Research Clusters and Technology Diffusion

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Research Clusters and Technology Diffusion: The Case of China

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Abstract

Much of the debate over income convergence hinges on whether technology diffusion is "global" or "local". In this paper, I address this question in a developing country setting and focus on the role of major research clusters in promoting *domestic* technology diffusion. I identify four *de facto* research centers in China and investigate whether the effect of R&D spillovers from these research clusters is related to both *geographic and technologica*l distances. I find that firms' productivity gains from R&D spillovers from the research cluster decline with (i) increasing geographic distance away from the research cluster, and (ii) the technological gap between technology senders and recipients.

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1. Introduction

Ever since Robert Solow presented his seminal finding regarding the central importance of technology in driving long-term economic growth, technology and its diffusion mechanism have occupied the center stage of economic development. One of the key issues remaining unresolved is whether technology and knowledge spillovers are global or local.[1] If technology spillover is global, poor countries (regions) are more likely to catch up with rich countries (regions). However, if technology spillover is local, the outlook for world development is much less optimistic. Rather than income convergence, we are more likely to observe a diverging growth pattern between poor and rich countries (or regions).

The question is not a settled one in economics in part because economic theory offers no clear predictions as to the scope of technology spillover. On one hand, there is every reason to believe technology diffusion is global, either through international trade (Feenstra, 1996; Keller, 2002b) and foreign investment, or through freer labor migration, better transportation and telecommunications, especially in the age of the Internet (see, for example, Glaeser and Kohlhase, 2004). Thomas Friedman, in his popular book (2006), "*The World Is Flat*", famously documented how the Internet and other modern logistic advances have fundamentally changed the world trade and the way multinational firms operate. It is plausible that with transportation and communications costs reduced to a much lower level than before, distance does not matter any more for technology diffusion. On the other hand, factors such as superior infrastructure, better opportunities

[1] "Global" means technology diffusion is not limited by distance; in contrast, "local" means technology spillovers are constrained by the distance from the source.

for exchanging ideas, and better institutions all attract highly skilled labor force to work and live in certain area;[2] these factors tend to produce large disparities in both technology and income across different regions and countries (see for example, Jacobs, 1970; Glaeser, 2007). As for developing countries, poor infrastructure, ill-designed government policies and weak institutions could also slow down or block the technology diffusion process (Easterly 2002). Adding to the severity of the problem is the high correlation between quality of infrastructure-institutions and country's level of development. The existence of these impediments in the technology diffusion process increases the possibility that income divergence may happen even when technology and knowledge are readily available to the general public. In short, arguments on both sides seem to be sensible. With little comfort from established theories, the answer to the question ultimately goes to empirical test with data in the real world.

When it comes to empirical research on the scope of technology diffusion, most research focuses on spillovers across rich countries (e.g. Keller, 2002; Eaton and Kortum, 1999; Coe and Helpman, 1995), or on spillovers within a developed country (e.g. Adams and Jaffe, 1996). And they generally confirm that distance does matter. However, there is a serious lack of research in both technology spillovers between rich and poor countries, and spillover *within* a developing country setting. Given the importance of technology-knowledge transfer to the welfare of the poorer countries and how little we know about the diffusion mechanism at the micro-level, the absence of relevant research should long have been rectified. In this paper, I intend to address the dearth of research in this area by investigating empirically how the productivity at the firm level is affected by the technology spillovers from the key R&D research clusters within China. Specifically, I

[2] Sometimes even better restaurants can have a large impact on people's choice for work locations.

am interested in finding out whether the productivity gains from technology spillovers decline with increasing distance, both in geographic and technological sense, between technology senders (research clusters) and recipients (firms). The research clusters in our research are defined as a bundle of firms performing R&D located within a major city. I focus on research clusters because it is widely believed that technology centers, like Silicon Valley in the U.S., have generated large positive externalities from their technological innovations, and firms closer to the cluster have enjoyed relatively high productivity gains.

I ask two related questions in this empirical analysis. The first question is whether technology spillovers from R&D research clusters are affected by the *geographic* distance between research clusters and firms. Unlike other research that focuses on patent citations in their research on technology spillovers (see Jaffe et al. 1993; Griffith et al. 2007), I use measures of firm-level labor productivity to assess the impact of technology spillovers from the research cluster. For technology diffusion to be local, I expect to observe a negative relationship between the effect of technology spillovers and increasing distance. However, if technology diffusions are global, I expect to find no such pattern.

The second question I ask is whether technology diffusion not only depends on *geographic* distance, but also depends on *technological* distance. Firms' relative position on the technology ladder affects the effectiveness of their technology adoption. The smaller the technology distance between technology senders and recipients, the more effective the new technology will be utilized by receiving firms. Easterly (2002) argues that technology adoption is also affected by the institutions that shape the incentives of individuals and firms. Institutions that are designed poorly or operate inefficiently will create fewer incentives for firms to absorb the existing technology, causing firms to lag further behind. Our definition of technological distance captures both the technology level and the institutional environment in which firms operate.

Here is a preview of my research findings. First, I find that geographic distance does matter: with increasing geographic distance between research clusters and firms, the effect of R&D spillovers from research clusters declines. Distance also matters in a technological sense. I find that the impact of R&D spillover decreases with increasing gap between the average productivity at research clusters and the average productivity of firms that are located in the same city. The rest of the paper is organized as follows. In Section 2, I describe the research data, how I identify China's research clusters and the main characteristics of these research centers. In Section 3, I introduce the empirical models and estimation strategies. This is followed by the analysis of the main regression results in Section 4. Then final section concludes.

2. Data

For this empirical research, I use the firm-level data out of China's Large and Medium-Size Enterprises (LME) database provided by National Bureau of Statistical (NBS) of China. The LME database includes over 20,000 firms per year, on average, and spans the years from 1995 to 2004. The database is one of the most comprehensive micro-level databases in China. In 2002, the total output of the sample firms in the database accounted for more than 60% of China's total industrial output.

2.1 Where are China's research clusters?

To spur regional economic growth and promote technology transfer, since the early 1990s, governments in China, both at the central and local levels, have established dozens of so-called "Technology Parks" in numerous cities. With concentrations of technology-intensive firms, some of these parks exhibit features very similar to Silicon Valley in the U.S. But the true nature of the majority of those parks is not clear. Do firms inside these parks truly engage in R&D activities? Or were these firms just set up to take advantage of the preferential tax treatments and subsidies offered by governments? Hu (2007) investigates 53 of such technology parks in his empirical research and he finds no evidence that firms benefit from concentrating in these technology parks. One potential explanation for this finding is some of these technology parks do not engage in R&D activities at all. Given insufficient information with regard to R&D firms inside these parks, in this paper, I take a different approach in defining what a research (technology) cluster is.

[Insert Figure 1 and Figure 2 here]

I identify the *de facto* research clusters by ranking the total R&D expenditure in each major Chinese city during 1995-2004 period. The city-level R&D spending comes from the aggregation of all the firms in LME located within the city. In Figure 1, I graph the top ten cities in China with the largest total LME R&D spending. Four cities stand out among China's cities: Shanghai, Shenzhen, Qingdao and Beijing. From 1995 to 2004, firms in these four cities had spent a total of 67 billion Yuan on R&D, which equals 25%

of total R&D spent by all Chinese firms during the same time period. Among these four cities, Shanghai leads the pack, accounting for nearly 9% of the total LME R&D spending , and it is followed by Shenzhen, with share of about 8.5% of the national total, and by Qingdao and Beijing, each spending nearly 4% of the total (see Figure 2). These four cities are the research clusters that I initially select for this empirical study. As additional proof that my pick is an appropriate one, Richard Florida, in writing on the rise of mega region,[3] cited three cities out of the four cities that I identify, namely, Shanghai, Beijing and Shenzhen. In addition, in Hu's documentation (2007), these four cities also appear on the list with the largest technology parks. The geographic location of the research clusters inside China is shown in Appendix A. And given China's large regional gap in economic development, it came as no surprise that all four cities are located along China's coastal line.

2.2 Source of R&D spillovers within the research cluster

After I have identified the *de facto* research clusters, I next decide whether to count all the firms in the center with R&D expenditure as the source of technology spillovers, or simply the top firms with the largest R&D spending. This is essentially a question about the R&D spillover dynamic. Is the source of spillovers limited to large firms that are intensively engaged in R&D, or does each Yuan of R&D spending, regardless of firm size make comparable contributions to R&D spillovers?

[Insert Figure 3 here]

[3] See Richard Florida (2008).

In Figure 3, I graph the R&D concentration ratios of the top 1, 3, 5, 10 and 20 firms in the four research clusters. The ratios are calculated using their average R&D spending from 2000 to 2004. As shown in the graph, R&D spending within each city is highly concentrated. If we look at the concentration ratios of the top 5 firms, Shenzhen and Qingdao appear to have the highest concentration ratios among the four, both exceeding 75%. In contrast, R&D in Shanghai is much less concentrated, with the 5-firm concentration ratio only slightly below 25%. This reflects the fact that Shanghai historically had a much larger industrial base than the other three, and R&D activities within the city are more dispersed.[4] If we move to look at the concentration ratios of the top twenty firms, we get a similar picture only with even higher concentration. The top twenty firms almost monopolized the whole R&D activities: in both Shenzhen and Qingdao, the top 20 firms accounts for 88% of total R&D spending; in Beijing, the number is 71%; Shanghai is again shown to have a more dispersed distribution of R&D, its 20-firm concentration ratio nonetheless still reaching 45%. Finally, if we just look at the top 1-firm concentration ratio, we observe the most stunning fact that in both Shenzhen and Qingdao, a single firm accounts for more than 40% of total R&D spending of the whole city.[5]

2.3 Which industries in China engage in most R&D activities?

Our dataset includes 31 2-digit industries by SIC classification in China's manufacturing space. In this section, I identify which industries have engaged in the

[4] Shanghai distinguishes itself from other centers by having a much more diverse R&D base and high concentration in education. It is reasonable to believe these two qualities place Shanghai in a more advantageous position in becoming the most important research center in China.
[5] For Shenzhen, this single firm is Huawei Technologies in the electronics and telecom industry; for Qingdao, this single firm is Haier in electric machinery industry.

most R&D activities, by looking at the industry-level R&D expenditure in each research cluster.

[Insert Figure 4 here]

As shown in Figure 4, each research cluster has established its relative strength in R&D. In Beijing and Shenzhen, the telecom and electronics industry occupies a disproportionately large share of the total R&D activities. In Beijing, the telecom and electronics industry accounts for 62% of the total R&D spending on average from 2000 to 2004; in Shenzhen, the same industry accounts for an overwhelmingly 96%! In Shanghai and Qingdao, most R&D is concentrated in transportation equipment and electric machinery industry, respectively. However, the telecom and electronics industry still accounts for a very large share in these two cities.

The nature of these R&D activities in China's telecom and electronics industry remains uncertain. Nonetheless, as above analysis shows, China's telecom and electronics industry has been investing heavily in R&D, and this industry may well emerge as one of the serious competitors in the world market in coming decades.

[Insert Figure 5 here]

Figure 4 focuses on industry R&D concentration in the four research clusters. To show a broader picture of which industries China's R&D activities are concentrated, in Figure 5, I graph the R&D activities by 2-digit industries. The top panel shows the top ten R&D spending by industries on a national level, including those four research clusters.

As shown in the graph, the telecom and electronics industry accounts for about a quarter of the total R&D expenditure, still the largest share among all industries. And it is followed by transportation equipment (mainly automobile) industry, at 14%; electric machinery, at 10%; ferrous metal at 8% and chemicals at 7%. On the lower panel of Figure 5, I show the top ten 2-digit industries with the highest R&D intensity, defined as the ratio between R&D expenditure and value added. By this measure, electric machinery industry overtakes telecom and electronics industry as the leading industry with the highest R&D intensity, 4.09%. This is followed by telecom and electronics at 3.74%, special equipment industry at 3.7% and general equipment industry at 3.5%. Transportation equipment industry, previously ranked at no. 2, now ranks no. 5, with R&D intensity at 2.98%.

Finally, in Figure 6, I show another graph of R&D by industry for firms with over 100 million Yuan R&D expenditure in 2004. Again, the telecom and electronics industry dominates all industries with the largest share of above 62% of the total R&D spending, and it is followed by transportation equipment at 15%, ferrous metal at 11% and electric machinery at 9%. By comparing Figure 4 and Figure 6, I arrive at the conclusion that for the largest firms, the industry concentration ratio is even higher.

[Insert Figure 6 here]

3. Estimation Strategies

In this section, I discuss the empirical modeling strategies. I first estimate how geographic distance affects technology spillovers, and then I add in technological distance into the equation and see how both distances affects technology spillovers.

3.1 Geographic distance

To estimate how geographic or physical distance affects the magnitude of technology spillovers, I use the following estimation equation:

$$\ln LP_{ijt} = \alpha + \beta \ln(K/L)_{ijt} + \delta \ln(CRD_{jt}^{top5,c}) \cdot e^{-dist_{n,(i\in n)}^{c}} + u_i + \eta_j + \tau_t + \varepsilon_{ijt} \qquad (1)$$

The dependent variable, $\ln LP_{ijt}$, or log of labor productivity, is measured by the value-added per employee-year at the firm level, $\ln(VA/L)_{ijt}$, and it is used to capture the impact of technology spillovers over firms. It is indexed for firm i, SIC 2-digit industry j, and year t. Equation (1) controls for variations in labor productivity that are associated with differences in capital-labor ratios, $\ln(K/L)_{ijt}$. I also included firm-level fixed effects u_i, industry dummies η_j, and time effects τ_t.

To estimate how geographic distance affects the effectiveness of technology spillovers on firm's productivity from R&D activities at the research cluster, I created an interactive term between the log of *cumulative* R&D spending,[6] or $\ln(CRD_{jt}^{c})$, and the geographic distance between the research cluster c, and the nearest city n, where the firm i is located, or simply $dist_{n,(i\in n)}^{c}$.[7] The interaction term is the main variable in our estimation. If technology diffusion is local, I expect the coefficient of the interactive term, δ, to be positive and significant. Following the approach in Keller (2002), I transform the geographic distance through an exponential function[8] to avoid the dropout

[6] Cumulative R&D spending is the sum of R&D expenditure from 1995 to year t.
[7] The superscript, c, stands for the nearest cluster.
[8] The exponential transformation: $e^{-dist} = \exp(-dist)$

of those firms whose geographic distances are zero.[9] By such transformation, I also generate a smooth declining curve, which allows the gains of technology spillovers to remain always positive, and only decline gradually with increasing distance between research cluster and the firm. Figure 7 shows the scatter plot on the actual geographic distance data expressed in exponential function.

[Insert Figure 7 here]

Here are some more details regarding how I calculate the geographic distance. I identify each firm's location in LME dataset by its administrative code. The administration code points out the nearest city, n, in which the firm, i, is located. I then use the geographic distance between the city n where the firm i is located and its nearest research cluster, c, as a proxy for the distance between the research cluster and the firm. To calculate this distance, I first obtain a matrix of the latitude and longitude of China's cities using the *Geographic Information System* (GIS). Then, I compute the distance using the *Great Circle Formula.*[10] Finally, I map the distance numbers back into the main LME dataset by matching the city codes between GIS and LME datasets. In total, I included 258 distinct city locations, i.e. n=258, and geographic distances in the empirical test. These 258 cities included almost all medium and above level cities in China. Each of these 258 distances is the minimum of the four geographic distances from the city, n, to the four research clusters, i.e.,

$$dist^{c}_{n,(i\in n)} = MIN(dist^{Shanghai}_{n,(i\in n)}, dist^{Beijing}_{n,(i\in n)}, dist^{Shenzhen}_{n,(i\in n)}, dist^{Qingdao}_{n,(i\in n)}) .$$

[9] The distance between firm and research cluster could be zero when the firm is in the same city as the research cluster.

[10] Great Circle Formula: distance= 6378km*arccos[sin(lat1)*sin(lat2) + cos(lat1)*cos(lat2)*cos(lon2 - lon1)]. (Lat1, Lon1) and (Lat2, Lon2) are latitudes and longitudes of the two locations, respectively.

I use cumulative R&D instead of R&D spending in each year t, as the impact of past R&D on productivity tends to have a time lag so the benefit of R&D investment won't show up until years later.[11] Cumulative R&D at the research cluster is index by cluster c, industry j and year t. In other words, I allow the cumulative R&D at each research cluster to vary across industries and years. But why include all industries, why not just focus on those industries with the highest R&D spending? As previously discussed in Section 2.2, R&D spending in each center city is highly concentrated among the top firms in a few industries. However, the previous discussion was based on a relative level. Although a handful of largest firms in a few industries dominate R&D spending, other industries may still have significant amounts of R&D on an *absolute* level. Another important reason is from the technical perspective of the estimation: for the main variable, the interactive term, it would be highly desirable to generate variations from both R&D spending at the cluster level and the geographic distances. The estimation results of equation (1) are presented in Table 2, and I will come to the analysis of the results in Section 4.

To calculate cumulative R&D spending at the research cluster, I aggregate the R&D expenditure of the *top5 firms* in industry j, year t and at each research cluster c. As discussed in Section 2.2, even without differentiating industries, the top twenty firms at each research cluster accounts for the overwhelming majority of the total R&D expenditure, so it's reasonable to use the R&D expenditure of the top 5 firms as a proxy to capture the majority of the R&D capability of each industry at the research cluster

[11] This lagging effect is well documented by Griliches (1995).

3.2 Estimation with technological distance

One important question in technology diffusion is whether firms on the lower end of technology ladder can effectively absorb knowledge and technology spillovers. I test a variation of this idea by including a measure of technological distance into equation (1) and estimate the following equation:

$$\begin{aligned}\ln LP_{ijt} &= \alpha + \beta \ln(K/L)_{ijt} + \delta \ln(CRD_{jt}^{top5,c}) \cdot e^{-dist_n^c} + \\ &\qquad \lambda \ln(CRD_{jt}^{top5,c}) \cdot tech\_dist_{njt}^{top5,c} + u_i + \eta_j + \tau_t + \varepsilon_{ijt}\end{aligned} \qquad (2).$$

with all other variables remaining unchanged. By including both distances into the equation, I essentially test how the productivity gains from technology spillover will change with increasing distance from the center, conditional upon the technological distance between the firms and the research cluster. As both geographic and technological distances could affect firms' productivity gains from technology spillovers, it's important to differentiate the two. Our priori expectation for the sign of the new interactive term is negative, as larger technological gap tends to disincentivize firms to adopt new technology. I report the regression results for equation (2) in Table 3.

To measure technological distance in equation (2), I use the following formula,

$$tech\_dist_{njt,(i \in n)}^{top5,c} = \log\left(\frac{\sum_{k=1}^{5} VA_{jt}^{topk,c}}{\sum_{k=1}^{5} L_{kjt}^{topk,c}}\right) - \log\left(\frac{\sum_{i=1}^{N} VA_{ijt}^{n}}{\sum_{i=1}^{N} L_{mjt}^{n}}\right) \qquad (3)$$

In equation (3), the first term is log of average labor productivity of the top 5 firms in research cluster c, and it is indexed by in industry j, and year t. The second term is the log of the *average* labor productivity of all firms located in city n, indexed by industry j and year t. There are a total number of N firms in city n, and it varies by each city. An alternative measurement for technological distance is the productivity gap between the research cluster and the *individual* firm i. I prefer the measurement defined in equation (3) for the following two reasons. First, by setup, the technological gap indexed at firm i is nearly perfectly correlated with the dependent variable, log of labor productivity. Second, from a theoretical perspective, our choice of measurement captures the different business environment in different cities, in which firms operate as well as the different technology level of each industry j. Different cities have quite different idiosyncratic (or local) characteristics: infrastructure, openness, human capital, economic policies, and others. It is true that the firm-level fixed effects estimator in equation (2) helps control some of these idiosyncrasies, but none of them is at the city level. Arguably, our choice of technological measurement could also be a good proxy for the quality of local institutions. Local institutions here are defined in broader sense and it includes infrastructure, pool of skilled workers, living conditions, legal and government transparency, etc. If this is the case, our estimation can be used as a direct test of Easterly's idea (2002) that incentives to adopt new technology are shaped by local institutions. In geographic areas where there exists a big technological gap with the technology frontier, referenced by Easterly as a "trap", technology is much less likely to be adopted; and even when the technology is readily available, the reach of technology spillovers could be very limited. The estimation results for equation (2) are presented in Table 3.

3.3 Model Extensions

In this section, I extend the models in section 3.1 and 3.2, and test several alternative specifications of the baseline models. In section 3.3.1, I change the source of R&D spillover from the *top 5 firms* by industry-year *to all firms* by industry-year in the center city. In section 3.3.2, I replace the R&D measure from R&D *level* to R&D *intensity,* where intensity is defined as total R&D divided by total value-added. In section 3.3.3, I differentiate the source of R&D spillover into two parts: domestic versus foreign.

3.3.1 Top 5 firms vs. all firms

Although section 2.2 shows with strong evidence that the R&D of the center cities is concentrated mostly by the very few firms at the top, there is some interest to see whether total R&D expenditure of whole center city would have the same spillover effect on firm productivity as the R&D of the top 5 firms in the research cluster. In equation (4), I test this alternative specification to equation (2) and the regression results are presented in Table 4.

$$\begin{aligned} \ln LP_{ijt} = \alpha + \beta \ln(K/L)_{ijt} + \delta \ln(CRD_{jt}^{c}) \cdot e^{-dist_{n}^{c}} + \\ \lambda \ln(CRD_{jt}^{c}) \cdot tech\_dist_{njt}^{c} + u_{i} + \eta_{j} + \tau_{t} + \varepsilon_{ijt} \end{aligned} \tag{4}$$

3.3.2 Does R&D concentration matter?

In this section, I extend the basic model in equation (2) by testing whether the R&D concentration ratio in the research cluster matters to technology spillover. Specifically, I test the following model in equation (5):

$$
\begin{aligned}
\ln LP_{ijt} = {} & \alpha + \beta \ln(K/L)_{ijt} + \delta_1 \ln(CRD)_{jt}^{top5,c} \cdot e^{-dist_n^c} + \delta_2 \ln(CRD)_{jt}^{top5,c} \cdot e^{-dist_n^c} \cdot CR_{jt}^c \\
& + \lambda_1 \ln(CRD)_{jt}^{top5,c} \cdot tech\_dist_{njt}^{top5,c} + \lambda_2 \ln(CRD)_{jt}^{top5,c} \cdot tech\_dist_{njt}^{top5,c} \cdot CR_{jt}^c \\
& + u_i + \eta_j + \tau_t + \varepsilon_{ijt}
\end{aligned} \tag{5}
$$

The R&D concentration ratio, CR_{jt}^c, is defined as the ratio of R&D of the top five firms to the total R&D expenditure in city c, both indexed by industry j and year t. By including the 5-firm R&D concentration ratio, I am interested in knowing whether a more dispersed or concentrated R&D inside the center city can produce productivity gains from technology spillover. The regression results of this alternative specification are reported in Table 5.

3.3.3 Source of R&D spillover: Domestic vs. foreign

Given that China is the third largest FDI recipient in the world, only after the US and UK, and foreign investment has always played a big role in China's technology diffusion and economic growth, in equation (6), I differentiate the source of R&D at the center city into two parts: domestic vs. foreign, and test how different sources of R&D spillover affect firm productivity.

$$
\begin{aligned}
\ln LP_{ijt} = {} & \alpha + \beta \ln(K/L)_{ijt} + \delta_1 \ln(CRD_{jt}^{domestic,c}) \cdot e^{-dist_n^c} \\
& + \lambda_1 \ln(CRD_{jt}^{domestic,c}) \cdot tech\_dist_{njt}^{domestic,c} + \delta_2 \ln(CRD_{jt}^{foreign,c}) \cdot e^{-dist_n^c} \\
& + \lambda_2 \ln(CRD_{jt}^{foreign,c}) \cdot tech\_dist_{njt}^{foreign,c} + u_i + \eta_j + \tau_t + \varepsilon_{ijt}
\end{aligned} \tag{6}
$$

In equation (6), $CRD_{jt}^{domestic,c}$ is the cumulative R&D expenditure of all the domestic firms in the center city c, by industry j and year t. Similarly, $CRD_{jt}^{foreign,c}$ is the cumulative R&D spending of all the foreign firms in the center city c, by industry-year jt. Foreign firms includes both foreign wholly-owned firms and the join ventures between foreign and domestic partners. I expect our hypothesis still holds after the differentiation of R&D source, but it would be interesting to see how the coefficients of different spillover sources compare. Arguably, foreign R&D source may have a *smaller* spillover effect on firm's productivity as foreign invested companies always have incentives to delay the diffusion process and tend to protect their in-house technology more vigorously. However, if we were to assume foreign technology is better and more productive than domestic technology, a smaller "leak" may still produce larger spillover effect on firm's productivity. The regression results of equation (6) are reported in Table 6.

4. Empirical Results

In this section, I present and analyze the regression results as modeled in equation (1) and (2). I also discuss the potential endogeneity problem in our estimation and how to deal with it.

The summary statistics of the variables used in regression are reported in Table 1. The average labor productivity of all firms located outside the research cluster is 61,000 Yuan (in current prices) per employee-year. In contrast, the labor productivity of the top 5 firms (by industry j) in the research cluster is averaged at 116,000 Yuan per employee-year, which almost doubles the average productivity of the firms outside of the center. The average geographic distance between firms and research cluster is 383 kilometers, and it ranges from zero, for those firms that located within the center, to the maximum distance of 3,400 km.

4. 1 Analysis of the results

Table 2 summarizes the regression results for equation (1), where I look at how geographic distance between firms and research cluster affects firms' productivity gains. I first run the simple OLS regression and the results are reported in Column (1). In Column (2) to (4), I move the test to a more robust level by sequentially adding in firm-level fixed effects, industry dummies and yearly time effects. The main control variable, capital intensity, is shown to be statistically significant throughout and its effect on firm's productivity is positive. The coefficient on the interactive term between the research cluster's cumulative R&D spending and the geographic distance is positive and statistically significant through Column (1) to Column (3), matching our priori expectations, i.e., when the distance between firms and the research cluster increases, firms' productivity gains decline. However, in Column (4), after addition of the year dummies, the coefficient on the interactive term becomes statistically insignificant.

[Insert Table 2 here]

Although only in the strictest test scenario did the coefficient on the interactive become insignificant, the result is still less satisfactory. One explanation could be that technology spillover can only affect firm's productivity within certain distance range. In Table 2b, I test this possibility by estimating equation (1) under different distance ranges. And I test the equation by including all kinds of strictest controls, i.e., firm-level fixed effects, industry dummies and yearly time effects. The results show the coefficient on the R&D-distance interactive term is statistically significant and positive only when the distance falls under 300 kilometers. The hypothesis still stands but with a twist. It nonetheless strongly confirms our hypothesis that distance matters in technology diffusion. Interestingly, for the test of observations under 100 km range, the coefficient turns negative but insignificant. There is no reason to believe that the effect of technology spillovers within 100 km will increase with firm's distance while it will decrease with the distance in 100-300 km range. A plausible explanation for such results is that the firm's distance in this research is calculated by the distance between the nearest city the firm is located and the research cluster. For firms that fall under 100km range, the nearest city is probably the center city itself. Therefore, for a large majority of these firms, the distances to the center are actually zero in our calculation. Since there are not many variations from distances in the regression, it came as no surprise that the coefficient for this sub-group is not statistically significant.

[Insert Table 2b here]

In Table 3, I report the estimation results for equation (2), where I control the technological distance between the research cluster and the firm and see how the effects will change. Similar to Table 2, Column (1) runs the basic OLS regression. Through Column (2) to (4), I add in firm fixed-effects, industry dummies and year dummies, one at a time. The coefficient on the interactive term between technological distance and cumulative R&D spending at the research cluster turns out to be highly significant statistically and has the negative sign as expected. The negative coefficient indicates the larger the technological distance between research cluster and the spillover receiving firm, the smaller the productivity gain for the firm. As defined by equation (3) in Section 3.2, the technological distance variable measures the average labor productivity of the top R&D firms at the research cluster, and average labor productivity of all the firms located in the receiving city, n. Both productivities are indexed at industry j and year t. Since firms' productivity in our definition captures certain idiosyncratic characteristics of the city where the firm is located, the negative coefficient may well capture the poorer quality of local institutions and business environment that makes it harder for firms in the city to absorb the benefits of technology spillover, resulting in less productivity gains.

[Insert Table 3 here]

In Table 4, I report regression results of equation (4) in section 3.3.1. The results that use all firms in the center city as the source of R&D spillover are shown in Column (3) and (4). For comparison purpose, results in Column (1) and (2) that uses the top 5 firms as the source of technology are taken directly from Table 3. The coefficients on both distance measures retain the same signs and remain statistically significant.

[Insert Table 4 here]

Table 5 presents the regression results of equation (5). What I try to find from this group of regression is whether the R&D concentration ratio at the center city matters for technology spillover. As a reminder, R&D concentration ratio is measured by R&D spending by the top 5 firms at research center city c, over the total R&D spending of all firms in the same city; and the ratio is indexed at industry-year, jt. As shown in the table, the coefficient of the interactive term between $\ln(CRD)_{jt}^{top5,c} \cdot e^{-\delta dist_n^c}$ and concentration ratio is negative and statistically significant. This seems to suggest that the higher the R&D concentration ratio the more slowly the productivity gains from R&D spillover will decline with increasing geographic distance from the research cluster. The coefficient of the interactive term between $\ln(CRD)_{jt}^{top5,c} \cdot tech\_dist_{njt}^{top5,c}$ and concentration ratio is positive and remains statistically significant most of the time (except in Column 4), and this suggests that giving the same technological distance between center and firm, the higher the R&D concentration ratio in the center city, the more productivity gains firms will get from technology spillover. In short, both results imply that higher R&D concentration ratio is good for technology spillover, everything being equal.

[Insert Table 5 here]

Table 6 presents the regression results of equation (6), where I differentiate the source of technology spillover at the research cluster. The estimation results are very similar to the previous results in Table 3: the coefficients on both domestic and foreign R&D, for both geographic and technological distances, have the same sign and remain statistically significant. For geographic distance, the smaller coefficient on foreign R&D indicates that the impact on firm's productivity from foreign R&D tends to decline more slowly than domestic R&D. However, for technological distance, the effects from both

R&D sources are very similar. Note that when I add in year dummies in the last column, the coefficients on the geographic distance for both R&D sources became not statistically significant, but their signs still remain positive. But in general, the regression results are quite robust.

[Insert Table 6 here]

4. 2 Endogeneity issue

One might argue that a firm's location and distance to the research cluster are endogenously determined by the firm's decision to locate or to move closer to the research cluster from a previous location so as to take advantage of the larger technology spillover. This could be a potential problem if firms with higher productivity take advantage of spillover opportunities by moving closer to the cluster. In this case, even when the productivity of these firms may not be affected by the technology spillover from the cluster as modeled in our estimation, we may still find a positive relationship between close proximity to the research cluster and higher productivity.

Of course, one might counter that some of these firms chose to move closer to the center simply because there exists a larger positive spillover effect with shorter distance to the research cluster, so their move simply reflects, if not reinforces, the causal relationship between the distance and higher productivity.

Still, we cannot exclude the possibility that some firms with pre-existing better technology locate/move closer to the center based on the factors other than distance. So how can we deal with this potential endogeneity problem? One easy way out is to look at only those firms that established their businesses *before* the beginning year of our testing period, i.e., 1995. So in the new test sample, I dropped all the firms that opened their businesses or changed locations after 1995. Since a firm's location and its distance are prefixed before the 1995-2004 period, this precludes any possibility of the endogeneity problem discussed above. By my calculation, this new testing sample still incorporates over 80% of the total observations of the previous sample.

[Insert Table 7 here]

The regression results for this sub-group are presented in Table 7. As shown, the coefficients on all our main variables still remain the same sign and they are statistically significant. In fact, if one compares the magnitude of all the coefficients in the whole sample and the sub-group sample, they are also very similar. This indicates that the endogeneity might not be a real concern in our empirical testing.

4.3 Distance effect from research cluster vs. from the coastal line

The major research clusters identified in this paper are all located along China's coastal line. One might argue that the distance effect captured in our empirical test actual reflects the distance from the coastal line, rather than the distance from the research clusters. To solve this potential identification problem, in this section, I include three additional cities from the interior region (other than from coastal line) as the source of R&D spillover, the purpose of which is to differentiate between the distance effect from research cluster and distance effect from the coastal line.

Among the top ten cities in our R&D expenditure ranking list, only Xi'an is located in the interior region. Further down on the R&D spending list, Shenyang is ranked 14th, and Wuhan is ranked 17th, respectively. I include these three inner cities. The regression results of equation (2) are reported in Table 8. As shown in the table, the distance effect from the research clusters in our previous regressions still holds and the coefficients on the two distance variables remain statistically significant and their signs are unchanged. This demonstrates that our estimation results are very robust.

In Column (5) of Table 8, to look at how the coastal location will affect firm's productivity gains from technology spillover, I further included a coastal dummy and let it interact with $\ln(CRD_{jt}^{top5,c}) \cdot e^{-dist_n^c}$ and $\ln(CRD_{jt}^{top5,c}) \cdot tech\_dist_{njt}^{top5,c}$. The results are very interesting. The first interactive term with geographic distance turns out to be negative and statistically significant. It suggests that firms located in the coastal region tend to have a smaller "negative" distance effect with increasing geographic distance between firm location and research clusters. The second interactive terms turns out to be positive and statistically significant, and it suggests that given the same technological distance between firms and research clusters, coastal firms tend to enjoy much larger productivity gains from technology spillover than firms in the interior region.

5. Conclusion and Remarks

Through a series of robust empirical tests, I confirm that distance does matter in technology spillovers. First, geographic distance matters and technology spillovers are largely local ---Firms' productivity gains decline as the geographic distance between the firm and the research cluster increases. Second, technological distance also matters ---

The larger the productivity gap between the research clusters and firms, the smaller the productivity gains from the technology spillover. The most obvious implication from this research is with the presence of “distance effects”, technology diffusion in reality has many frictions and income inequality tends to persist. It’s still too early to proclaim the “death of distance”.

The estimation results in our extended models suggest that higher R&D concentration ratio in research clusters and exposure to foreign R&D activities both have larger positive spillover effects on firms’ productivity gains. Given that most of China’s research clusters are highly concentrated and its high degree of openness to foreign direct investment, China seems to be well positioned to absorb the benefits of technology diffusion.

The results from this empirical study also have important implications for policy makers in urban planning and regional development alike. One such implication is that in order to receive greater benefits from technology spillovers, firms with better technologies may cluster together as close as possible to the research cluster, where most R&D activities take place. But over time this tends to result in over-crowdedness in cluster cities. The high concentration of the most productive firms also has implications on income equality. In China’s case, since all big research clusters are located along the coastal line, the “distance effect” on technology spillover tends to magnify the already highly skewed income distribution between the urban and rural area, as well as the gap between the coastal and interior regions.[12] The policy alternative should aim to establish multiple research clusters across different regions, not just along the coastal area. This

[12] According to National Statistics Bureau of China, in 2006, the urban-rural income ratio is 3.3:1.

will help technology spillovers to expand its scope without requiring firms to change their current locations.

Another important policy implication from this study is: firms with more backward technology may not receive the same great benefits as those firms with similar technologies with the cluster. So in order for technology spillover to be more effective, policy makers should not rush into building more “technology parks”, but should instead focus on how to improve the quality of local institutions.

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Figure 1

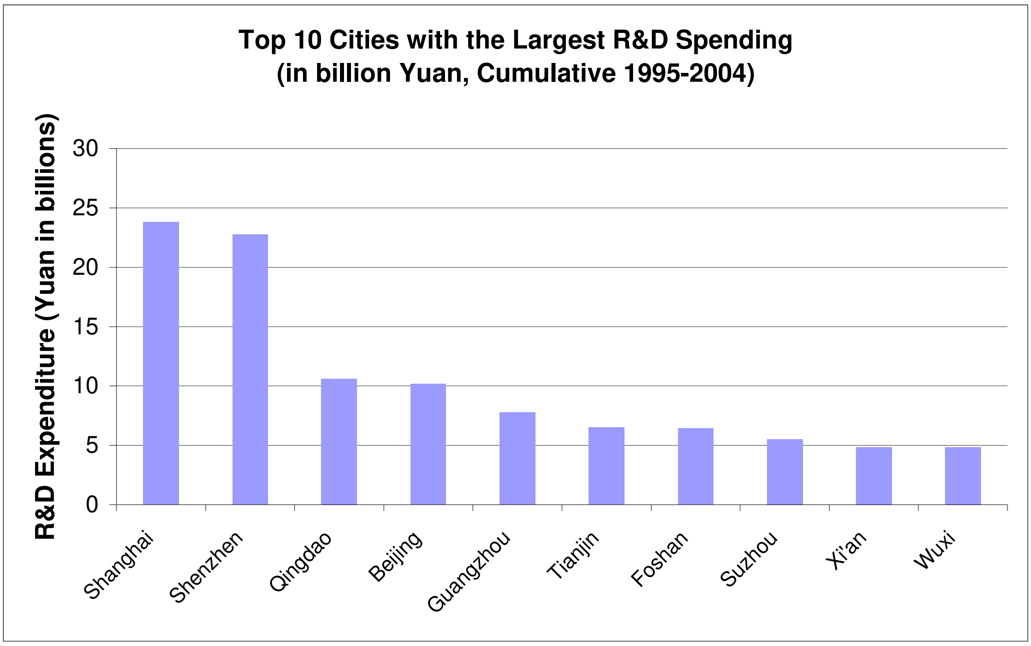


Figure 2

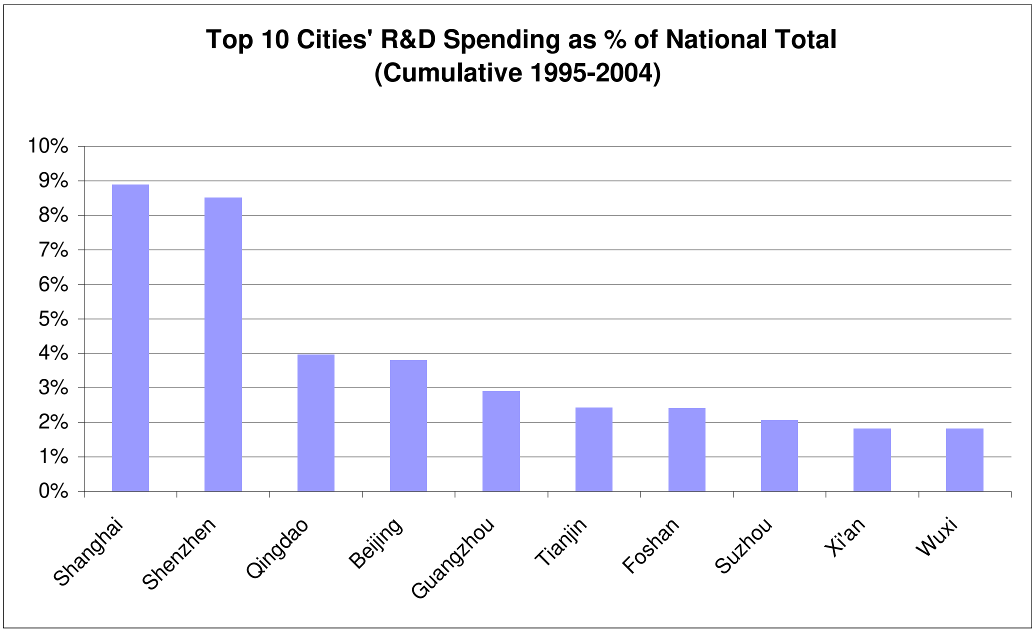


Figure 3

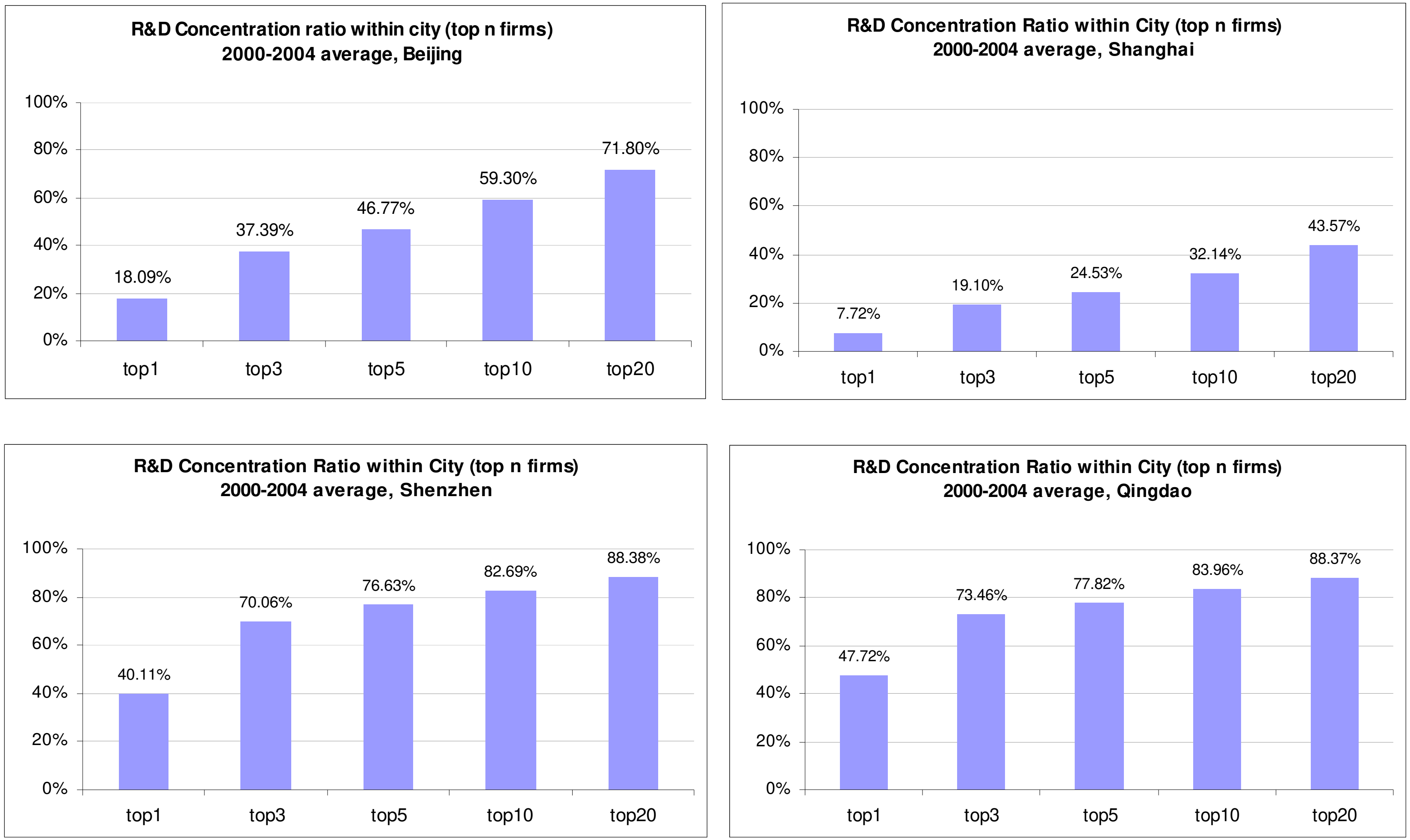

R&D Concentration ratio within city (top n firms)
2000-2004 average, Beijing
100%
80%
60%
40%
20%
0%
18.09%
37.39%
46.77%
59.30%
71.80%
top1
top3
top5
top10
top20
R&D Concentration Ratio within City (top n firms)
2000-2004 average, Shanghai
100%
80%
60%
40%
20%
0%
7.72%
19.10%
24.53%
32.14%
43.57%
top1
top3
top5
top10
top20
R&D Concentration Ratio within City (top n firms)
2000-2004 average, Shenzhen
100%
80%
60%
40%
20%
0%
40.11%
70.06%
76.63%
82.69%
88.38%
top1
top3
top5
top10
top20
R&D Concentration Ratio within City (top n firms)
2000-2004 average, Qingdao
100%
80%
60%
40%
20%
0%
47.72%
73.46%
77.82%
83.96%
88.37%
top1
top3
top5
top10
top20

Figure 4

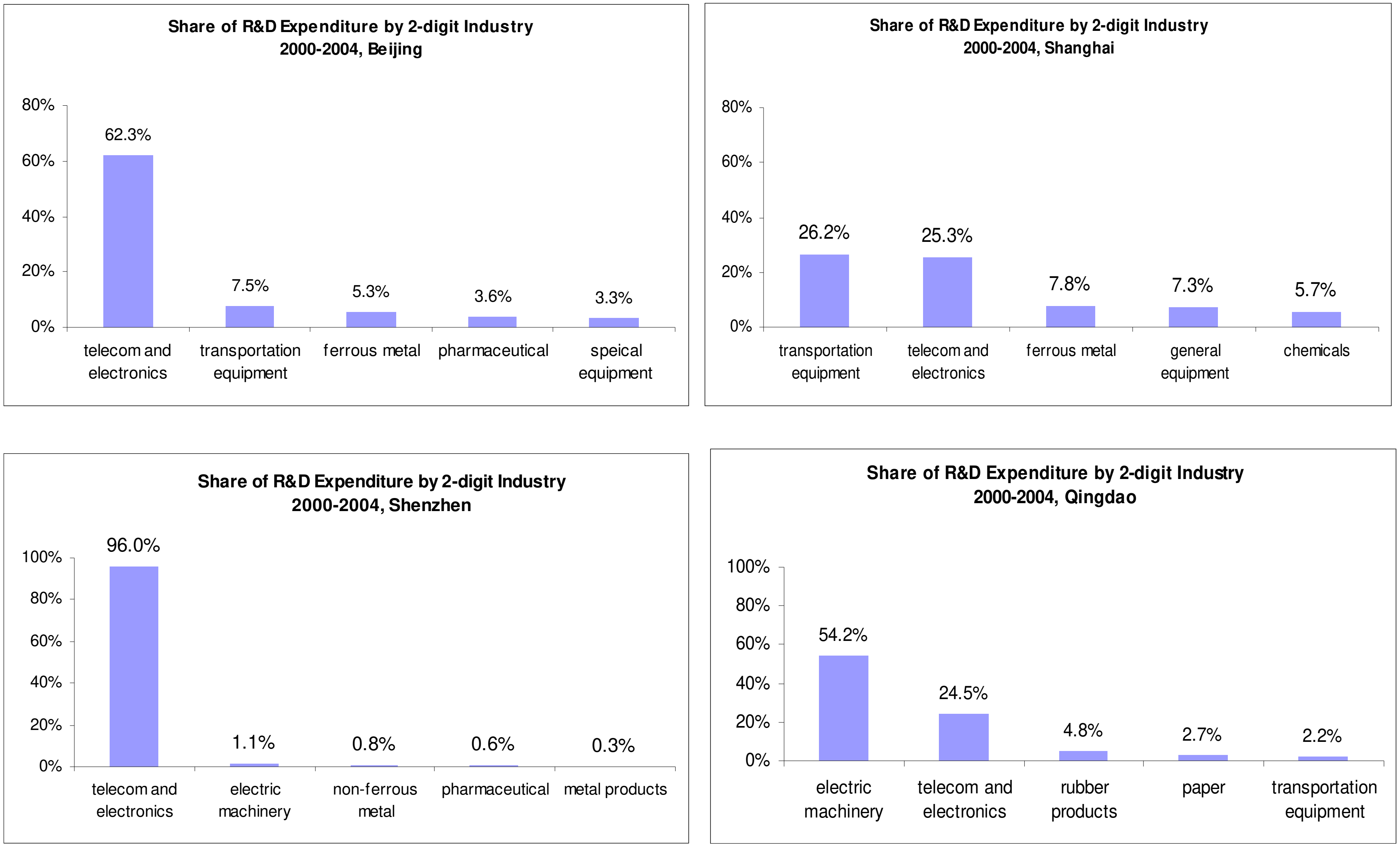
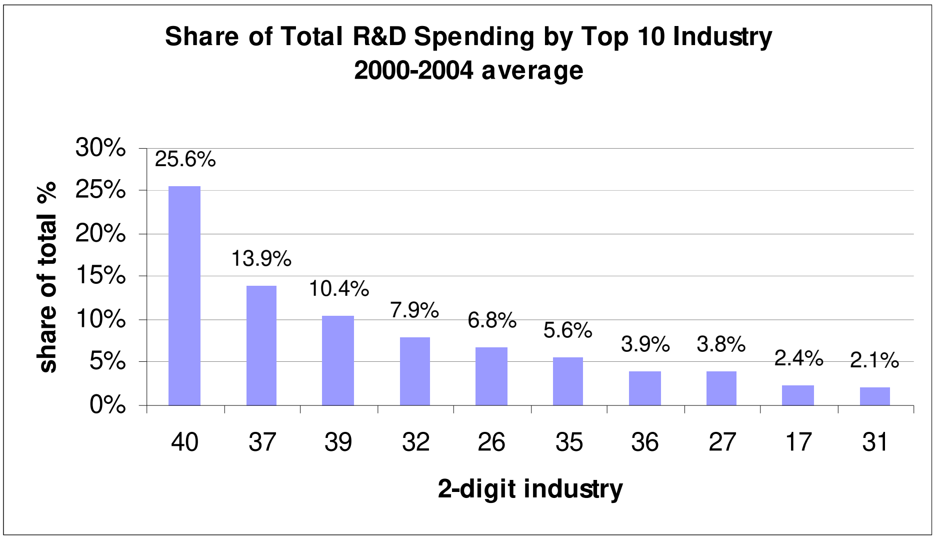

Share of R&D Expenditure by 2-digit Industry
2000-2004, Beijing
80%
60%
40%
20%
0%
62.3%
7.5%
5.3%
3.6%
3.3%
telecom and electronics
transportation equipment
ferrous metal
pharmaceutical
speical equipment
Share of R&D Expenditure by 2-digit Industry
2000-2004, Shanghai
80%
60%
40%
20%
0%
26.2%
25.3%
7.8%
7.3%
5.7%
transportation equipment
telecom and electronics
ferrous metal
general equipment
chemicals
Share of R&D Expenditure by 2-digit Industry
2000-2004, Shenzhen
100%
80%
60%
40%
20%
0%
96.0%
1.1%
0.8%
0.6%
0.3%
telecom and electronics
electric machinery
non-ferrous metal
pharmaceutical
metal products
Share of R&D Expenditure by 2-digit Industry
2000-2004, Qingdao
100%
80%
60%
40%
20%
0%
54.2%
24.5%
4.8%
2.7%
2.2%
electric machinery
telecom and electronics
rubber products
paper
transportation equipment

Figure 5



SIC2	Industry	SIC2	Industry
17	textile	33	non-ferrous metal processing
26	chemicals	35	general equipment
27	pharmaceutical	36	special equipment
28	chemical fiber	37	transportation equipment
29	rubber	39	electric machinery
31	non-metal minerals manufacturing	40	telecom and electronics
32	ferrous metal		

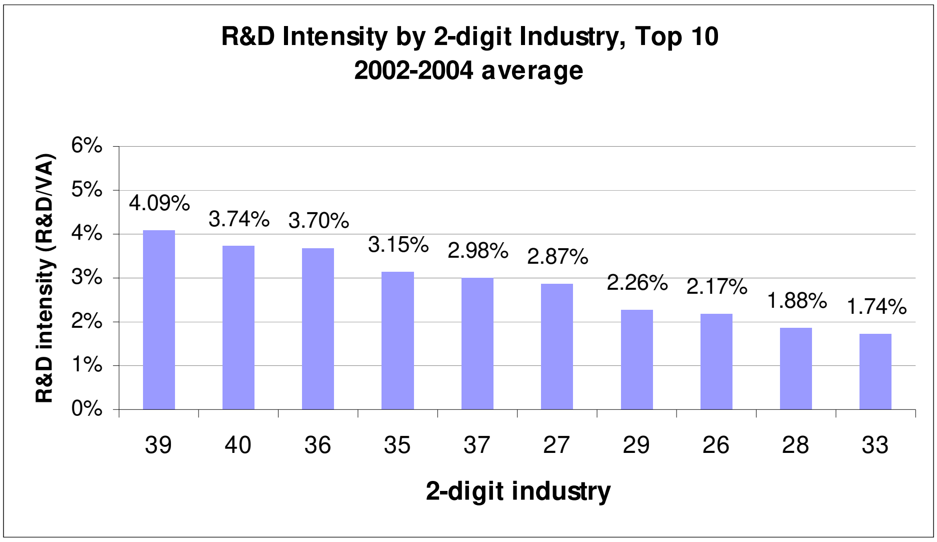


Figure 6

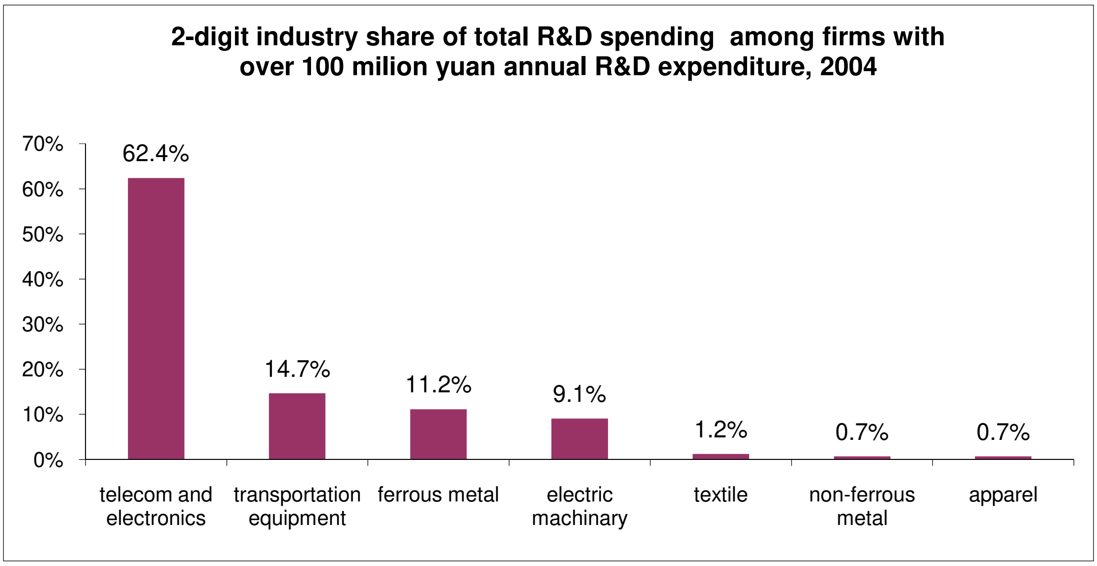

2-digit industry share of total R&D spending among firms with over 100 milion yuan annual R&D expenditure, 2004
70%
60%
50%
40%
30%
20%
10%
0%
62.4%
14.7%
11.2%
9.1%
1.2%
0.7%
0.7%
telecom and electronics
transportation equipment
ferrous metal
electric machinary
textile
non-ferrous metal
apparel

Figure 7 Exponential function on distance, $e^{-x},(x = dist)$

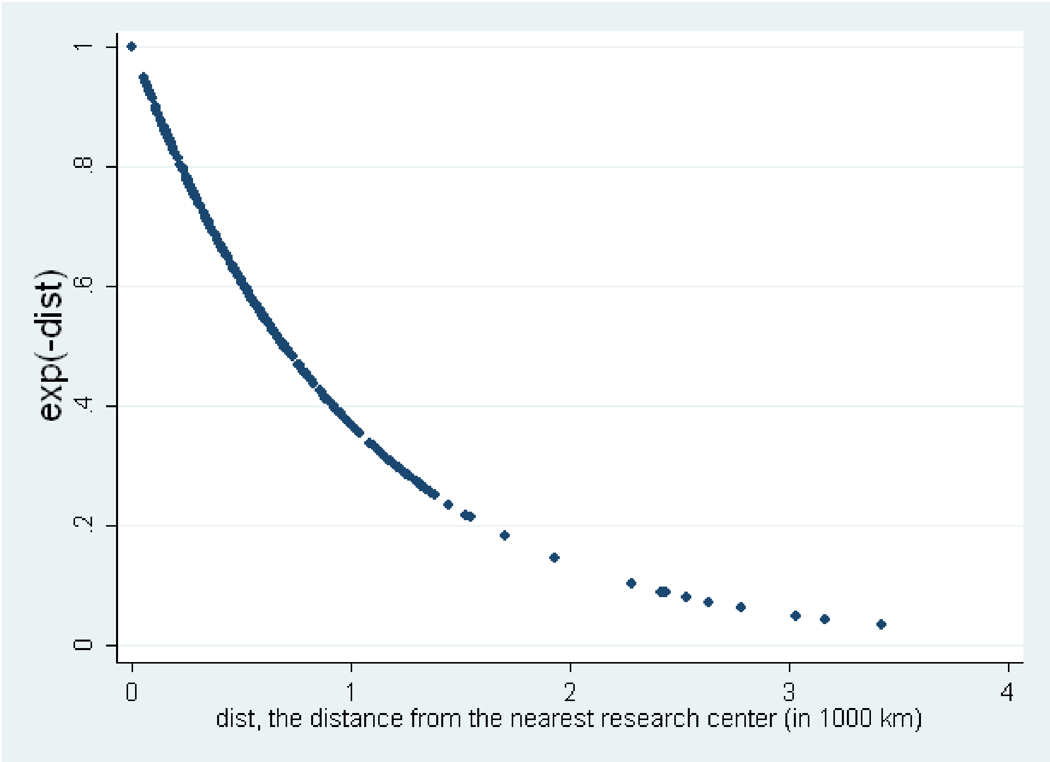


Table 1. Descriptive statistics

	Mean	Std. dev	Min	Max	Obs
Dependent variable:					
Log of labor productivity at firm-level (ijt)	3.25	1.31	-7.27	10.18	134540
Labor productivity at firm-level (ijt)	61.21	214.91	0.00	26253	135141
Independent variables:					
Log of capital intensity, firm level (ijt)	4.01	1.07	-8.07	11.82	135141
Capital intensity, firm level (ijt)	114.20	739.06	0.00	136,341	135141
Log of cumulative R&D of top 5 firms at research cluster, by industry-year (njt)	10.47	2.29	0.69	16.80	124231
Cumulative R&D of top 5 firms at research cluster, by industry-year (njt)	312,833	1,285,573	0.00	19,800,000	135141
Geographic distance to the nearest research cluster (n)	0.383	0.383	0.000	3.427	135141
Technological distance between firm and the average of the *top 5 firms* in the nearest research cluster (njt)	0.63	1.07	-4.27	8.95	135087

Notes:

* The unit of measurement for labor productivity and capital labor ratio 1,000 Yuan per employee-year.
* R&D numbers are all in thousands of Yuan.
* Geographic (physical) distances are in 1000 kilometers.
* (njt) means the variable is indexed by city n, industry j and year t.
*Technological distance is defined in equation (3).

Table 2. The Impact of R&D Spillovers on Firm's Productivity: Geographic Distance

	Dependent variable: ln(VA/L)$_{ijt}$, Log of labor productivity at firm level			
Independent variables:	(1)	(2)	(3)	(4)
ln(K/L)$_{ijt,}$ log of capital intensity	0.572***	0.245***	0.245***	0.225***
	(0.003)	(0.004)	(0.004)	(0.005)
ln(CRD)*exp(-dist), log of cumulative R&D of the top5 firms at research cluster interacting w/ geographic distance between cluster 'n firm	**0.076*****	**0.103*****	**0.104*****	0.003
	(0.001)	(0.003)	(0.003)	(0.004)
constant	0.375***	1.481***	1.619***	2.248***
	(0.015)	(0.024)	(0.086)	(0.087)
firm fixed effects	No	Yes	Yes	Yes
industry dummies	No	No	Yes	Yes
year dummies	No	No	No	Yes
obs	123,659	123,659	123,659	123,659
adj. (or overall) R-sq.	0.254	0.203	0.212	0.292

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

Table 2b. The Impact of R&D Spillovers on Firm's Productivity: Geographic distance in different ranges

	Dependent variable: ln(VA/L)$_{ijt}$, Log of labor productivity at firm level							
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
distance range	no limit	<500km	<400km	<300km	<200km	<100km	100-200km	100-300km
ln(K/L)$_{ijt}$, log of capital intensity	0.225***	0.218***	0.221***	0.218***	0.218***	0.193***	0.232***	0.225***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.011)	(0.009)	(0.007)
ln(CRD)*exp(-dist), log of cumulative R&D of the top5 firms at research cluster interacting w/ geographic distance between cluster 'n firm	0.003	0.007	0.006	**0.009****	**0.013*****	-0.002	**0.023*****	**0.016*****
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.009)	(0.007)	(0.006)
constant	2.248***	2.317***	2.371***	2.311***	2.451***	2.297***	2.425***	2.270***
	(0.087)	(0.099)	(0.102)	(0.110)	(0.135)	(0.307)	(0.154)	(0.118)
firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
obs	123,659	88,270	80,062	70,259	54,531	23,782	30,749	46,477
adj. (or overall) R-sq.	0.292	0.290	0.288	0.284	0.281	0.200	0.273	0.284

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

Table 3. The Impact of R&D Spillovers on Firm's Productivity: <u>Geographic & Technological Distance</u>

	Dependent variable: ln(VA/L)$_{ijt}$, Log of labor productivity at firm level			
Independent variables:	(1)	(2)	(3)	(4)
ln(K/L)$_{ijt,}$ log of capital intensity	0.551***	0.241***	0.241***	0.217***
	(0.003)	(0.004)	(0.004)	(0.004)
ln(CRD)*exp(-dist), log of cumulative R&D of the top5 firms at research cluster interacting w/ geographic distance between cluster 'n firm	**0.077*** **	**0.133*** **	**0.133*** **	**0.025*** **
	(0.001)	(0.003)	(0.003)	(0.004)
ln(CRD)*techdist, log of cumulative R&D of the top5 firms at research cluster interacting w/ tech. distance between cluster 'n firm	**-0.022*** **	**-0.019*** **	**-0.019*** **	**-0.019*** **
	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.601***	1.394***	1.544***	2.211***
	(0.015)	(0.023)	(0.085)	(0.086)
firm fixed effects	No	Yes	Yes	Yes
industry dummies	No	No	Yes	Yes
year dummies	No	No	No	Yes
obs	123,659	123,659	123,659	123,659
adj. (or overall) R-sq.	0.287	0.217	0.234	0.354

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

Table 4. The Impact of R&D Spillovers on Firm's Productivity: <u>all firms vs. top 5 firms</u> as source of R&D spillover at research cluster

	Dependent variable: ln(VA/L)$_{ijt}$, Log of labor productivity at firm level			
Independent variables:	(1)	(2)	(3)	(4)
	top 5 firms		all firms	
ln(K/L)$_{ijt}$, log of capital intensity	0.241***	0.217***	0.243***	0.214***
	(0.004)	(0.004)	(0.004)	(0.005)
ln(CRD)*exp(-dist), log of cumulative R&D at research cluster interacting w/ geographic distance between cluster 'n firm	**0.133*** **	**0.025*** **	**0.148*** **	**0.026*** **
	(0.003)	(0.004)	(0.003)	(0.005)
ln(CRD)*techdist, log of cumulative R&D at research cluster interacting w/ tech. distance between cluster 'n firm	**-0.019*** **	**-0.019*** **	**-0.027*** **	**-0.027*** **
	(0.000)	(0.000)	(0.000)	(0.000)
constant	1.544***	2.211***	1.653***	2.324***
	(0.085)	(0.086)	(0.087)	(0.088)
firm fixed effects	Yes	Yes	Yes	Yes
industry dummies	Yes	Yes	Yes	Yes
year dummies	No	Yes	No	Yes
obs	123,659	123,659	110,599	110,599
adj. (or overall) R-sq.	0.234	0.354	0.252	0.369

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

Table 5. The Impact of R&D Spillovers on Firm's Productivity: Does R&D concentration matter?

	Dependent variable: ln(VA/L)$_{ijt}$, Log of labor productivity at firm level			
Independent variables:	(1)	(2)	(3)	(4)
ln(K/L)$_{ijt,}$ log of capital intensity	0.547***	0.525***	0.255***	0.229***
	(0.004)	(0.004)	(0.005)	(0.005)
ln(CRD)*exp(-dist), log of cumulative R&D of the top5 firms at research cluster interacting w/ geographic distance between cluster 'n firm	**0.134*****	**0.146*****	**0.186*****	**0.044*****
	(0.002)	(0.002)	(0.006)	(0.008)
ln(CRD)*exp(-dist) interacting with R&D concentration ratio* of the top 5 firms	**-0.091*****	**-0.099*****	**-0.021*****	**-0.011*****
	(0.002)	(0.002)	(0.001)	(0.004)
ln(CRD)*techdist, log of cumulative R&D of the top5 firms at research cluster interacting w/ tech. distance between cluster 'n firm		**-0.028*****	**-0.021*****	**-0.019*****
		(0.001)	(0.001)	(0.001)
ln(CRD)*techdist interacting with R&D contration ratio of the top 5 firms		**0.011*****	**0.004*****	0.002
		(0.001)	(0.001)	(0.001)
constant	0.492***	0.683***	1.016***	2.035***
	(0.019)	(0.018)	(0.034)	(0.172)
firm fixed effects	No	No	Yes	Yes
industry dummies	No	No	No	Yes
year dummies	No	No	No	Yes
obs	82,932	82,932	82,932	82,932
adj. (or overall) R-sq.	0.256	0.289	0.176	0.358

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.
*R&D contration ratio is measured by R&D of top 5 firms over total R&D expenditure of all firms of cluster city,
indexed by industry-year.

Table 6. Differentiating Source of R&D Spillovers: Domestic vs. Foreign

	Dependent variable: ln(VA/L)$_{ijt}$, Log of labor productivity at firm level			
Independent variables:	(1)	(2)	(3)	(4)
ln(K/L)$_{ijt,}$ log of capital intensity	0.474***	0.238***	0.237***	0.219***
	(0.004)	(0.006)	(0.006)	(0.006)
ln(CRD)*exp(-dist), log of **domestic** cumulative R&D at research cluster interacting w/ geographic distance between cluster 'n firm	**-0.033*** **	**0.086*** **	**0.085*** **	0.009
	(0.002)	(0.005)	(0.005)	(0.006)
ln(CRD)*exp(-dist), log of **foreign*** cumulative R&D at research cluster interacting w/ geographic distance between cluster 'n firm	**0.118*** **	**0.052*** **	**0.051*** **	0.006
	(0.002)	(0.004)	(0.004)	(0.004)
ln(CRD)*techdist, log of **domestic** cumulative R&D at research cluster interacting w/ tech. distance between cluster 'n firm	**-0.009*** **	**-0.018*** **	**-0.018*** **	**-0.019*** **
	(0.000)	(0.000)	(0.000)	(0.000)
ln(CRD)*techdist, log of **foreign** cumulative R&D at research cluster interacting w/ tech. distance between cluster 'n firm	**-0.036*** **	**-0.017*** **	**-0.017*** **	**-0.014*** **
	(0.000)	(0.001)	(1.001)	(0.000)
constant	1.218***	1.560***	1.768***	2.407***
	(0.021)	(0.034)	(0.128)	(0.129)
firm fixed effects	No	Yes	Yes	Yes
industry dummies	No	No	Yes	Yes
year dummies	No	No	No	Yes
obs	66,441	66,441	66,441	66,441
adj. (or overall) R-sq.	0.342	0.276	0.285	0.379

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.
*foreign R&D includes R&D expenditure of both pure foreign firms and foreign-domestic joint ventures.

Table 7. Deal with potential endogeneity problem: estimation using only those firms that opened their businesses BEFORE 1995, the beginning year of the data

	Dependent variable: ln(VA/L)$_{ijt}$, Log of labor productivity at firm level							
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	firms that existed before 1995				vs. all firms			
ln(K/L)$_{ijt}$, log of capital intensity	0.559***	0.250***	0.250***	0.224***	0.551***	0.241***	0.241***	0.217***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
ln(CRD)*exp(-dist), log of cumulative R&D of the top5 firms at research cluster interacting w/ geographic distance between cluster 'n firm	**0.073*** **	**0.125*** **	**0.124*** **	**0.018*** **	0.077***	0.133***	0.133***	0.025***
	(0.001)	(0.003)	(0.003)	(0.005)	(0.001)	(0.003)	(0.003)	(0.004)
ln(CRD)*techdist, log of cumulative R&D of the top5 firms at research cluster interacting w/ tech. distance between cluster 'n firm	**-0.022*** **	**-0.019*** **	**-0.019*** **	**-0.019*** **	-0.022***	-0.019***	-0.019***	-0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.514***	1.321***	1.457***	2.118***	0.601***	1.394***	1.544***	2.211***
	(0.017)	(0.025)	(0.093)	(0.094)	(0.015)	(0.023)	(0.085)	(0.086)
firm fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
industry dummies	No	No	No	Yes	No	No	Yes	Yes
year dummies	No	No	No	Yes	No	No	No	Yes
obs	102,632	102,632	102,632	102,632	123,659	123,659	123,659	123,659
adj. (or overall) R-sq.	0.272	0.210	0.221	0.311	0.287	0.217	0.234	0.354

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

Table 8. Identifying Distance Effect from the R&D at the Research Clusters: with research clusters from the interior region

	Dependent variable: ln(VA/L)$_{ijt}$, Log of labor productivity at firm level				
Independent variables:	(1)	(2)	(3)	(4)	(5)
ln(K/L)$_{ijt}$, log of capital intensity	0.570***	0.238***	0.235***	0.212***	0.212***
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
ln(CRD)*exp(-dist), log of cumulative R&D of the top5 firms at research cluster interacting w/ geographic distance between cluster 'n firm	**0.073*****	**0.100*****	**0.130*****	**0.029*****	**0.051*****
	(0.001)	(0.003)	(0.003)	(0.004)	(0.006)
ln(CRD)*techdist, log of cumulative R&D of the top5 firms at research cluster interacting w/ tech. distance between cluster 'n firm			**-0.019*****	**-0.019*****	**-0.026*****
			(0.000)	(0.000)	(0.001)
ln(CRD)*exp(-dist) interacting w/ coastal dummy					**-0.037*****
					(0.005)
ln(CRD)*techdist interacting w/ coastal dummy					**0.013*****
					(0.001)
constant	0.358***	1.463***	1.328***	2.249***	2.259***
	(0.018)	(0.025)	(0.024)	(0.092)	(0.092)
firm fixed effects	No	Yes	Yes	Yes	Yes
industry dummies	No	No	No	Yes	Yes
year dummies	No	No	No	Yes	Yes
obs	102,436	102,436	102,436	102,436	102,436
adj. (or overall) R-sq.	0.232	0.185	0.210	0.329	0.263

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

Appendix

Geographic Locations of China's Key Research Clusters