found consistently in industries where ICT are more widely adopted, and the association is stronger at higher geographic levels. Furthermore, young firms that have adopted ICT, although they are more footloose, contribute to industrial agglomeration. High-tech industries with advanced ICT also tend to agglomerate. Contrary to the prevalent argument that ICT lead to more dispersion, our study suggests that ICT promote industrial agglomeration.

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1. Introduction

Economists have long recognized that agglomeration – of both population and firms – in cities, yields economic benefits. In Marshall's (1920) view, firms of the same industry concentrate in a city to incorporate specialized labor pooling, the availability of intermediate inputs, as well as information and knowledge spillovers. In Jacobs' opinion (Jacobs, 1969), firms of different industries concentrating in a city can facilitate cross-fertilization of new ideas. In both arguments, the underlining determinant of agglomeration economies is geographic proximity.

Many recent studies have confirmed the existence and significance of agglomeration economies among firms, and among workers in cities. Further, economists have tried to disentangle the microfoundations of agglomeration economies. For example, Rosenthal and Strange (2001) examined the impact of knowledge spillovers, labor market pooling, input-sharing, and natural advantage on manufacturing industrial agglomeration. Audretsch and Feldman (1996) found that industries that emphasize research and development (R&D) are more likely to concentrate in an area. Lovely et al. (2005) investigated whether the need to acquire information contributes to spatial concentration, while Nakamura (2005) focused on the forward and backward linkage externalities.[1]

However, along with the rapid progress and wide application of information and communication technologies (ICT) during the past few decades, an interesting research question arises: If people can communicate over a long distance at decreasing cost via phones, fax machines, internet, and emails, is it still necessary for people and firms to be located close to each other? Or, put in another way, will the improvement of ICT attenuate, or even eliminate the geographic concentration of economic activities, or even cities? There is no consensus, either theoretically or empirically.

Existing studies on the relationship between ICT and geographic concentration can be grouped into roughly three strands. The first strand found that agglomeration economies are localized, and decay with geographic distances. For example, Jaffe et al. (1993) found that patent citations decrease when distance from the company holding the patent increases. Rosenthal and Strange (2003) found that business agglomeration economies, and Fu (2007) labor market agglomeration economies, attenuate rapidly with distance. Though these studies did not explicitly predict the impact of ICT on agglomeration, the implication is that a decrease in the cost of communication and transportation over distance will attenuate agglomeration and lead to more dispersion.

The second strand of literature predicts that ICT will attenuate the demand for

[1] For more related studies, see the literature review by Duranton and Overman (2004) and Rosenthal and Strange (2004).

face-to-face communications, and thus will result in greater dispersion of economic activities. Ota and Fujita (1993) constructed a general equilibrium model of multi-unit firms' location and showed that the development of information technology will lead to a greater concentration of front-units in the city center and to a dispersion of back-units in the far suburbs. Sivitanidou (1997) found that between 1989 and 1994 the office-commercial land value gradients within polycentric Los Angeles flattened. His interpretation was that the recent information revolution has weakened the attractiveness of large business centers to office-commercial activities, resulting in the increasingly dispersed patterns of business locations. Ioannides et al. (2007) developed a formal model showing that the improvement of ICT will increase the dispersion of economic activities across cities, suggesting that city sizes would be more uniform. They also used cross-country city size data and found supportive evidence.[2]

The third strand, however, has an opposite viewpoint. Gaspar and Glaeser (1998) developed a theoretical model and demonstrated that ICT and face-to-face interactions could be complementary, rather than substitute goods. The reason is that while some face-to-face contacts will be replaced and conducted electronically, the improved ICT may result in more face-to-face interactions. If the second force is dominant, then ICT may strengthen agglomeration. They also provided some suggestive evidence, such as the negative connection between geographical distance and number of phone calls, the complementary relationship between business travel and telecommunications, and the increase in co-authorship in economics. Panayides and Kern (2005) extended Gaspar and Glaeser's model and found that improvements in ICT may increase or decrease the demand for face-to-face interactions, depending on the cross-price elasticity. If the cross-elasticity is negative, then city size may increase with electronic communications. Another argument is that a firm's investment in ICT could lead to the shift of economic activity to smaller firms, and lead to downsizing (Brynjolfsson et al., 1994). Since small firms depend more on a diverse external industrial environment (Jacobs, 1961), the adoption of ICT might promote the concentration of diverse industries in cities. Finally, ICT may have different impacts on different industries. Glaeser and Ponzetto (2007) argued that improvement in ICT helps idea-producing sectors and cities, while hurting goods-producing sectors and cities. Not surprisingly, the net effect of ICT on the growth of business service is found to be positive in large cities (Kolko, 1995).

This study contributes to the literature by providing new evidence for unraveling the dispute between the competing hypotheses regarding the relationship between ICT and the geographic concentration of manufacturing industries. Specifically, we examine the impact of ICT on the spatial concentration of manufacturing industries in China, controlling for other main determinants of industrial agglomeration. All data used in this research are from the 2004 China economic census database, which is believed to be the most comprehensive micro-level database in China thus far. It contains detailed information on the entire universe of manufacturing firms in China. For each 4-digit manufacturing industry, we compute the Ellison-Glaeser index (Ellison and Glaeser,

[2] There are a few futurists predicting the disappearance of cities, see Toffler (1980) and Naisbitt (1995).

1997) to measure the level of geographic concentration at the zip code, county, city, and province levels, respectively. The econometric analyses are carried out separately, at these four different geographic levels. The empirical results show a strong association between the adoption of ICT and industrial concentration. These results are quite robust to a variety of alternative specifications as well as at different geographical levels. Furthermore, we find that young firms that have adopted ICT contribute to industrial agglomeration, and high-tech industries with advanced ICT are associated with higher geographic concentration, even after controlling for two-digit industry fixed effects. Since young firms with ICT are more footloose, and high-tech industries involve more face-to-face communications and knowledge spillovers, our findings suggest that ICT have not weakened the benefit from agglomeration, and they have resulted in more industrial agglomeration. This tentative conclusion is contrary to the argument that ICT lead to more dispersion of economic activities.

The next section describes the measurement of variables and econometric model specifications. Section 3 introduces the data and provides some summary statistics. Section 4 presents the estimate results, and section 5 concludes.

2. Variable definitions and econometric model specification

This section begins by discussing the measurement of geographic concentration. The variables that proxy for ICT, and other determinants of industrial agglomeration, are then defined, followed by the specification of econometric models to be estimated.

2.1. Measuring geographic concentration

The two widely-used indexes of geographic concentration are the Gini coefficient, proposed by Krugman (1991), and the Ellison-Glaeser (EG, for abbreviation) index (Ellison and Glaeser, 1997). The difficulty with the Gini coefficient is that an industry will be regarded as highly localized if there are several very large firms concentrating in a limited number of areas. The EG index, however, can control for differences in firm size. This paper uses the EG index, calculated according to the following formula:

$$\gamma = \frac{G-(1-\sum_i m_i^2)H}{(1-\sum_i m_i^2)(1-H)}, \tag{1}$$

where γ is the EG index (also called the Gamma index), for a particular industry; $G=\sum_i (s_i - m_i)^2$, and s_i is the ratio of area *i*'s employment in a particular industry to the national employment in that industry, m_i is the ratio of area *i*'s total employment to the national employment; and $H=\sum_j z_j^2$ denotes the (employment)

Herfindahl index of the J plants in the industry, with z_j representing the employment share of the jth plant. The expected value of the Gamma index is between zero and one. If the spatial location of manufacturing employment is random, then the Gamma index equals zero. The Gamma index has been widely employed in recent studies on industrial agglomeration (e.g., Lovely et al., 2005; Rosenthal and Strange, 2001).

Next, we turn to the selection and measurement of explanatory variables, including variables that proxy for ICT and other important determinants of industrial agglomeration, such as labor market pooling, natural advantages, and knowledge spillovers.

2.2. Measuring information and communication technologies

Geographic distance is a hindrance to face-to-face contacts and the communication of ideas. With the improvement of ICT, some face-to-face contacts are replaced electronically and the costs of communicating ideas over distance are reduced, implying that advanced ICT may affect agglomeration forces. The focus of this paper is to test the impact of ICT on industrial agglomeration.

The rapid development of ICT is characterized by the ever-increasing use of phones, fax machines, personal computers, internet and emails, over the past few decades.[3] Many companies have their own website where various information is posted, including description of companies and products, company and industrial news, career information, and after-sale services. Some company sites also support business transactions and conduct electronic commerce. With the popularity of the internet, a company's website has become increasingly important. One can expect that the companies that have their own website may have more advanced information technology. Thus, we use *share of companies that have a website* in an industry, as a proxy of ICT.

Emails and fax machines also have been widely used in business, and generate new options for communication. Some relationships that previously would have been conducted face-to-face have been replaced by telecommunications. For instance, a company manager now can send an email to the clients instead of meeting them in person. Business partners can fax or email draft contracts to each other instead of delivering them by hand. However, as noted by Gaspar and Glaeser (1998), there is an opposing effect when telecommunication improves: Advanced ICT make communication easier, and hence increase the number of relationships. For example, with improved ICT, a company manager can have more clients, and run more projects, which implies that the manager needs more face-to-face contacts. Since the requirement of face-to-face contacts contributes to agglomeration, the net effect of telecommunication improvement on industrial agglomeration is unknown. Therefore, we also use the *share of firms that have a fax number* or an *email address* in an industry,

[3] We do not test the impact of phone lines, because almost all firms use telephones.

as a proxy for ICT.

To test the robustness of our models, we also try two alternative measures of ICT. We define a dummy variable "IT" that equals one if a firm has either a website, or a fax number, or an email address. We then add *share of firms that have IT* to the model. Since firms that have more computers per worker are believed to have better ICT, we also try *share of firms with above-average computer share,* as an additional proxy.[4]

2.3. Controls for other variables

Following Rosenthal and Strange (2001), we include a set of other important controlling variables that affect industrial agglomeration. The first set of control variables are for labor market pooling. If little skilled labor is needed, then production will be more likely to disperse. Thus, we use *share of workers with a master's* or *diploma degree* in an industry, respectively, as proxies for labor pooling. We also use *average labor intensity* in an industry, to examine the impact of the labor market. The basic idea is that labor-intensive companies may have a higher incentive to concentrate in an area, in order to share the advantages of labor pooling.

The second set of variables control for natural advantages and knowledge spillovers. Industries concentrate, partially due to natural advantages, as discussed in Ellison and Glaeser (1999). We use *energy consumption per worker,* as a proxy for natural advantage. Knowledge spillovers are also an important factor in determining industrial concentration. Because knowledge spillovers are found to be significant in R&D intensive industries, we use *technological funds per worker* in an industry, as a proxy for knowledge spillovers

We also consider the impact of firm age. As ICT become more prevalent and affordable, new firms are more likely to adopt ICT. Rosenthal and Strange (2001) found that, compared to the agglomeration of all establishments, agglomeration of new establishments is not as strongly related to agglomerative spillovers and natural advantages. It would be interesting to test whether young firms equipped with ICT in an industry contribute to further agglomeration or dispersion in China. Therefore, we include *share of young firms* in an industry, in the model.

Information and search costs are higher for foreign investors than for those of domestic firms (Caves, 1996). To overcome this disadvantage, foreign firms are more likely to agglomerate. Specifically, foreign investors may be attracted to areas with existing concentrations of foreign-owned firms (Guimaraes et al., 2000). Thus, the *share of foreign firms* is included in the model, and we expect that industries with a higher share of foreign firms are more likely to concentrate.

[4] We do not use average computer share of an industry as a proxy, because a small proportion of companies have a very large number of computers. Instead, we use share of firms with above-average computer share, in order to avoid outlier bias.

Blonigen et al. (2005) found that the stock of investment in a region by a firm's vertical partners increases the probability of co-location, and recent flow of investment into a region by a firm's horizontal partners increases the probability of investment to the region. This implies that firms under an industrial grouping are more likely to agglomerate in the same region. Thus, we include the *share of firms in an industrial grouping,* in the model.

2.4. Econometric model specification

We estimate how the Gamma index is affected by ICT, controlling for other determinants of industrial agglomeration, as defined above. The econometric model is specified as follows:

$$\gamma_{ij} = \delta X_j + e_{ij}, \tag{2}$$

where γ_{ij} is the Gamma index for industry *j* (4-digit code) at geographical level *i*, X_j is a vector of industrial characteristics, including variables that proxy for ICT, labor pooling, knowledge spillovers and natural advantages, δ is the coefficient vector to be estimated, and e_{ij} is an error term, assumed to be independently and identically distributed. The model is estimated at the zip code, county, city, and province levels, respectively.

3. Data and summary statistics

The data used for this research are drawn from the first economic census in China, conducted by the Chinese government from 2004 to 2005. It is believed to be the most comprehensive micro-level database on Chinese industries thus far. We obtained the manufacturing industry data from the State Statistical Bureau of China. The dataset contains detailed information on all manufacturing firms (over 1.3 million) at the end of 2004, including firm location, year of entry, ownership, employees, and the like.

Two characteristics of this database make it distinct from those used in previous studies. First, the dataset contains information on the entire universe of manufacturing firms in China, while many recent studies (e.g., Lovely et al., 2005; Maurel and Sedillot, 1999; Rosenthal and Strange, 2001) used only a proportion of manufacturing firms in a country.[5] Second, all data used in this research are from the same census database, therefore the consistency of data is guaranteed. However, the census database available is only at the firm level, and not at the establishment or plant level. One concern is that if a firm has several plants located in different places, and all employees are assigned to

[5] An exception is a recent paper by Lu (2008) that examined the relationship between ownership and concentration, using the first and second Chinese national establishment censuses in 1996 and 2001, which cover all the manufacturing establishments in China.

the address where the firm registers, a measurement bias arises when we calculate industrial agglomeration. Fortunately, only a very small proportion (about 1.778%) of firms have multiple plants. In addition, according to the rule of the State Statistical Bureau of China, all employees of a multi-plant firm are allocated to the address where the main production takes place. Thus, we believe that this issue does not lead to significant bias, especially, at the higher geographic levels.

The data cover 482 four-digit manufacturing industries. For each 4-digit industry, we calculate the Gamma index at the zip code, county, city, and province level, respectively.[6] Table 1 shows that there is substantially more concentration at the higher geographic levels: the mean value of the Gamma index at the province level is 0.0657, while at the zip code level it is only 0.0065. These results are quite consistent with previous studies (e.g., Rosenthal and Strange, 2001), suggesting that spillovers may go beyond a small area (Ellison and Glaeser, 1997).

[Insert Table 1 here]

Table 2 reports descriptive statistics of explanatory variables. The shares of firms that have their own website, email address, and fax number are, on average, 6.58%, 8.16% and 42.04%, respectively, and the share of firms that have IT is 42.91%. There are 33.4% of firms with a computer share above the average level. The correlation coefficients among these ICT-related variables are quite high. To avoid multicollinearity, we will not include them in the same equation.

Table 2 also reports descriptive statistics for the other control variables. Two variables, *Technological funds per worker* (at the three-digit industry level) and *energy consumption per worker* (at the two-digit level), are drawn from the China Economic Census Yearbook (State Statistical Bureau, 2006), since we have no other access to these data. All other variables are computed directly from the census database, and are at the four-digit industry level.

[Insert Table 2 here]

4. Estimation results

4.1. Benchmark model results

Table 3 presents the estimation results for the benchmark model (2). The adjusted R^2 ranges from 0.028 to 0.033 at the zip code level, and is improved significantly at higher geographical levels. It reaches 0.131 at the city level. The pattern is consistent with that in Rosenthal and Strange (2001).

The labor market pooling effect is represented by three variables: *share of workers with*

[6] In China, a city is larger than a county, in terms of land area. A city normally contains a number of counties.

master's degree, share of workers with diploma degree, and *average labor intensity*.[7] The results in Table 3 consistently show that *share of workers with diploma degree* has negative and significant impact. The coefficient estimates range from –0.053 to –0.698. The variable *share of workers with master's degree* is positive and significant at the city level, but is insignificant at other geographic levels. The above results show that labor quality, in terms of education, is associated with geographic concentration of manufacturers, which again is consistent with the findings in Rosenthal and Strange (2001). The coefficient of *average labor intensity* is insignificant at all geographic levels, meaning that labor intensity has no significant influence on industrial agglomeration.

We also examine the impact of natural advantages and knowledge spillovers. *Energy consumption per worker* is a proxy for natural resources, and its coefficient is positive and insignificant in most models, consistent with Rosenthal and Strange (2001). The coefficient of *technological funds per worker*, a proxy for knowledge spillovers, is negative and insignificant at the zip code level. Its importance increases, in terms of both magnitude and significance, when the model is estimated at higher geographic levels. Possibly, R&D and innovations are more likely to take place and concentrate in large cities and provinces.

The variable *share of foreign firms* is a proxy for ownership.[8] Since information and search costs are higher for foreign investors than for domestic investors, we expect that industries with a higher *share of foreign firms* are more likely to concentrate. But, if foreign firms export most of their products to oversea markets, where they already have acquired good information sources, then we expect that foreign firms will not differ greatly from domestic firms, in geographic concentration. Table 3 shows that the coefficient is insignificant and negative in most cases, suggesting that the second explanation may be more relevant. The coefficient of the variable *share of firms in an industrial grouping* is positive and significant at all geographic levels. Its value is between 0.081 and 0.342, providing strong support for the theory that firms in an industrial grouping are more likely to concentrate geographically.

The variable *share of young firms*, the percentage of firms that are five years old, or younger, in an industry, is worth noting. The coefficient is consistently positive and significant at the city or lower geographic levels, though it loses some significance at the province level. Since young firms are easily exposed to ICT, this may suggest that ICT have not weakened the incentives of new firms to concentrate.

The key interest of this paper is to investigate the impact of ICT on geographical concentration. Three variables are used to measure the adoption of ICT in an industry:

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[7] The variable *share of workers with bachelor's degree* is not included, since it is highly correlated with some other variables.
[8] We have also used the *share of state-owned firms* as a proxy of ownership, and found that it has insignificant impact on industrial agglomeration. In addition, the inclusion of *share of state-owned firms* does not influence substantially other variables' coefficient estimates and the models' goodness of fit.

share of firms that have website, *share of firms that have fax*, and *share of firms that have email*. Table 3 indicates that all the coefficient estimates are consistently positive at different geographical levels, and most of them are significant. These results provide strong evidence that the development of ICT is associated with a higher degree of geographical concentration of manufacturers. One possible explanation is that improved ICT may result in more face-to-face relationships (Gaspar and Glaeser, 1998), which motivates firms to agglomerate.

We note that the impact of *share of firms that have email* is the strongest, in terms of both magnitude and significance. At the province level, the coefficient estimate for *share of firms that have email* is 0.391, while the estimates for *share of firms that have fax and website* are 0.100 and 0.162, respectively. This pattern implies that communications through emails might have been more efficient, and generated more new relationships. On the other hand, the impact of *share of firms that have website* is not as strong as the other two ICT variables. One possible interpretation is that in China, a large proportion of company websites are used as a channel for publicizing news, but are not used as an interactive communication platform. Another interesting finding is that ICT effects on industrial agglomeration are weak at the zip code level, but become stronger at higher geographic levels. This could be because advanced ICT are more effective in facilitating information spillovers over longer distances.

[Insert Table 3 here]

4.2. Robustness test

To check the robustness of our models, we first use two alternative measures of ICT: *share of firms that have IT*, and *share of firms with computer share above the average level.* Table 4 reports the results, where each entry is taken from a separate regression. The coefficients of both variables are positive in all cases. The coefficient of *share of firms that have IT* is insignificant at the zip code level, but becomes significant at all higher geographical levels. On the other hand, the coefficient of *share of firms with above-average computer share* is insignificant at the zip code and province levels, but becomes significant at the county and city levels. The above results support the hypothesis that advanced ICT are positively associated with geographic concentration.

[Insert Table 4 here]

We also check to see if observed outliers result in bias. Compared with most other industries, the electronics and telecommunication industry has, as expected, a significantly higher Gamma index, as well as better ICT. A natural concern is that the estimation results may be subject to outlier bias. To experiment, we drop this industry and re-run the regressions. The estimation results show that dropping the electronics and telecommunication industry does not change the coefficient estimates substantially.[9] Most ICT variables are still positively associated with geographic concentration. This provides an additional piece of evidence that our regression results are robust.

4.3. Omitted variable problem

One potential identification problem in our model is omitted variable bias. Glaeser and Ponzetto (2007) provided suggestive evidence that, in the U.S.A., the development of ICT and the decrease of transportation costs have resulted in suburbanization and in the decline of manufacturing cities, but also in the rapid growth of idea-producing cities. One natural inference, based on their study, is that ICT may lead to dispersion of goods-producing manufacturing industries. Our estimates show that ICT are positively correlated with manufacturing concentration in China. Could our results be mainly driven by the dominant effect of rapid industrialization and urbanization in China? If this were true, since omitted information on industrialization and urbanization is likely to be positively correlated with ICT, our benchmark model results would have overestimated the coefficients of ICT variables.

We deal with this issue in two ways. First, based on the same data set, we estimate a production function at the firm level with external scale economies. We find that firms in manufacturing industries in China benefit from both localization economies and human capital externalities, even after controlling for city size effect and urbanization economies from industrial diversity.[10] The result confirms Henderson's (2003) finding of Marshallian-localization economies and Moretti's (2004) finding of human capital externalities in manufacturing industries. These studies show that significant knowledge spillovers in manufacturing industries do exist, suggesting that face-to-face interaction is, like in idea-producing industries, also important in manufacturing industries. Therefore, we conclude that ICT do not necessarily lead to decline and dispersion of manufacturing industries. Second, even during the stage of rapid industrialization, different manufacturing industries could be in different stages of their life cycle: Some industries are booming, while others are declining. Therefore, we propose using industry fixed effects to absorb the omitted variable bias.

Another advantage of including industry fixed effects is that we can also control for other unobserved industrial characteristics that may affect geographic concentration. We add 29 two-digit industrial fixed effects, and re-run the regressions. The results are reported in Table 5. Overall the results are encouraging: All coefficient estimates for ICT variables are positive. The *share of firms that have fax, share of firms that have email* and *share of firms that have IT* are significant at the county, city, and province levels. The *share of firms that have website* is significant at the county level. The coefficient estimates of other control variables are very consistent with those in Table 3, in terms of both significance and magnitude (to save space, the results for other

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[9] To save space, the estimation results are not reported here, but are available from the authors upon request.
[10] The results are presented in a separate paper.

variables are not reported here). One exception is that the coefficient of *share of foreign firms* becomes significant in some models, while the coefficient of *technological funds per worker* loses significance at the province level.

[Insert Table 5 here]

Other important omitted variables that we can think of are government policy, export-orientation of industries, and firms' organizational structure. In China, government policies have played an important role in both business location and ICT adoption. The central, provincial, and even municipal governments have established high-tech industrial parks to promote industrial clustering. Within high-tech industrial parks, some preferential policies (such as tax holidays, preferential accounting treatments) are implemented to promote adoption of new technologies, especially in ICT industries. Therefore, the presence of high-tech industrial parks could have driven up both concentration and ICT usage. Export-oriented industries tend to be located close to exporting ports in coastal provinces.[11] Because these industries are more exposed to international trading practices and standards, they are more likely to adopt advanced ICT as well. Firms' organizational structure also can be correlated with concentration and ICT adoption. Previous studies (e.g., Henderson, 2003; Moretti, 2004) found that single-plant firms benefit more from agglomeration, probably because single-unit firms rely more on the external environment than multi-plant firms do, and are more likely to concentrate geographically. On the other hand, multi-plant firms may have better ICT, to facilitate within-firm communications.

To deal with the above concerns, we add three variables to our model. The first is a dummy for high-tech industries, used to capture the effect of government policy towards high-tech industries. The classification of high-tech industries is based on the standard used by the State Statistical Bureau of China. There are 59 high-tech manufacturing industries at the 4-digit level. The second variable is a dummy for export-oriented industries. It equals one, if an industry has an above-average export share. The third variable is the *share of multi-plant firms*. The new estimation results are reported in Table 6. Almost all the coefficient estimates of ICT variables are still positive, though some of them lose significance. The coefficients of *share of firms that have website, share of firms that have fax*, and *share of firms that have IT* are significant at the county level, while the coefficient of *share of firms that have email* is significant at the county and province levels. Taken as a whole, these results also support the idea that advanced ICT are positively associated with geographic concentration.

[Insert Table 6 here]

4.4. Suggestive causality analysis

[11] Lovely et al. (2005) found that exporter headquarters are more agglomerated when foreign market information is difficult to obtain.

The results from the cross-sectional regressions in Tables 3-6 provide evidence on the positive association between the adoption of ICT in an industry and industrial concentration. However, the causality direction can run both ways.[12] It is possible that ICT cause more concentration by facilitating more face-to-face interactions or through other channels; it is also possible that concentration causes firms to adopt more ICT because of the harsh competition among firms in the same geographic cluster. Such an endogeneity problem could be partially remedied if we had a panel data set. Another approach is to use instrumental variables estimation. However, in our data, we know of no such variables that correlate with ICT variables but not with the error terms. We proceed to present some suggestive evidence to disentangle the causality directions.

We begin with some relevant summary statistics, presented in Table 7. On average, among young firms, the percentage of firms adopting ICT is not larger than that among old firms. This is not surprising since ICT diffuse rapidly. What is interesting is that the average size of young firms is much smaller than old firms, hinting that ICT may have led to downsizing. Since small firms depend more on a diverse external environment (Jacobs, 1961), they are more likely to concentrate in large cities. Therefore, downsizing might be a channel through which ICT result in more concentration.

[Insert Table 7 here]

Since the production and application of ICT have progressed rapidly over the past few decades, ICT should be more efficient and easily accessible for young firms, upon their entry into the market. As the costs associated with moving people, ideas, and goods decrease, young firms, equipped with state-of-the-art ICT, should be more footloose, when confronting the location choice problem. If young firms with advanced ICT contribute to the industrial concentration, then, it must be the case that ICT have not weakened the benefit of industrial agglomeration, rather, ICT have strengthened the incentive of young firms to co-agglomerate.

Based on the above argument, we construct a set of variables to measure the share of young firms with ICT in an industry and add them to the benchmark model separately. Table 8 presents the results. In the models without two-digit industry fixed effects, the coefficients of the variables *share of young firms that have website* (*fax, email, IT, above-average computer share*) are all positive and significant, at least at the 10% level in the county, city, and province levels. After controlling for two-digit industry fixed effects, all coefficients are still positive, though most of them become less significant. The coefficient of *share of young firms that have website* is still significant in the county and city level model; and the coefficient of *share of young firms that have email* is still significant in the county and province level models. Overall, the results show that even controlling for unobserved industrial heterogeneity, there is some suggestive

[12] The causality direction between some industrial characteristics (such as labor quality) and agglomeration can run both ways. For these variables, the coefficients may reflect the equilibrium relationship rather than causal effects. Since our focus is the impact of ICT, we will conduct causality analysis only on ICT effects.

evidence supporting the hypothesis that ICT encourage industrial agglomeration.

[Insert Table 8 here]

Workers in high-tech industries need more face-to-face contacts with their peers to exchange ideas, and thus benefit more from knowledge spillovers than workers in low-tech industries (Henderson 2003; Moretii 2004). If we found that high-tech firms with ICT tend to disperse geographically, then it would suggest that advanced ICT decrease the need for face-to-face contacts. We interact the high-tech dummy with each ICT variable and re-estimate the models separately. Table 9 reports the results. All coefficient estimates are positive. Though at the zip code and county levels, most coefficients are insignificant, they become significant at the city and province levels, even after controlling for industry fixed effects. Results in Table 9 indicate that high-tech firms with ICT are more likely to agglomerate. This tentative conclusion is contrary to the argument that ICT decrease face-to-face interactions. Taken together, this section lends support to the argument that the estimates of ICT effects are not completely spurious, and ICT have increased the incentive of firms to co-agglomerate.

[Insert Table 9 here]

5. Conclusions

This research examines the impact of advanced information and communication technologies on the geographic concentration of manufacturing industries. We use the 2004 China economic census data and compute the Ellison-Glaeser index, to measure geographic concentration of four-digit industries. Controlling for the main industrial characteristics that may influence geographic concentration, such as labor pooling, natural advantage, knowledge spillovers, firm age and ownership, we stress the impact of ICT. The regression results provide strong evidence that the improvement of ICT is positively correlated with geographic concentration, and the association is stronger at higher geographic levels. These estimation results are quite robust to a variety of alternative specifications, as well as at different geographic levels.

We also investigate the direction of causality from ICT to concentration. We found that the share of young firms with ICT in an industry is positively associated with concentration. Since young firms, with state-of-the-art ICT, are more footloose, we interpret this as evidence that ICT promote industrial agglomeration. In addition, we also found that high-tech industries with advanced ICT are more likely to agglomerate. Given that high-tech industries need more face-to-face contacts and benefit more from information spillovers, we interpret this result as another piece of evidence that ICT promote face-to-face interactions and industrial agglomeration. Overall, our results lend support to the hypothesis that ICT have strengthened the incentives of firms to co-agglomerate. The future research would be to investigate the exact mechanisms through which ICT affect industrial agglomeration.

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Table 1. Summary of E-G Gamma index at different levels

					Correlation with gamma at the level of		
γ	Mean	SD	Min.	Max.	County	City	Province
Zip code	0.0065	0.0147	-0.0008	0.1788	0.8017	0.7164	0.4433
County	0.0155	0.0231	-0.0188	0.1931		0.8482	0.6531
City	0.0287	0.0370	-0.0186	0.2919			0.7373
Province	0.0657	0.0718	-0.0812	0.5195			

Table 2. Descriptive statistics of explanatory variables

Variables	Mean	S.D.	Min	Max
Share of workers with master's degree	0.0044	0.0094	0.0001	0.1668
Share of workers with diploma degree	0.0910	0.0443	0.0115	0.2679
Average labor intensity	0.0385	0.1038	0.0047	2.2233
Share of firms that have website	0.0658	0.05197	0.0020	0.3622
Share of firms that have fax	0.4204	0.1534	0.0186	0.8175
Share of firms that have email	0.0816	0.0580	0.0000	0.3151
Share of firms that have IT (IT=either website, fax, or email)	0.4291	0.1544	0.2136	0.8306
Share of firms with above-average computer share	0.3340	0.0982	0.0351	0.7273
Share of young firms (5 years old or younger)	0.5166	0.0800	0.0945	0.7807
Share of young firms that have website	0.0304	0.0268	0.0000	0.1996
Share of young firms that have fax	0.2135	0.0856	0.0079	0.5319
Share of young firms that have email	0.0384	0.0300	0.0000	0.1954
Share of young firms that have IT	0.2183	0.0864	0.0088	0.5551
Share of young firms with above-average computer share	0.1718	0.0589	0.0133	0.5048
Share of foreign firms	0.0572	0.0460	0.0000	0.3106
Share of firms in an industrial grouping	0.0256	0.0307	0.0000	0.3272
Energy consumption per worker	0.0008	0.0015	0.00005	0.0113
Technological funds per worker	0.3444	0.4537	0.0003	5.0879
High-tech dummy × Share of firms that have website	0.0186	0.0539	0.0000	0.3425
High-tech dummy × Share of firms that have fax	0.0775	0.2110	0.0000	0.8175
High-tech dummy × Share of firms that have email	0.0225	0.0642	0.0000	0.3151
High-tech dummy × Share of firms that have IT	0.0791	0.2151	0.0000	0.8306
High-tech dummy × Share of firms with above-average computer share	0.0556	0.1525	0.0000	0.7273

Note: Two variables, *energy consumption per worker* and *technological funds per worker*, are drawn from the China Economic Census Yearbook, while all other variables are computed based on the census database by authors.

Table 3. Benchmark model results

	Zip code level			County level			City level			Province level		
Share of workers with master's degree	-0.007	0.014	-0.017	-0.070	0.0003	-0.105	0.916***	0.980***	0.856***	-0.168	-0.041	-0.373
	(-0.08)	(0.16)	(-0.19)	(-0.52)	(0.002)	(-0.79)	(4.34)	(4.72)	(4.06)	(-0.40)	(-0.10)	(-0.90)
Share of workers with diploma degree	-0.059***	-0.053**	-0.063***	-0.189***	-0.19***	-0.202***	-0.320***	-0.334***	-0.347***	-0.602***	-0.644***	-0.698***
	(-2.77)	(-2.54)	(-2.93)	(-5.82)	(-5.94)	(-6.27)	(-6.28)	(-6.70)	(-6.83)	(-5.93)	(-6.50)	(-6.96)
Average labor intensity	0.002	0.001	0.002	0.007	0.004	0.007	0.006	0.003	0.007	-0.003	-0.010	-0.001
	(0.28)	(0.17)	(0.27)	(0.71)	(0.41)	(0.72)	(0.42)	(0.21)	(0.45)	(-0.10)	(-0.33)	(-0.03)
Share of firms that have website	0.029			0.093***			0.083*			0.162		
	(1.39)			(2.94)			(1.65)			(1.63)		
Share of firms that have fax		0.006			0.035***			0.044***			0.100***	
		(0.81)			(3.34)			(2.66)			(3.05)	
Share of firms that have email			0.037*			0.124***			0.145***			0.391***
			(1.78)			(3.96)			(2.95)			(4.02)
Share of young firms	0.018**	0.018**	0.019**	0.033**	0.029**	0.033**	0.056**	0.051**	0.056***	0.316	0.021	0.032
	(2.07)	(2.01)	(2.09)	(2.39)	(2.14)	(2.43)	(2.58)	(2.37)	(2.61)	(0.73)	(0.49)	(0.75)
Share of foreign firms	-0.022	-0.020	-0.033	-0.006	-0.023	-0.042	0.002	-0.034	-0.051	0.017	-0.075	-0.151
	(-1.25)	(-1.02)	(-1.63)	(-0.21)	(-0.80)	(-1.39)	(0.05)	(-0.74)	(-1.08)	(0.20)	(-0.83)	(-1.61)
Share of firms in an industrial grouping	0.104***	0.109***	0.103***	0.084**	0.090**	0.081*	0.199***	0.195***	0.187***	0.342**	0.325**	0.288**
	(3.73)	(4.00)	(3.76)	(1.99)	(2.18)	(1.96)	(3.00)	(3.00)	(2.86)	(2.59)	(2.51)	(2.24)
Energy consumption per worker	0.250	0.181	0.360	0.092	0.178	0.488	-0.268	0.041	0.354	2.243	3.098	4.265*
	(0.52)	(0.38)	(0.73)	(0.13)	(0.24)	(0.66)	(-0.23)	(0.04)	(0.30)	(0.98)	(1.36)	(1.85)
Technological funds per worker	-0.002	-0.002	-0.002	0.001	0.0003	0.001	0.006	0.005	0.005	0.022**	0.019**	0.019**
	(-1.09)	(-1.05)	(-1.17)	(0.42)	(0.13)	(0.23)	(1.38)	(1.04)	(1.16)	(2.51)	(2.08)	(2.15)
Adjusted R^2	0.031	0.028	0.033	0.086	0.090	0.099	0.120	0.128	0.131	0.074	0.087	0.100

Note: Dependent variable is Y. The number of observations is 482. Constant terms are not reported.

Table 4. Robustness test: alternative measures of ICT

	Zip code level	County level	City level	Province level
Share of firms that have IT	0.008	0.039***	0.047***	0.101***
	(1.21)	(3.67)	(2.86)	(3.08)
Share of firms with above-average computer share	0.011	0.027**	0.036*	0.070
	(1.24)	(2.02)	(1.70)	(1.64)

Note: Each estimate in the table is taken from a separate regression. All other variables in table 3 are included, but the coefficients are not reported here.

Table 5. Estimation results: adding 2-digit industry fixed effects

	Zip code level	County level	City level	Province level
Share of firms that have website	0.031	0.085**	0.070	0.001
	(1.25)	(2.26)	(1.20)	(0.01)
Share of firms that have fax	0.0001	0.034**	0.054***	0.103**
	(0.007)	(2.53)	(2.62)	(2.58)
Share of firms that have email	0.036	0.121***	0.153**	0.288**
	(1.38)	(3.12)	(2.53)	(2.46)
Share of firms that have IT	0.005	0.039***	0.059***	0.104***
	(0.51)	(2.95)	(2.83)	(2.60)
Share of firms with above-average computer share	0.0002	0.011	0.020	0.017
	(0.02)	(0.65)	(0.76)	(0.34)

Note: (1) Each estimate is taken from a separate regression with 29 two-digit industry fixed effects included.

(2) All other variables in table 3 (except *energy consumption per worker*) are included, but the coefficients are not reported here. *Energy consumption per worker* is dropped because it is at the two-digit level.

(3) Dependent variable is Y. The number of observations is 482. Constant terms are not reported.

Table 6. Estimation results: adding dummies for high-tech and export-oriented industries, and share of multi-plant firms

	Zip code level	County level	City level	Province level
Share of firms that have website	0.014	0.065**	0.009	0.013
	(0.63)	(1.99)	(0.19)	(0.12)
Share of firms that have fax	-0.001	0.023**	0.017	0.045
	(-0.18)	(2.14)	(1.05)	(1.35)
Share of firms that have email	0.018	0.094***	0.059	0.229**
	(0.79)	(2.82)	(1.14)	(2.19)
Share of firms that have IT	0.002	0.026**	0.021	0.047
	(0.26)	(2.52)	(1.30)	(1.40)
Share of firms with above-average computer share	0.006	0.018	0.016	0.024
	(0.70)	(1.33)	(0.77)	(0.59)

Note: (1) Each estimate is taken from a separate regression.

(2) Three variables are added to the benchmark model: *high-tech industry dummy*, *export-oriented industry dummy*, and *share of multi-plant firms*. The classification of high-tech industries is based on the standard used by State Statistical Bureau, PRC. Export-oriented industries are defined as industries that have above-average export share, where export share = sales of exporting goods/total sales.

(3) All other variables in table 3 are included, but the coefficients are not reported.

(4) Dependent variable is Y. The number of observations is 482. Constant terms are not reported.

Table 7. Firm age, size and ICT adoption

Firm age	% IT=1	% email=1	% fax=1	% web=1	% firms with high computer share	Average employment per firm
1-2	0.336	0.043	0.329	0.029	0.275	40.369
3-5	0.368	0.056	0.361	0.042	0.306	53.662
6-9	0.357	0.061	0.349	0.048	0.300	65.264
10-21	0.356	0.059	0.350	0.044	0.300	83.310
22+	0.301	0.052	0.295	0.040	0.243	106.367

Table 8. Causality link: young firms, ICT and geographic concentration

	Zip code level		County level		City level		Province level	
Share of young firms that have website	0.117***	0.132***	0.230***	0.220***	0.237***	0.191*	0.420**	0.128
	(3.30)	(3.17)	(4.25)	(3.51)	(2.78)	(1.93)	(2.47)	(0.67)
Share of young firms that have fax	0.011	-0.001	0.060***	0.046*	0.051*	0.036	0.153***	0.092
	(0.92)	(-0.07)	(3.21)	(1.96)	(1.76)	(0.96)	(2.67)	(1.29)
Share of young firms that have email	0.074**	0.069	0.196***	0.171**	0.211**	0.174	0.687***	0.046**
	(2.02)	(1.49)	(3.52)	(2.49)	(2.41)	(1.61)	(3.97)	(2.23)
Share of young firms that have IT	0.018	0.010	0.067***	0.060**	0.060**	0.047	0.157***	0.096
	(1.48)	(0.65)	(3.64)	(2.52)	(2.05)	(1.26)	(2.73)	(1.34)
Share of young firms with high computer share	0.032**	0.015	0.057**	0.026	0.070*	0.028	0.143*	0.022
	(2.06)	(0.74)	(2.38)	(0.86)	(1.87)	(0.61)	(1.92)	(0.25)
Two-digit industry fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

Note: Each estimate is taken from a separate regression. All other variables in the models without industry fixed effects are the same as those in table 3. In the fixed effects models, we drop *energy consumption per worker,* as in table 4. Estimates for control variables and summary measures for the regressions are suppressed.

Table 9. Causality link: high-tech Industries, ICT, and geographic concentration

	Zip code level		County level		City level		Province level	
High-tech dummy × Share of firms that have website	0.145	0.019	0.032	0.030	0.056	0.077	0.163**	0.018
	(0.86)	(0.74)	(1.24)	(0.79)	(1.40)	(1.31)	(2.04)	(0.16)
High-tech dummy × Share of firms that have fax	0.004	0.007	0.010	0.013	0.023**	0.041***	0.061***	0.050*
	(1.03)	(1.08)	(1.55)	(1.32)	(2.34)	(2.75)	(3.07)	(1.70)
High-tech dummy × Share of firms that have email	0.016	0.025	0.035	0.043	0.063*	0.099*	0.195***	0.133
	(1.15)	(1.16)	(1.59)	(1.33)	(1.84)	(1.95)	(2.89)	(1.36)
High-tech dummy × Share of firms that have IT	0.004	0.007	0.010	0.013	0.023**	0.041***	0.060***	0.049*
	(1.05)	(1.10)	(1.56)	(1.33)	(2.36)	(2.78)	(3.07)	(1.71)
High-tech dummy × Share of firms with high computer share	0.008	0.014	0.015*	0.021	0.031**	0.055**	0.074***	0.037
	(1.32)	(1.43)	(1.70)	(1.46)	(2.19)	(2.51)	(2.63)	(0.88)
Two-digit industry fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

Note: Each estimate is taken from a separate regression. All other variables in the models without industry fixed effects are the same as those in table 3. In the fixed effects models, we drop *energy consumption per worker,* as in table 4. Estimates for control variables and summary measures for the regressions are suppressed.