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Localization, knowledge spillover, and R&D investment: Evidence of Chinese cities



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ABSTRACT

We develop a simple Cournot type, two-stage competition model that reveals that firms tend to reduce their R&D investment more in denser locations than in lesser ones with the presence of knowledge spillover. This implies that local agglomeration increases the negative impact of knowledge spillover on firms' R&D efforts. We then use high-tech, firm-level data from China to test our theoretical predictions. We develop a technological similarity index as a proxy for knowledge spillover and use total employment in the same two-digit Chinese Standard Industry Classification System industry as a proxy for localization agglomeration. Our Tobit model yields estimated results that are consistent with our predictions. That is, R&D effort is negatively correlated with knowledge spillover, and the magnitude of the negative relationship increases with localization agglomeration. These results are robust by different subsamples and different estimators. We also find evidence suggesting that cost-saving, rather than expropriation-avoidance, is the primary reason for firms' R&D investment reduction with knowledge spillover.

1. Introduction

Countries and regions worldwide often offer considerable tax credits, subsidies, and rewards to promote the R&D investment of individual firms (Czarnitzki, Hanel, & Rosa, 2011; Guo, Guo, & Jiang, 2016; Wallsten, 2000), based on the understanding that investment in innovation and knowledge contributes to long-run economic growth (Romer, 1986, 1990). While firms positively respond to those incentives, there are external factors that influence their R&D investment (Czarnitzki & Hottenrott, 2009; Smith, Broberg, & Ovegaard, 2002). One of these is knowledge spillover, which disincentives firms from investing in their R&D investment. This negative effect of spillover on R&D is based on the premise that external knowledge (from R&D investment made by other firms) is a substitute for internal knowledge (d'Aspremont & Jacquemin, 1988; Kamien, Muller, & Ziang, 1992).

Although the transport of information has never been easier than today, face-to-face interaction remains the most important method of knowledge transmission, especially for industries characterized by highly novel and complex technologies (Aharanson, Baum, & Feldman, 2007; Glaeser, 2010). Knowledge quickly disseminates among neighboring high-tech firms in Silicon Valley through spying, imitation, and the rapid interfirm movement of highly skilled labor (Glaeser, Kallal, Scheinkman & Shleifer, 1992). Localized knowledge spillover has been viewed as one of the primary causes for the spatial concentration of economic activities (Marshall, 1895). Spillover, geographic concentration of firms, and firm's R&D investment should, thus, be intertwined. If the

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strength of knowledge spillover is bounded by the magnitude of local agglomeration, its impact on firms' R&D investment reduction should be positively associated with agglomeration. However, previous theoretical research does not provide a clear answer to how the relationship between knowledge spillover and R&D investment is affected by agglomeration.

Limited empirical studies that examine the relationship between agglomeration and R&D investment seem to support the notion that firms invest less in R&D when they locate in economic clusters or cities (implying a larger agglomeration, especially localization agglomeration). Two different effects, however, have been proposed to explain the finding. One is the cost-saving effect, which emphasizes that agglomeration provides the opportunity for firms to save self-financing R&D activities by freeriding the R&D input of other similar firms (Lamin & Ramos, 2016; Leppälä, 2016). The other is the expropriation-avoidance effect, which refers to firms intentionally reducing R&D investment in dense areas due to strong knowledge expropriation (Leahy & Neary, 2007; Lee, 2009). It is not clear which effect plays a larger role, which is an empirical research question.

Our paper attempts to fill the literature gap by investigating the relationship between knowledge spillover and firms' R&D investment with respect to localization agglomeration and by gauging the magnitude of the negative effect of localization agglomeration on R&D investment. We first develop a simple Cournot type, two-stage competition model in which firms simultaneously determine their non-cooperative R&D investment in the first stage and product output in the second. Our theoretical model shows that firms tend to reduce their R&D efforts with the presence of knowledge spillover and reduce them more with a higher level of localization agglomeration. We then conduct empirical analyses by using Chinese firm-level data. Our estimated results, as expected, are consistent with our theoretical predictions. By comparing the agglomeration effect on R&D investment by firm category (size and sector), the empirical examination suggests that the cost-saving effect, rather than the expropriation-avoidance effect, explains the negative impact of knowledge spillover on firms' R&D investment and the impact of localization agglomeration on the relationship between knowledge spillover and firms' R&D investment.

This paper is organized as follows. In Section 2, we review the literature on agglomeration, knowledge spillover, and R&D investment; in Section 3, we present the model; and, in Section 4, we discuss the data and variables; we interpret the results in Section 5; and, in Section 6, we conclude the paper with final remarks.

2. Literature review

Economists have long hypothesized the spillover of knowledge. Marshall (1895) first discusses how the learning process of firms fosters the spatial concentration of industries. He argues that the agglomeration of firms facilitates the transfer of knowledge, such that “if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and it thus becomes the source of further new ideas” (p. 352). However, knowledge spillover is the least understood factor driving the spatial concentration of economic activities (Vernon Henderson, 2007; Puga, 2010). The primary reason for this is due to a lack of direct measurement that captures knowledge flows across firms. Krugman (1991) points out that “knowledge flows are invisible, they leave no paper trail by which they may be measured and tracked” (p. 53). Given these problems, the empirical verification of knowledge spillover can only rely on indirect evidence. Previous research studies have localized knowledge spillover primarily through the examination of the geographical pattern of patents and patent citations (Carlino & Kerr, 2015; Vernon Henderson, 2007). The idea is that an inventor would be more likely to learn from other inventors and cite their works if they are geographically close to him/her. Empirical evidence shows that patent citations disproportionately come from local areas and patent intensity is higher in denser markets (Carlino, Chatterjee, & Hunt, 2007; Jaffe, Trajtenberg, & Henderson, 1993; Murata, Nakajima, Okamoto, & Tamura, 2013).

The spatial distribution of patents, however, does not necessarily parallel the spatial distribution of R&D investment. The literature investigating the relationship between patent and R&D expenditure reveals that the patent intensity of a firm or an area is higher if the firm or area invests more in R&D and if its neighboring firms and areas with similar technologies invest in R&D (Deltas & Karkalakos, 2013; Griliches, 1990). This suggests that a firm or an area may achieve a high level of innovation by accessing a large public “pool” of knowledge, even with limited self-financing R&D activities (Aharonson et al., 2007; Koo, 2005).

The effect of knowledge spillover on R&D effort has been examined in the spatial industrial organization literature. d'Aspremont and Jacquemin (1988) first introduce the Cournot oligopoly model for firms engaging in a two-stage game. Identical firms conduct R&D activities in the first stage, and they then become Cournot competitors and choose final good outputs in the second stage. They assume that the effective R&D output of firms comes from both self-financing R&D investment and R&D spillovers from other firms and conclude that a high level of knowledge spillover may lead to a large total effective R&D output, while a firm's self-financing R&D input may simultaneously decline. Since knowledge spillover is localized, this then suggests that the negative role of knowledge spillover in a firm's R&D investment reduction should be strengthened by agglomeration. If this is the case, we should observe a negative relationship between agglomeration and firm R&D investment.

The literature reveals that the negative impact of knowledge spillover on R&D investment may result from a cost-saving effect, an expropriation-avoidance effect, or both. The flows of knowledge are bi-directional; while a firm freerides other firms' R&D outputs, its own R&D effort could be observed and utilized by rival firms (Amir, Evstigneev, & Wooders, 2003; Lee, 2009; Poyago-Theotoky, 1999). The magnitude of these two effects may differ across firms and industrial sectors. The cost-saving effect is more relevant to less technologically competitive firms, i.e., new entrants in knowledge-intensive industries. Those firms that lack the resources and experience of R&D activities, hence, rely heavily on external knowledge (Aharonson et al., 2007; Feldman, 1994; 2003). The expropriation-avoidance effect, on the other hand, is more relevant to technologically advanced firms. Leaders of high-tech firms may experience a more intensive outward knowledge spillover than inward knowledge spillover (Jo & Lee, 2014; Lee, 2009). The presence of knowledge expropriation then causes technologically advanced firms to reduce their R&D investment if they cannot restrict the flow of ideas to others (Glaeser et al., 1992).

It is interesting to note that both the cost-saving and expropriation-avoidance effects have important implications in terms of the location preference/choice for firms. Technological leaders are found to prefer isolated locations, while less technologically competitive firms favor the agglomeration of industry activities (Alcacer & Chung, 2007; Jo & Lee, 2014; Shaver & Flyer, 2000).

Leppälä (2016) studies the location and R&D choice of firms with the same level of technological competence. He extends the Cournot model developed by d'Aspremont and Jacquemin (1988) into a three-stage game in which firms choose distance between each other in the first stage and choose R&D and product outputs in the second and third stages, respectively. He assumes that the level of spillover depends on spatial proximity between firms and concludes that localized knowledge spillover creates a centripetal force when three or more firms are involved in location choice. This means that the incentive to freeride on rivals' R&D efforts is stronger than the incentive to minimize knowledge leaking. Locating within an agglomeration implies more spillover and less own R&D investment and, hence, a higher profit.

Although most studies reveal a negative relationship between knowledge spillover and firms' R&D investments, several papers mention that knowledge spillover could also raise firms' R&D expenditures. For example, Cohen and Levinthal (1990) argue that, in order to absorb and utilize incoming spillover of rivals' R&D, a firm would need to promote its absorptive capability, which largely depends on its own R&D level. In particular, investment in R&D is found to raise a firm's capability in absorbing external incremental/process R&D (Leahy & Neary, 2007). Besides absorptive capability, investment in R&D may also increase firms' abilities to protect their knowledge through secrecy, complexity, or lead time advantage (Cassiman & Veugelers, 2002). This is more relevant to product R&D—the idea being that there is a considerable technological gap between technological leaders and laggards. There is, however, a lack of empirical support for the positive relationship between knowledge spillover and firms' R&D investments.

It is worth pointing out that agglomeration could influence firm R&D investment in the absence of knowledge spillover. Agglomeration aggravates competition, giving firms an incentive to invest more in R&D to pursue product differentiation (Hughes, 1986). Coad and Rao (2010) find that firms' R&D expenditures are proportionate to their sales. If competition in denser markets limits the revenue that a typical firm can make, this may then suggest that, on average, lower R&D expenditures of firms in location is characterized by larger agglomeration.

Significant empirical evidence on the relationship between agglomeration and R&D investment supports the negative role of agglomeration in the literature. Suarez-Villa and Walrod (1997) study the R&D activities of a sample of electronic manufacturing plants in the Los Angeles basin and find that clustered plants have lower R&D intensities than plants located in the periphery. Meanwhile, Bagella and Becchetti (2002) report the low R&D intensities of Italian manufacturing firms located in an industrial district. Beal and Gimeno (2001) investigate the R&D investment of a sample of prepackaged software companies and conclude that agglomeration reduces a firm's R&D commitment. Using survey data from the World Bank, Lee (2009) finds that locating in clusters decreases R&D intensity but only for firms in developed countries and regions. Lamin and Ramos (2016) show that the negative relationship between agglomeration and R&D investment is also presented in an environment with weak intellectual property rights protection. Most of these studies attribute the negative impact of agglomeration on R&D investment reduction to firms' attempts to reduce knowledge leakage.

However, a conclusive consensus has not been reached regarding the impact of firm agglomeration on R&D effort. For instance, Antonietti and Cainelli (2009) find little evidence of localization agglomeration influencing R&D input. Smith, Broberg, and Overgaard (2002) focus on R&D investment of Danish firms and conclude that, while firms in rural municipalities present a higher probability of committing R&D investment, they do not vary in R&D intensity compared to their counterparts in urban municipalities.

Zhang, He, and Sun (2014) identify an overall positive relationship between localization and R&D intensity of electronic and telecommunication firms in China. However, when we disaggregate firms based on the value chain of industries, only the concentration of downstream firms generates a positive impact on R&D intensity, while the concentration of midstream and upstream firms, in most cases, presents negative impact. One concern about the study's conclusion is that it measures localization based on administrative boundaries of prefecture cities. In China, prefectural cities are defined according to administrative arrangements, whereby a typical prefectural city contains a city proper in the center and several scattered townships surrounded by less developed rural areas. The knowledge transferred between city proper and townships might be quite limited, if it exists at all. For instance, the biggest prefecture city, Bayingolin in Inner Mongolia, is 462,700 km². It is not likely that knowledge generated in a city proper will spill across a vast, sparsely populated rural area to its remote townships on the periphery.

In the following sections, we first examine the potential impacts of localization agglomeration and knowledge spillover on R&D investment by considering the spatial aspect of the Cournot model and then assess the predictions of the theoretical model and address the concerns of previous studies with new empirical evidence.

3. The model

We present a simple Cournot type model. Consider an industry of n identical firms that produce a homogeneous product. We define q_i as the output of firm i , and the output of the industry is determined by $Q = \sum_{i=1}^n q_i$. Assuming a perfectly segmented market, and, in each market, firms face a linear demand curve: $P = a - Q$. The initial production cost of all firms is the same c and $a > c$ (a is a constant).

Firms engage in a two-stage Cournot competition. They simultaneously decide non-cooperative R&D effort in the first stage and product output in the second stage. Following d'Aspremont and Jacquemin (1988), we assume that R&D outputs spill over in the first stage of the game. R&D outputs can be more easily recognized, absorbed, and utilized by other kindred firms. The production of R&D outputs is subject to decreasing return as in previous studies. To simplify calculation, we define that firm i 's own R&D outputs y_i is the

square root of its R&D investment x_i .¹ Besides its own R&D outputs, firm i also adopts external R&D outputs in its product production. The applied effective (total) R&D outputs X_i are defined as

$$X_i = \sqrt{x_i} + \beta \sum \sqrt{x_k}, \quad (1)$$

where $\sum \sqrt{x_k}$, $k \neq i$, is the total effective R&D outputs of other firms in the industry, and $\beta \in (0,1)$ is R&D spillover rate. The second term ($\beta \sum \sqrt{x_k}$) in Eq. (1) then captures the applied external effective R&D output of firm i . We assume knowledge spillover only happens among firms in the same city. The proximity between firms located in the same city allows for high labor mobility and chances of site observation and facilitates face-to-face communication, which is important for knowledge spillover.

Effective R&D outputs are considered as a cost reduction or a quality-enhancing invention that affects the final good output that firms choose to produce in the second stage of the Cournot competition. In the second stage, the profit function of firm i is given by $\pi_i = (a - Q - c + X_i)q_i - x_i = (a - Q - c + \sqrt{x_i} + \beta \sum \sqrt{x_k})q_i - x_i$. The Cournot equilibrium output of the industry is obtained as follows: $Q = \frac{n(a-c) + (1+\beta(n-1)) \sum \sqrt{x_k}}{n+1}$. The equilibrium output of each firm is $q_i^* = \frac{Q}{n}$.

The profit function in stage two, thus, can be rewritten as $\pi_i = (q_i^*)^2 - x_i$. By applying the first order condition to the profit function and assuming that firms make a symmetric R&D choice—that is, $x_i = x$ and $y_i = y$, $\forall i \in n$ —we obtain a firm's own optimal R&D output as:²

$$y^* = \frac{(a-c)(\beta + (1-\beta)n)}{(n+1)^2 - (\beta + (1-\beta)n)(1 + \beta(n-1))} \quad (2)$$

Eq. (2) shows that firms' R&D output from self-financing investments is jointly determined by initial market size ($\sigma = a - c$), number of firms in industry (n), and the knowledge spillover rate between firms (β).

From the partial derivatives of Eq. (2) and $\frac{\partial x^*}{\partial y^*} > 0$,³ we obtain the following relations: $\frac{\partial x^*}{\partial \sigma} > 0$, $\frac{\partial x^*}{\partial n} < 0$, and $\frac{\partial x^*}{\partial \beta} < 0$. Those relations reveal that a larger market size would imply a larger R&D investment ($\frac{\partial x^*}{\partial \sigma} > 0$), localization agglomeration is negatively related to R&D investment ($\frac{\partial x^*}{\partial n} < 0$), and a higher spillover rate causes a lower R&D investment ($\frac{\partial x^*}{\partial \beta} < 0$).

Our model also presents an interesting finding: even if knowledge spillover is absent ($\beta = 0$), there may still exist a negative relationship between local agglomeration and R&D investment (as illustrated by $\frac{\partial x^*}{\partial n} < 0$). The specification of the production function indicates that R&D investment is upper-bounded by the final good output q^* , which declines along with the number of firms ($\frac{\partial q^*}{\partial n} < 0$) when $\beta = 0$.

A way to identify the spillover effect on R&D investment is to examine the sign of the cross partial derivative of x^* over n and β ($\frac{\partial^2 x^*}{\partial n \partial \beta}$). We show that $\frac{\partial^2 x^*}{\partial n \partial \beta} < 0$.⁴ This means that the negative effect of knowledge spillover on R&D investment increases with localization agglomeration.⁵

When spillover rate is exogenous, as assumed in our model, an increase in the number of agglomerated firms should not change the knowledge that a firm could gain from other firms. However, larger and denser agglomeration may augment the match of knowledge and information, and raise the efficiency of knowledge exchange through more frequent formal and casual contacts between firms and employees (Glaeser et al., 1992; Glaeser, 2010). This suggests that spillover rate could be endogenous, which is partially determined by the magnitude of agglomeration. In other words, an increase in the number of agglomerated firms would allow a firm to gain more knowledge from another firm.

Assume spillover rate $\beta(n, \gamma)$ as a function of number of firms n in an industry and the technological similarity γ between kindred firms. By assumption, $\frac{\partial \beta}{\partial n} > 0$ and $\frac{\partial \beta}{\partial \gamma} > 0$. Defining x^E and y^E as the equilibrium of R&D investment and the firm's own R&D outputs given the endogenous spillover rate, we have $\frac{\partial x^E}{\partial n} = \left(\frac{\partial y^*}{\partial \beta} \frac{\partial \beta}{\partial n} + \frac{\partial y^*}{\partial n} \right) \frac{\partial x^E}{\partial y^E} < 0$, $\frac{\partial x^E}{\partial \gamma} = \frac{\partial y^*}{\partial \beta} \frac{\partial \beta}{\partial \gamma} \frac{\partial x^E}{\partial y^E} < 0$.⁶ This means that 1) the spillover rate,

¹ The industrial organization literature specifies the R&D investment a firm make as $x_i = \frac{1}{2}\gamma y_i^2$. $\gamma > 0$ is an inverse measure of the efficiency of R&D activity. This paper takes $\gamma = 2$ to ease calculations.

² The first order condition is: $x_i = \frac{(a-c + (2\beta-1) \sum \sqrt{x_k})^2 (\beta + (1-\beta)n)}{(n+1)^2 - (\beta + (1-\beta)n)^2}$, so that we have $y_i = \frac{(a-c + (2\beta-1) \sum y_k)(\beta + (1-\beta)n)}{(n+1)^2 - (\beta + (1-\beta)n)^2}$.

³ $\frac{\partial y^*}{\partial \sigma} = \frac{(\beta + (1-\beta)n)}{(n+1)^2 - (\beta + (1-\beta)n)(1 + \beta(n-1))}$, $\frac{\partial y^*}{\partial n} = -\frac{\sigma((n-1)(1-\beta+\beta^2)((1-\beta)n + (1+\beta)) + 3\beta)}{((n+1)^2 - (\beta + (1-\beta)n)(1 + \beta(n-1)))^2}$, and, $\frac{\partial y^*}{\partial \beta} = -\frac{\sigma(n-1)((n-1)\beta + 1)((2-\beta)n + \beta + 1)}{((n+1)^2 - (\beta + (1-\beta)n)(1 + \beta(n-1)))^2}$. Thus, we have $\frac{\partial y^*}{\partial \sigma} > 0$, $\frac{\partial y^*}{\partial n} < 0$, and, $\frac{\partial y^*}{\partial \beta} < 0$ (since $0 \leq \beta \leq 1$, $n > 1$, $a > c$).

⁴ $\frac{\partial^2 y^*}{\partial n \partial \beta} = \frac{\sigma((- \beta^2 + \beta - 1)n^2 + (\beta^2 - \beta + 1)((3\beta^2 - 6\beta)n^2 + (-6\beta^2 + 8\beta - 4)n + (3\beta^2 - 2\beta + 1)) + \sigma((2\beta^2 - 2\beta + 2)n + (-2\beta^2 + 2\beta + 1))((\beta^2 - 2\beta)n^3 - (3\beta^2 - 2\beta + 1)n^2 + (2\beta^2 - 2))}{((n+1)^2 - (n-\beta(n-1))(1+\beta(n-1)))^3}$. By taking extreme values of β , it can be derived that the denominator of the cross partial derivative is larger than $2n + 1$, so is larger than 0, and the nominator is smaller than $\sigma(-10/3n)$, which is smaller than zero. So $\frac{\partial^2 y^*}{\partial n \partial \beta} < 0$.

⁵ It should be noted that although localization agglomeration and knowledge spillover reduce self-financing R&D investment, they do not necessarily lead to lower effective R&D outputs that firms utilize in their product production. Let E^* denote the equilibrium external effective R&D outputs firms apply through spillover. $\frac{\partial E^*}{\partial n} = \frac{\sigma\beta((\sqrt{3}+2-\beta) + (\sqrt{3}+1+\beta)n)((\sqrt{3}-1-\beta)n + (\sqrt{3}-2+\beta))}{((n+1)^2 - (n-\beta(n-1))(1+\beta(n-1)))^2}$ and $\frac{\partial E^*}{\partial \beta} = \frac{\sigma(n-1)((n+1)^2(n-2(n-1)\beta) - (n-\beta(n-1))^2)}{((n+1)^2 - (n-\beta(n-1))(1+\beta(n-1)))^2}$. From Eq. (2), we obtain $\frac{\partial E^*}{\partial n} > 0$ when $\beta > 0$, implying that the absorbed external effective R&D outputs rise with localization agglomeration when knowledge spillover is present. Also, we have $\frac{\partial E^*}{\partial \beta} > 0$, suggesting firms can acquire more external effective R&D outputs when the spillover rate is higher.

⁶ By using the equations in the footnote 3.

which may or may not be affected by the magnitude of localization agglomeration, does not change the negative relationship between localization and R&D investment; and 2) the technological similarity between firms is expected to reduce R&D investment as long as knowledge spillover is present. We also have $\frac{\partial^2 x^E}{\partial n \partial \gamma} = \left(\frac{\partial y^*}{\partial \beta} \frac{\partial^2 \beta}{\partial n \partial \gamma} + \frac{\partial^2 y^*}{\partial n \partial \beta} \frac{\partial \beta}{\partial \gamma} \right) \frac{\partial x^E}{\partial y^E}$, so the negative indirect impact of localization and technological similarity on R&D investment is sustained if $\frac{\partial^2 \beta}{\partial n \partial \gamma} \geq 0$. The negative relationship is violated only when $\frac{\partial^2 \beta}{\partial n \partial \gamma} \leq -\left(\frac{\partial^2 y^*}{\partial n \partial \beta} \frac{\partial \beta}{\partial \gamma} \right) / \left(\frac{\partial y^*}{\partial \beta} \right) < 0$. The violation, however, may never occur. Intuitively, it is quite unlikely to see the relationship between technological similarity and spillover rate be negatively affected by localization. If spillover rate is simply determined by technological similarity, then $\frac{\partial x^E}{\partial n} = \frac{\partial x^*}{\partial n}$, $\frac{\partial x^E}{\partial \gamma} = \frac{\partial x^*}{\partial \gamma}$, and $\frac{\partial^2 x^E}{\partial n \partial \gamma} = \frac{\partial^2 x^*}{\partial n \partial \gamma}$. Thus, we conclude that our model predictions on the relationships among knowledge spillover, R&D investment, and localization agglomeration hold constant even though the knowledge spillover (rate) is endogenous with localization agglomeration.

To investigate the effect of knowledge spillover on firms' R&D investments and the impact of localization on the effect, we use the following reduced form in our empirical examination. The baseline model is expressed as

$$x_{ijk} = \beta_0 + \beta_1 N_{jk} + \beta_2 T_{ijk} + \beta_3 M_k + \beta_4 C_{ijk} + \varepsilon_{ijk}, \quad (3)$$

where N_{jk} is the number of firms in specified industry j in city k , T_{ijk} is the technological similarity between firm i and other firms in industry j in city k , M_k is the market size of city k , and C_{ijk} is a vector of control variables capturing other firm-, industry-, and city-specific characteristics. It is expected that $\beta_1 < 0$, $\beta_2 < 0$, and $\beta_3 > 0$ according to our model.

Eq. (3) is expanded by adding an interactive term to examine the impact of localization on spillover effect on R&D investment. It is expressed as

$$x_{ijk} = \beta_0 + \beta_1 N_{jk} + \beta_2 T_{ijk} + \beta_3 M_k + \beta_4 C_{ijk} + \beta_5 N_{jk} \times T_{ijk} + \varepsilon_{ijk}, \quad (4)$$

β_5 is expected to be negative.

4. Study area, data, and variables

An implicit understanding of agglomeration economies is that their micro-foundations, such as input sharing, labor pooling, labor matching, and knowledge spillover, have a geographic limitation. This makes China an interesting case to examine because it has both physical and institutional barriers that disintegrate its domestic markets.⁷ From a physical aspect, China is heavily dependent on land-based transport networks (roads, railroads, and water transport) for the inter-regional movement of people and goods. In 2006, volumes of movement of people and goods by roads and railroads accounted for 98% and 86%, respectively.⁸ China has been investing in highways and high-speed railroads at an amazing rate in the past two decades. However, the coverage of road and railroad networks in 2007 was still pretty low compared to developed countries. For instance, in 2007, the highway density (length/area) was 0.81 km per 100 sq. km in China, much lower than the 2.07 km per 100 sq. km in USA and 4.82 km per 100 sq. km in the European Union. Furthermore, the railroad density was 0.56 km per 100 sq. km in China, while the highway density for the USA and the European Union was 0.97 and 1.47 km per 100 sq. km, respectively.⁹

Institutional barrier refers to regional protectionism that is blamed for the fact that China is more integrated into the world's economy but less into its own domestic markets (Poncet, 2003; Young, 2000). Anecdotal examples include Henan and Anhui provinces banning tobacco products from Guizhou province and Shenzhen city banning sales of a newspaper from Guangzhou city (Gilley, 2001). A bottle of Beijing's Yanjing's beer was sold for the equivalent of \$0.18 in Beijing but \$1.00 in Sichuan province (Gilley, 2001). The domestic market segmentation in China is indirectly reflected in the shipping distance of goods. This was only 69 km by highway and 757 km by railway in 2007, much lower than the same distances in Europe and the USA.¹⁰ Despite the tremendous development in transportation network, the average shipping distance of goods increased by margin. For example, in 1990–2007, the average shipping distance of goods by railway increased by only 7.4%, much less than the growth rate of 94.8% in the average travel distance of railway passengers and of 34.7% in the total length of operating railways.

The primary data source of the paper is the Annual Survey of Industrial Firms (ASIF) conducted by the National Bureau of Statistics (NBS) of China. It provides detailed information on firms' locations, industries, ownership structures, employment, and the financial status of all state-owned enterprises (SOEs) and non-state-owned manufacturing enterprises with annual sales of 5 million RMB or more (above scale enterprises). The above scale of enterprises accounts for 90% of the total output and revenue of all industrial firms, making the dataset a good representative of the national economy. Data from 2007 are drawn to generate the dependent variable, and data from 2006 are used to measure the scale of localization and generate part of the control variables.¹¹ The

⁷ China's market fragmentation fits our model well, too.

⁸ Data is drawn from the China Statistical Yearbook 2007.

⁹ Data is drawn from European Road Statistics 2010.

¹⁰ In USA, a ton of rail shipments traveled on average 662 miles (1059 km), and a ton of truck shipments traveled 158 miles (253 km) in 2002 (http://www.rita.dot.gov/bts/sites/rita.dot.gov/bts/files/publications/freight_shipments_in_america/html/entire.html). In European Union, the 2014 data suggests that 56% of road shipment volumes are longer than 300 km, and only 7.5% of volumes are within 50 km (http://ec.europa.eu/eurostat/statistics-explained/index.php/Road_freight_transport_statistics#Longer_distance_class_recorded_highest_rise_compared_with_2010).

¹¹ China has published fewer data items for the industrial surveys after 2008 than before. Key variables, such as R&D input, are no longer available now. The year of 2007 is the latest with the most data publicly available.

rest of the control variables are constructed by using data from China's City Statistics Yearbook, which provide economic and demographic data for cities.

Firms are classified according to the Chinese Standard Industry Classification System 2002. We examine only high-tech industries because they are more likely to engage in innovative activities than conventional machinery industries and are the primary targeted industries under China's national strategy of building an innovation-oriented country. The high-tech industries are defined in the High-Tech Industries Classification 2013 by the NBS.¹² High-tech firms are located in city-proper areas (*Shiqu*) of prefecture-level cities, which are included in the sample.¹³ In 2007, there were 14,828 high-tech firms in 273 cities. Industries are excluded if they are vaguely defined or defined as a combination of different industries, i.e., CSICS 4090 Other Electronic Equipment. We end up with 12,933 firms in the sample.

We use both absolute and relative measures for firms' R&D investment. Total R&D spending (*RD*) captures the size of a firm's R&D investment. We use R&D intensity, the ratio of R&D spending over revenue of firms, as the relative measure (*RDI*). These two indicators are most frequently used to monitor the resources firms devote to science and technology research and development (OECS, 2012).

In our data sample, approximately 66% of firms did not make any R&D investment. With so many zero entries, the OLS estimator might be biased. The Tobit model can provide consistent estimation. We, hence, apply the Tobit model to deal with the large number of zeros in the dependent variables. Both *RD* and *RDI* are censored at 0.

We use employment of firms in the same two-digit CSICS industry in the same city (*LOC*) as the proxy of localization agglomeration.¹⁴ We use employment rather than establishment number to measure agglomeration for two reasons. First, firms are not identical, so employment can better capture the actual magnitude of agglomeration. Second, the transfer of knowledge largely relies on the interaction between people.

Previous studies measure technological similarity using patent data (Deltas & Karkalakos, 2013; Younge & Kuhn, 2016). However, as discussed by Cohen, Nelson, and Walsh (2000), patent applications bias firms' real technology portfolios. A firm may apply technologies that are not patentable or have already been patented by other firms. The incentive for patent application is also heterogeneous among firms. For instance, given the cost of patent litigation, smaller firms are less likely to pursue patents (Cohen et al., 2000). In contrast, big firms often apply similar patents on close substitutes for their primary patent to block follow-on patenting by rival inventors (Carlino & Kerr, 2015).

Spillover rate is primarily determined by the technological similarity and absorptive capability of firms (Cohen & Levinthal, 1990; Leahy & Neary, 2007; Wiethaus, 2005). However, absorptive capability is not observable. Empirical studies, thus, use technological similarity between firms to measure the possibility of knowledge spillover. The technological distance between firms underlies whether and to what degree external knowledge is transferrable or absorbable (Jaffe, 1986). It is easy for a firm to recognize potential applications of and effectively absorb external knowledge from other firms if they share a similar production technology.

We then develop a technological similarity index (*TS*) as a proxy for knowledge spillover rate among firms using industrial classification codes. The technological similarity index is constructed as

$$TS = \frac{\text{same 4d emp} \times 3 + \text{same 3d different 4d emp} \times 2 + \text{same 2d different 3d emp}}{\text{same 2d emp} \times 3},$$

where *same 2d emp* is the employment of the same two-digit CSICS industry in the same city, *same 4d emp* is the employment of the same four-digit CSICS industry in the same city, *same 3d different 4d emp* is the employment of the same three-digit CSICS industry subtracted by the employment of the same two-digit CSICS industry in the same city, and *same 2d different 3d emp* is the employment of the same two-digit CSICS industry subtracted by the employment of the same three-digit CSICS industry in the same city. If a firm co-locates with other firms in the same two-digit CSICS industry, then the technological similarity index will fall between 0.33 and 1. If a firm is the only firm in its two-digit CSICS industry in the city, *TS* is set to be zero.

A set of firm-specific control variables is included in the estimation. *SIZE* measures a firm's employment. *AGE* is the number of years a firm has survived since its birth. The impact of ownership is captured by two dummies *STATE* and *NONCON*. *STATE* equals 1 if the state owns the firm or is the controlling shareholder, while *NONCON* equals 1 if the firm is owned or controlled by foreign investors or by investors from Taiwan, Hong Kong, and Macau. If both *STATE* and *NONCON* equal 0, the firm is a private mainland firm. *EXPORT* calculates the portion of output that has been exported. *INDRD*, which is calculated by summing the R&D investment of all co-located same two-digit CSICS firms in 2006, controls the heterogeneous city specific industry R&D level. *COMP* is a competition indicator, calculated as the number of firms per workers in an industry in a city relative to the number of firms per worker in that industry in the country (Glaeser et al., 1992). By its definition, the indicator can also be interpreted as the relative average firm size of an industry in a specific city. The coefficient of *COMP*, thus, will have a dual implication since average firm size is also a typical indicator of entrepreneurship. In addition, three variables are used to control city-specific features. *POP* is the population of a city and is expected to capture the effects associated with market size and urbanization agglomeration. An industrial Herfindahl–Hirschman index (HHI) is created by summing the square of industry employment share at three-digit CSICS level. *DIVERSITY* measured by 1

¹² The document provides detailed descriptions of the direct relationships between classification systems, so industries defined by CSICS 2013 can be matched by those defined by CSICS 2002.

¹³ Approximately 33% of high-tech firms that are located in non-city-proper areas (suburban and rural areas) are excluded for analysis. See Ding (2013) for a better discussion of the definition of city-proper and non-city-proper. In this paper, city always represents city-proper areas (*Shiqu*).

¹⁴ CSICS two-digit classification is equivalent to NAICS three-digit classification.

Table 1
Descriptive statistics of variables.

Variable	Description	Mean	Std. Dev.	Min	Max
RD	Firm R&D spending (RMB, in log form)	2.263	3.411	0	15.782
RDI	Firm R&D spending/revenue	0.012	0.048	0	2.349
LOC	Employment number in the same industry in city (in log form)	10.351	2.296	0	13.757
TS	Technological similarity in the same industry in city	0.491	0.152	0	1
SIZE	Firm employment number (in log form)	5.061	1.310	0.693	12.145
AGE	Firm age (in log form)	2.064	0.744	0	6.011
STATE	Dummy; 1 if state owned	0.112	0.315	0	1
NONCON	Dummy; 1 if non-continental owned	0.381	0.486	0	1
EXPORT	Percentage of exported output	0.253	0.392	0	5.839
POP	Population in city (million, in log form)	6.090	1.002	2.708	7.504
DIVERSITY	Industry diversity in city	0.947	0.061	0.186	0.981
HUMAN	College students in city (thousand, in log form)	11.540	1.475	0	13.380
INDRD	Total R&D spending in the same industry in city (RMB, in log form)	11.301	3.386	0	16.114
COMP	Competition index for firms in the same industry	1.390	1.023	0	21.422

subtracting HHI reflects how Jacob's externality affects R&D expenditure. *HUMAN* is the number of college students in a city, representing the human capital level of the city. Finally, industry fixed effect is considered in the final model to gauge the heterogeneous nature of industry R&D preference. All continuous variables are included in their log forms.

Table 1 presents the descriptive statistics of the variables. The high-tech firms, on average, have 466 workers and invest approximately 3.5 million RMB, which is approximately 1.2% of their revenue in R&D. The average co-located workers in the same two-digit industry is approximately 17,000, and the average technological similarity between high-tech firms and their neighboring firms in the same two-digit industry is 0.491. Approximately 11% of firms are owned or controlled by the State, and 38% of firms are owned or controlled by foreign investors or by investors from Taiwan, Hong Kong, and Macau. On average, the high-tech firms export a quarter of their products abroad.

5. Results

5.1. Basic results

Table 2 presents the basic estimates of the Tobit model. As expected, our estimated results reveal that knowledge spillover disincentives a firm's R&D investment and that the negative impact of knowledge spillover on a firm's R&D investment is not trivial. The coefficient of the technological similarity index is significantly negative. The estimated values of the coefficient show that a 1% increase of technological similarity would result in 0.2% reduction in R&D spending and a 0.19% decrease in R&D intensity without controlling for the industry fixed effect, or a 0.4% reduction in R&D spending and 0.29% decrease in R&D intensity when the industry fixed effect is considered.¹⁵

As expected, the results show that the variable of localization agglomeration has a negative sign significant at the 99% level. The estimated values of the coefficient suggest that a 1% increase in the employment of the same two-digit firms leads to a 0.47% decrease in a firm's R&D spending without controlling for the industry fixed effect (Column 1) or a 0.3% decrease when the industry fixed effect is controlled for (Column 2). Both values of the variable's elasticity conclude that the negative impact of localization agglomeration on R&D is substantial. We obtain a similar conclusion by using a R&D intensity measure. The elasticity of R&D intensity is calculated by using the coefficients in Columns 4 and 5. They illustrate that a 1% increase in the employment of the same two-digit firms reduces a firm's R&D intensity by 0.32% or 0.23% depending on the control of the industry fixed effect.

Columns 3 and 6 of Table 2 show the estimates of Eq. (4). We report the marginal effects of three key variables (technological similarity index, localization, and the interactive term of those two) based on a calculation using the delta method rather than the estimated coefficients. This is because the coefficients of the interaction and main effect variables do not reflect the real interaction effect and the main effect in nonlinear models. For instance, the real main effect of the technological similarity index is jointly decided by the coefficients of the technological similarity index and the interaction term, the value of the localization variable, and the standard normal cumulative distribution of the latent variable. Our results reveal that adding the interactive term affects neither the sign nor the significance level of the localization and technological similarity index variables and that the marginal effect of the interactive term between localization agglomeration and technological similarity has a significant and negative relationship with R&D investment, as expected. We then conclude that the negative effect of knowledge spillover on firms' R&D investments increases with localization agglomeration. In other words, localization agglomeration increases the negative impact of knowledge spillover on firms' R&D investments. More specifically, our estimates show a non-trivial marginal effect of localization on the relationship. When industrial employment increases from 10,000 to 20,000, a 0.01 increase of technological similarity index would cause a firm to reduce 0.18% more in R&D investment and 0.00002 more in R&D intensity. The results also lend support on the argument made in Nakamura (2013) that localization externalities can only be maximized when the pooling labors share unique skills.

¹⁵ These elasticities are calculated at the mean of the variables.

Table 2
Tobit estimation on firm R&D investment.

	Dependent variable: RD			Dependent variable: RDI		
	(1)	(2)	(3)	(4)	(5)	(6)
LOC	−1.323*** (0.088)	−0.849*** (0.099)	−0.617*** (0.061)	−1.496E-02*** (1.155E-03)	−1.084E-02*** (1.299E-03)	−8.334E-03* * * (8.573E-04)
TS	−1.136** (0.536)	−2.295*** (0.553)	−2.641*** (0.386)	−1.809E-02* * * (6.990E-03)	−2.728E-02* * * (7.249E-03)	−3.380E-02*** (5.475E-03)
LOC × TS			−0.757* * * (0.127)			−9.663E-03* * * (1.799E-03)
SIZE	2.062*** (0.071)	2.157* * * (0.072)	2.161*** (0.072)	1.388E-02*** (9.151E-04)	1.491E-02*** (9.342E-04)	1.496E-02*** (9.343E-04)
AGE	0.613*** (0.113)	0.487*** (0.113)	0.478*** (0.113)	3.915E-03*** (1.472E-03)	2.774E-03* (1.484E-03)	2.658E-03* (1.484E-03)
STATE	2.038*** (0.251)	2.225*** (0.254)	2.182*** (0.254)	2.255E-02*** (3.240E-03)	2.490E-02*** (3.297E-03)	2.445E-02*** (3.295E-03)
NONCON	−1.883*** (0.206)	−1.731* * * (0.205)	−1.687*** (0.205)	−2.158E-02*** (2.678E-03)	−2.026E-02*** (2.687E-03)	−1.977E-02*** (2.688E-03)
EXPORT	−1.933*** (0.267)	−1.820*** (0.267)	−1.762*** (0.267)	−2.202E-02*** (3.514E-03)	−2.136E-02*** (3.538E-03)	−2.067E-02*** (3.539E-03)
POP	0.556*** (0.133)	0.012 (0.142)	0.195 (0.145)	8.560E-03*** (1.745E-03)	3.476E-03* (1.867E-03)	5.653E-03*** (1.919E-03)
DIVERSITY	1.417 (1.475)	1.184 (1.465)	1.361 (1.468)	1.739E-02 (1.908E-02)	1.456E-02 (1.907E-02)	1.689E-02 (1.914E-02)
HUMAN	0.388*** (0.078)	0.324*** (0.078)	0.307*** (0.078)	4.244E-03*** (1.022E-03)	3.687E-03*** (1.033E-03)	3.472E-03*** (1.035E-03)
INDRD	0.742*** (0.056)	0.752*** (0.057)	0.779*** (0.057)	8.801E-03*** (7.377E-04)	8.984E-03* * * (7.443E-04)	9.298E-03*** (7.457E-04)
COMP	0.335*** (0.084)	0.691*** (0.091)	0.487*** (0.098)	5.007E-03*** (1.080E-03)	8.019E-03*** (1.187E-03)	5.658E-03*** (1.274E-03)
Industry fixed effect	No	Yes	Yes	No	Yes	Yes
Total obs.	12933	12933	12933	12933	12933	12933
Uncensored obs.	4373	4373	4373	4373	4373	4373
LR χ^2	1982.27	2115.36	2149.57	1151.45	1223.76	1251.3
Log likelihood	−19219.77	−19153.228	−19136.124	557.889	594.043	607.810

***Denotes Statistical significance at the 1% level, * * denotes Statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses.

The model yields expected coefficients for the control variables. Theoretically, R&D investment varies with a firm's accessibility to funding resources and operation management (i.e., the capability of risk diversification). Firm size is one common indicator of a firm's financial capacity and risk spread ability (Smith et al., 2002). Big firms have adequate financial resources to invest in R&D and a strong financial capacity to spread risks associated with unsuccessful R&D investment. Firm age is another widely-used indicator of a firm's accessibility to external funding and capability of risk diversification. Older (long-survived) firms—usually with a more stable funding stream and more successful experience of risk aversion—are more likely to invest more in R&D activities than younger ones. As expected, the regression results show that R&D investment is positively correlated with both firm size and firm age at the 1% significance level.

Firms' ownership also significantly influences their decisions on R&D investments. We find that state-owned enterprises have consistently higher R&D investment than non-state-owned domestic firms, while foreign-owned firms and non-continental Chinese firms present lowest R&D input level. State-owned firms that are considered by central government as the lifelines of national economy receive numerous funding for R&D to promote their technological competence. In contrast, foreign-owned firms and non-continental Chinese firms produce and assemble products in Mainland China to take advantage of the cheap labor force. They are more likely to set up R&D facilities and direct their R&D investment in their home country. A firm's R&D investment decreases when the share of its exported goods increases. Given China's position in the value chain of international trade at the time, most of the export products are either assembled high-tech equipment or low-end commodities, neither of which requires high-level technological innovations.

The positive coefficient of *INDRD* suggests that firms increase R&D investment when the R&D investment of neighboring firms is high. This can be interpreted as evidence of R&D incentives brought by peer competition. One can also interpret *INDRD* as the cost of research and development. More industry R&D in a city might suggest that the cost of R&D in that city is cheaper. For instance, firms have a larger chance to share R&D labs and equipment if a city has a bigger R&D base in that given industry. When the marginal effect on outputs of R&D investment are larger than the marginal effect on outputs of other factors (labor, land, other capital), firms would have a much stronger incentive to make R&D investment. We find a positive impact of competition. This result is consistent with Glaeser et al. (1992) and supports Porter and Jacob's theory that competition encourages innovation. One can also take the view that smaller firms bring more entrepreneurship with stronger R&D intention.

Table 3
Two-step Tobit estimation on firm R&D investment.

	Dependent variable: RD		Dependent variable: RDI	
	(1)	(2)	(3)	(4)
LOC	−0.956*** (0.117)	−0.659*** (0.068)	−1.221E-02*** (1.539E-03)	−8.951E-03*** (9.616E-04)
TS	−3.099*** (0.649)	−3.178*** (0.423)	−3.981E-02*** (8.513E-03)	−4.291E-02*** (5.957E-03)
LOC × TS		−1.112*** (0.191)		−1.488E-02*** (2.714E-03)
SIZE	2.164*** (0.072)	2.160*** (0.072)	1.501E-02*** (9.352E-04)	1.496E-02*** (9.353E-04)
AGE	0.485*** (0.113)	0.472*** (0.113)	2.752E-03* (1.485E-03)	2.563E-03* (1.484E-03)
STATE	2.204* * * (0.254)	2.168*** (0.254)	2.463E-02*** (3.302E-03)	2.421E-02*** (3.300E-03)
NONCON	−1.717* * * (0.205)	−1.670*** (0.205)	−2.008E-02*** (2.690E-03)	−1.952E-02*** (2.691E-03)
EXPORT	−1.797* * * (0.268)	−1.751* * * (0.268)	−2.108E-02*** (3.544E-03)	−2.052E-02*** (3.545E-03)
POP	0.054 (0.147)	0.255* (0.151)	3.953E-03** (1.931E-03)	6.465E-03*** (1.995E-03)
DIVERSITY	1.352 (1.470)	1.321 (1.474)	1.671E-02 (1.913E-02)	1.645E-02 (1.921E-02)
HUMAN	0.295*** (0.079)	0.320*** (0.080)	3.299E-03*** (1.047E-03)	3.626E-03*** (1.060E-03)
INDRD	0.797*** (0.062)	0.767*** (0.062)	9.568E-03*** (8.088E-04)	9.185E-03*** (8.162E-04)
COMP	0.682*** (0.093)	0.378*** (0.108)	7.974E-03*** (1.214E-03)	4.178E-03*** (1.411E-03)
Industry fixed effect	Yes	Yes	Yes	Yes
Total obs.	12933	12933	12933	12933
Uncensored obs.	4373	4373	4373	4373
Wald χ^2	1878.19	1902.25	1068.66	1091.7
Wald test of exogeneity	7.2	11.61	9.19	16.6
P-value of Wald test	0.0273	0.0088	0.0101	0.0009

***Denotes Statistical significance at the 1% level, * * denotes Statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses.

Our results indicate that firms invest more R&D in larger cities. This is consistent with the theoretical prediction. Big cities generate big market demands that support the experiment of new ideas and products. Although industry diversity is argued to facilitate cross-industry spillover (Jacobs, 1969), we find no evidence that it influences firms' R&D investment. Finally, firms' R&D investment is found to be high in cities with rich human capital.

5.2. Robustness check

Estimate problems may present when there are omitted variables and/or there is an endogenous issue. For instance, unobserved local industry policy may affect agglomeration, technological similarity, and R&D investment simultaneously. A way to correct estimate biases is to run a two-step Tobit regression. We use instrument variables defined by using time-lag data. Data generating the instrument variables is drawn from the China Economic Census 2004 (CES 2004). The dataset includes all individual firms in China in 2004. Industry employment, technological similarity index and their interaction terms computed using CES2004 data are applied to instrument the three key variables in the basic estimation.

Table 3 presents the results of the two-step Tobit estimation. The estimated coefficients/marginal effects of localization, technological similarity, and their interaction term are consistently negative and significant, as in the basic estimation. The two-step estimator even suggests a stronger influence of localization and knowledge spillover on firms' R&D choice. The estimated coefficient of localization is approximately 7% larger in absolute value in the two-step Tobit estimation than in the basic estimation. The coefficients of technological similarity and the interaction term have even larger differences, more than 20% and 45% in absolute value, respectively, between the two estimations. This indicates that the negative impact of knowledge spillover and the conditional effect of localization on spillover's impact on R&D is robust.

Table 4 presents results, by sample size (above and below median-size firms, respectively), for both Tobit and Tobit Two-Step estimates with industry fixed effect. Interpreting the results leads us two conclusions. The first is that our estimates are robust. All key variables (knowledge spillover, localization agglomeration, and the interaction term of those two) have significant and expected (negative) signs at the 5% significance level or better. The second conclusion is that firm size matters. Using the full sample as the reference, the estimated value of the coefficient of TS suggests that the negative impact of knowledge spillover on R&D investment

Table 4
Localization, knowledge spillover, and R&D investment by firm size.¹⁶

	Dependent variable: RD				Dependent variable: RDI			
	Tobit		Two-Step		Tobit		Two-Step	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Above median-size firms								
LOC	−0.809*** (0.124)	−0.579*** (0.078)	−0.776*** (0.153)	−0.544*** (0.090)	−8.152E-03*** (1.154E-03)	−6.269E-03*** (7.726E-04)	−8.222E-03*** (1.424E-03)	−6.011E-03*** (8.874E-04)
TS	−1.888*** (0.731)	−2.252*** (0.525)	−2.103** (0.897)	−2.413*** (0.582)	−1.358E-02** (6.784E-03)	−2.167E-02*** (5.224E-03)	−1.772E-02** (8.338E-03)	−2.368E-02*** (5.744E-03)
LOC × TS		−0.599*** (0.162)		−0.865*** (0.257)		−6.820E-03*** (1.665E-03)		−9.303E-03*** (2.590E-03)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total obs.	6433	6433	6433	6433	6433	6433	6433	6433
Uncensored obs.	2661	2661	2661	2661	2661	2661	2661	2661
LR χ^2	1197.57	1210.55			797.56	814.02		
Log likelihood	−11148.659	−11142.17			1756.192	1764.422		
Wald χ^2			1088.37	1097.45			701.97	713.98
Wald test of exogeneity			0.46	3.27			0.78	2.51
P-value of Wald test			0.793	0.3515			0.679	0.4738
B. Below median-size firms								
LOC	−0.866*** (0.164)	−0.637*** (0.098)	−1.129*** (0.186)	−0.775*** (0.108)	−1.432E-02*** (2.846E-03)	−1.077E-02*** (1.795E-03)	−1.807E-02*** (3.228E-03)	−1.302E-02*** (1.976E-03)
TS	−2.756*** (0.855)	−3.188*** (0.586)	−4.154*** (0.969)	−4.044*** (0.636)	−4.349E-02*** (1.486E-02)	−5.078E-02*** (1.075E-02)	−6.912E-02*** (1.686E-02)	−6.830E-02*** (1.164E-02)
LOC × TS		−1.035*** (0.209)		−1.451*** (0.300)		−1.576E-02*** (3.812E-03)		−2.353E-02*** (5.497E-03)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total obs.	6500	6500	6500	6500	6500	6500	6500	6500
Uncensored obs.	1712	1712	1712	1712	1712	1712	1712	1712
LR χ^2	502.08	526.36			413.73	430.46		
Log likelihood	−7978.900	−7966.758			−701.210	−692.844		
Wald χ^2			450.9	467.6			377.97	390.72
Wald test of exogeneity			19.09	23.46			17.28	25.72
P-value of Wald test			0.000	0.000			0.000	0.000

***Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses.

decreases for the above median-size firms and increases for the below median-size firms. For instance, the elasticity of TS decreases to −1.888 and increases to −2.756 from −2.295 in absolute terms for the above and below median-size firms, respectively (Column 1 in Table 4 and Column 2 in Table 2). The conclusion holds for the results from Eq. (4) as well as for the Tobit Two-Step estimator. We obtain the similar results by using RDI as the dependent variable. The changing pattern of the value of the interactive term (LOCxTS) follows the pattern of the variable TS. The estimated value of the coefficient reveals that the negative impact of localization agglomeration on the negative relationship between firms' R&D and knowledge spillover decreases for the above median-size firms and increases for the below median-size firms. More specifically, the elasticity of TS decreases to −0.599 and increases to −1.035 from −0.757 in absolute terms for the above and below median-size firms, respectively (Column 1 in Table 4 and Column 2 in Table 2). Again, the changing pattern holds by using RDI. The differences of the estimated coefficients between sub-samples by size (TS and LOCxTS) are substantial. For instance, the estimated coefficient of TS is about 68% larger in absolute value for below median-size firms than for above median-size firms. The difference in the estimated coefficient of the interactive term is in the same range of percentage change.

The differences in the key variables' estimation by sample size may explain the micro-foundation of the negative effect of knowledge spillover on firms' R&D investment. Big firms are not always technological leaders, but they always undertake the majority share of R&D inputs (Scherer, 1992). When they co-locate with small firms, the knowledge spillover from big firms to small firms should be higher than the knowledge spillover from small firms to big firms. The asymmetry knowledge spillover would become more severe as the number of co-located small firms increases. The knowledge expropriation assumption suggests that the return to R&D investment of big firms would be less if they locate in cities characterized by larger localization agglomeration (which contains more small firms). Big firms in those more locally agglomerated cities should have a stronger motivation to reduce their R&D effort. Therefore, our results suggest the cost-saving effect of the negative relationship between knowledge spillover and firms' R&D investment. Our results are in line with Acs, Audretsch, and Feldman (1994) who speculate that small enterprises exploit external knowledge, especially those created by universities and large corporations, in producing innovative outputs.

¹⁶ The estimated coefficients of control variables are not reported in Tables 4 and 5 for saving the space.

Table 5
Localization, knowledge spillover, and R&D investment by new product production.

		Dependent variable: RD				Dependent variable: RDI		
		Tobit		Two-Step		Tobit		Two-Step
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. New products launched in 2007								
LOC	−0.174 (0.127)	−0.122** (0.058)	−0.128 (0.155)	−0.081 (0.068)	−3.835E-03 (2.723E-03)	−3.261E-03** (1.650E-03)	−3.147E-03 (3.319E-03)	−2.770E-03 (1.921E-03)
TS	−1.327* (0.686)	−0.897*** (0.338)	−1.809** (0.821)	−0.964** (0.379)	−2.272E-02 (1.465E-02)	−2.060E-02** (9.571E-03)	−3.713E-02** (1.752E-02)	−2.812E-02*** (1.068E-02)
LOC × TS		−0.224* (0.120)		−0.209 (0.180)		−5.270E-03 (3.384E-03)		−7.656E-03 (5.168E-03)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total obs.	2861	2861	2861	2861	2861	2861	2861	2861
Uncensored obs.	1894	1894	1894	1894	1894	1894	1894	1894
LR χ^2	520.15	523.57			200.03	202.37		
Log likelihood	−6591.143	−6589.435			984.084	985.253		
Wald χ^2			536.81	539.01			196.51	198.66
Wald test of exogeneity			1.96	1.99			3.03	3.55
P-value of Wald test			0.376	0.5755			0.220	0.3141
B. No new products launched in 2007								
LOC	−0.585*** (0.135)	−0.525*** (0.088)	−0.628*** (0.160)	−0.537*** (0.098)	−6.117E-03*** (1.261E-03)	−5.568E-03*** (8.665E-04)	−6.823E-03*** (1.496E-03)	−5.812E-03*** (9.643E-04)
TS	−2.635*** (0.760)	−3.337*** (0.577)	−3.491*** (0.892)	−4.111*** (0.626)	−2.107E-02*** (7.090E-03)	−3.088E-02*** (5.703E-03)	−2.972E-02*** (8.336E-03)	−3.833E-02*** (6.158E-03)
LOC × TS		−0.900*** (0.181)		−1.413*** (0.271)		−8.947E-03*** (1.794E-03)		−1.375E-02*** (2.681E-03)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total obs.	10072	10072	10072	10072	10072	10072	10072	10072
Uncensored obs.	2479	2479	2479	2479	2479	2479	2479	2479
LR χ^2	931.17	955.86			595.25	620.07		
Log likelihood	−11820.362	−11808.015			182.730	195.142		
Wald χ^2			801.78	821			519.24	540.5
Wald test of exogeneity			3.44	10.98			4.25	10.89
P-value of Wald test			0.179	0.0118			0.120	0.0123

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses.

We further examine how the impact of localization agglomeration and knowledge spillover on R&D effort varies between firms that launched new products in 2007 and those that did not. For a given period, firms that launch new products are likely to be more technologically advanced than their counterparts and might face a higher risk of knowledge expropriation in localization agglomeration (Jo & Lee, 2014). If the expropriation-avoidance effect dominates the reduction in R&D investment, we should expect a stronger negative effect of localization agglomeration and technological similarity on firms' launched new products. The estimation results in Table 5, however, show that localization and technological similarity have much weaker impacts on R&D spending and R&D intensity for firms that launched new products. When applying a two-step Tobit estimator, Columns 4 and 8 of Table 5 show that the coefficients/marginal effects of localization and the interactive term are no longer significant for firms' launched new products. The coefficient of technological similarity for firms' launched new products is significant; however, the magnitude is much smaller than the coefficient of technological similarity for firms that did not launch new products. Specifically, the coefficient for the latter is 4.3 times and 1.3 times larger using R&D spending and R&D intensity as dependent variables, respectively. This suggests that the decrease in firm R&D investment caused by expropriation-avoidance is potentially quite limited. Rather, the finding indicates that the flow of product R&D is slower than the flow of process R&D. Technological leaders may achieve high knowledge appropriability from their R&D investment as technological laggards do not have the baseline knowledge and skills to identify, absorb, or benefit from the novel technologies and knowledge of technological leaders (Cassiman and Veugelers, 2002; Cohen & Levinthal, 1990; McEvily & Chakravarty, 2002; Shefer & Frenkel, 1998).

6. Final remark

To build an innovative economy has become the goal of an increasing number of countries and regions. However, public policies cannot efficiently promote and channel the innovation of the private sector without fully understanding how firms are involved in the production of knowledge. Previous research reveals that both external and internal R&D investment contributes to the knowledge creation of firms. This paper takes one more step to show that firms can take advantage of external knowledge and save from self-

financing R&D investments. As knowledge spillover is localized, firms' R&D investment reduction presents a geographic pattern: firms reduce R&D more in locations characterized by greater localization agglomeration. The idea is demonstrated by a simple Cournot type, two-stage competition model which theoretically shows that localization strengthens the spillover effect on firms' R&D reduction. An empirical examination of Chinese high-tech firms verifies the theoretical predictions. Evidence based on a subsample regression further reveals that the negative impact is more due to the cost-saving effect than the expropriation-avoidance effect. The findings coincide well with agglomeration theory, which states that firms form clusters to benefit from a general pool of public knowledge. The benefits from knowledge spillover are quite considerable since a firm can achieve major innovative outputs with little R&D input (Bagella & Becchetti, 2002).

The paper provides two policy implications. First, public policy and planning should facilitate the spatial concentration of economic activities to promote knowledge transmission since it saves firms' R&D investment, especially in process innovation. Second, since firms can acquire process R&D by freeriding neighboring firms, preferential fiscal policies should mainly target product innovation.

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