Technological Forecasting & Social Change 183 (2022) 121886

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Effective R&D capital and total factor productivity: Evidence using spatial panel data models

Lu Dai, Jiajun Zhang, Shougui Luo *

Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai 200052, China

ARTICLE INFO

Keywords:
Time-varying endogenous weights
R&D capital stocks
Knowledge spillovers
Total-factor productivity

ABSTRACT

It is widely accepted that R&D investment improves technological progress. The R&D capital that boosts a firm's production efficiency has various sources. This paper uses "effective" R&D capital, which represents not only a firm's internal R&D input but also the benefit derived from R&D collaboration and accessible knowledge capital, to empirically examine its effects on a firm's productivity. Accounting for technological distance and the endogeneity problem of weights matrices, we use spatial panel data models to estimate the return of R&D capital within the framework of the production function. We estimate the production function using the firm-year data of Shanghai technological enterprises from 2009 to 2017. The results show positive, significant relationships between each element of "effective" R&D capital and total-factor productivity (TFP). Knowledge spillovers have greater impacts on a firm's TFP than its internal R&D input and R&D collaboration. The contribution of R&D collaboration to TFP is less than that of internal R&D, indicating that R&D collaboration is not fully internalized. The results imply that a better environment for R&D collaboration and technology exchange is needed.

1. Introduction

Technological progress plays a crucial role in economic growth (Solow, 1956). R&D activities are regarded as an important driving factor of a firm's technological progress, and the effect of R&D investment on productivity has been extensively discussed (Minasian, 1969; Griliches and Mairesse, 1983; Hall and Mairesse, 1995; Bloom et al., 2013). Most studies show a positive relationship between R&D activities and productivity growth. An important question is how to measure R&D capital (Griliches, 1979). A firm's own R&D investment is not the only source of corporate productivity improvement. Existing research shows that problems such as patent protection and the uncertainty of innovation output make it difficult for companies to fully internalize their R&D investment. To achieve higher innovation performance, firms seek external resources. On the one hand, an increasing number of companies are pursuing "open innovation" (Chesbrough, 2003) and regard R&D cooperation as an important complement to internal R&D input (Becker and Dietz, 2004). On the other hand, due to the public good nature of knowledge, the research results of one firm can be shared by other firms without compensation, which is known as the knowledge spillovers. Because of the growing complexity and risk of innovative processes in the modern economy, firms seek to collaborate in R&D activities for various reasons (Hagedoorn, 2002). First, cooperative R&D activities are cost-saving since they increase a firm's R&D input by enabling it to leverage its knowledge pool with other firms' contributions and thus achieve a certain innovative output with fewer research efforts. Second, it reduces the degree of uncertainty and risk in innovative processes because of the reduction in internal R&D expenditure. Bloom et al. (2007) investigated the dynamics of R&D and uncertainty regarding future productivity and economic conditions and found that the effect of uncertainty depends on the level of R&D. The effect is negative when firms increase their R&D, but if firms reduce their R&D, then the effect can be positive. Third, firms engaged in R&D cooperation can benefit from economies of scale in innovation production and increase efficiency by the complementarities of R&D factors and by avoiding repetition. Colombo (1995) demonstrated the complementary relationship between firm cooperation and R&D intensity. Veugelers (1998) noted that firms choose to cooperate with others in research and development based on motivations such as opening up new markets, mastering new technologies, achieving economies of scale, and sharing costs and risks. R&D cooperation affects innovation output by affecting the "effective" level of R&D capital (Katz, 1986). Ahuja et al. (2008) summarized a firm's effective R&D level as:

$$R\&D_{EFF} = R\&D_{INT} + \theta R\&D_{COLLAB}, \tag{1.1}$$

* Corresponding author.
E-mail addresses: dailu23@sjtu.edu.cn (L. Dai), aljszl@sjtu.edu.cn (J. Zhang), sgluo@sjtu.edu.cn (S. Luo).

https://doi.org/10.1016/j.techfore.2022.121886
Received 4 January 2022; Received in revised form 6 July 2022; Accepted 14 July 2022
Available online 5 August 2022

where θ is interpreted as the degree that a unit of R&D collaboration is equivalent to a unit of internal R&D. Ahuja et al. (2008) argued that in (1.1), $0 < \theta < 1$. This is because of the coordination and management costs in R&D collaboration, as well as the problem of information asymmetry, leading to R&D collaboration, may not contribute entirely to the effective R&D capital. It is also possible that $\theta > 1$, which indicates that R&D collaboration is more efficient than internal R&D. Therefore, if in-house and cooperative R&D activities are not distinguished, which is equivalent to the case that $\theta = 1$, it may lead to underestimation or overestimation of the contribution of the effective R&D capital to TFP.

Another problem is that because the amount of R&D collaboration of firms is often unobservable in the data, in many studies only regions' or firms' internal R&D expenditures are in the specification of the empirical model, which is equivalent to the case that $\theta = 0$. However, the impact of R&D collaboration cannot be ignored, especially in the case where there is a high proportion of R&D collaboration. Using balanced panel data of 1018 Shanghai technology companies from 2009 to 2017, we find that the proportion of companies whose R&D collaborations accounted for >15 % of the total R&D expenditure was 10 % to 30 % (see Fig. 3). Ignoring the contribution of R&D collaborations to TFP will lead to omitted variable bias because R&D collaboration has a positive influence on internal R&D and internal R&D can also stimulate the probability and the incidence of R&D collaboration (Becker and Dietz, 2004).

Knowledge transfer occurs not only through formal R&D collaboration but also through informal and uncompensated leakages. Unlike cooperative R&D activities, knowledge spillover refers to unintentional knowledge flow (Ibrahim et al., 2009). Knowledge externalities or spillovers are "the effects of nonmarket interactions which are realized through processes directly affecting the utility of an individual or the production function of a firm" (Fujita and Thisse, 1996). Fischer et al. (2009) defined knowledge spillovers as "the benefits of knowledge to firms, industries, or regions not responsible for the original investment in the creation of this knowledge". Because of the public good nature of knowledge, the related research of other firms adds additional knowledge to the knowledge pool and, therefore, can reduce a firm's needed R&D input to achieve certain output. However, for a relatively long time, the influence of external knowledge capital stock on a firm's output drew little attention since knowledge leakages are assumed away in traditional economic growth theory. The ignorance of spatial dependence among economic units might lead to unreliable statistical inferences (Ho et al., 2018). Eberhardt et al. (2013) indicated that spillovers are not separable from a firm's own R&D, even if the exclusive interest lies in the impact of R&D on TFP. Most empirical evidence has been shown with respect to the impact of knowledge spillovers on innovation or productivity across regions or countries through trade or geographic proximity (Coe and Helpman, 1995; Peri, 2005; Madsen, 2007; Fischer et al., 2009; Sun et al., 2021a,b). Coe and Helpman (1995) indicated that the growth of a country's productivity depends not only on its own R&D capital stock but also on the R&D capital stock of its trade partners. Fischer et al. (2009) investigated the impact of knowledge capital on a firm's TFP through cross-regional knowledge spillovers and found that the output elasticity of inter-regional spillovers is 0.12. In this work, knowledge diffusion decay with geographic distance is characterized by an exponential specification of weights. Sun et al. (2021a,b) observed positive impacts on energy efficiency resulting from both domestic knowledge stocks and international knowledge spillovers, accounting for geographical distance. Sun et al. (2021a,b) found empirical evidence of cross-country spatial dependence of institutional quality and energy efficiency. There is also evidence show positive relationship between knowledge spillovers and firm or industry TFP (Branstetter, 2001; Tsai and Wang, 2004; Higon, 2007).

In addition to the above-mentioned geographic proximity and trade channels, another proven mechanism of knowledge spillovers is technological proximity. For example, the interaction between high-tech clusters in Beijing and Shanghai is more likely to involve technological proximity than geographical proximity. LeSage and Fischer (2012) gave a concrete example of a skilled worker moving to another region as one way that knowledge spillovers take place. The movement of labor can lead to this externality (Moretti, 2004, 2021). This kind of knowledge transfer is more likely to be caused by technological proximity than by geographic proximity because workers tend to find jobs that match their skills. Empirical evidence also suggests that spillovers in the technological dimension are greater than those in the geographic dimension (LeSage and Fischer, 2012). Griliches (1979) gave several alternatives for measuring technological distance and emphasized the data limitations of very refined approaches. Jaffe (1986) presented a simple method to calculate technological similarity, characterizing a firm's technological position by patent vectors $P = (P_1, \ldots, P_K)$ in a K-dimensional technology space, where $P_{i,\ i=1,\ \ldots K}$ denotes the number of patents in i_{th} technological area. Therefore, the measure of technological proximity can be given by the correlation coefficients between two firms' patent vectors. The potential external knowledge pool is calculated by the weighted sum of other firms' knowledge capital, where the weights are correlation coefficients between 0 and 1. The smaller the correlation coefficients, the more difficult it is for the firm to benefit from the knowledge of other firms. Bloom et al. (2013) used this method to construct the weight matrix and found a positive relationship between technological spillovers and firm output. LeSage and Fischer (2012) found that knowledge spillover through technological proximity has a larger magnitude of impact on TFP than geographical proximity.

Although the current literature uses some alternatives to characterize firms' pairwise technological distance, there are still some problems in empirical model specification and identification. One problem is using a single technological distance weight matrix to capture knowledge spillover effects. However, the proximities of technology among firms can be time-varying. Technological distance might be time-varying not only because technology grows and changes quickly but also because firms adjust their research areas and R&D activities according to corporate development strategies. Therefore, a time-invariant weight matrix fails to capture time-varying technological spillovers. Second, unlike geographic distance, which is usually exogenous, technological distance might be endogenous because a firm's technological development could influence its productivity, while the growth of productivity might also change the structure of its R&D activities. In addition, some unobserved characteristics, such as the quality of employees, are related to technological proximity and will affect outcomes. To address this, the current paper attempts to allow time-varying technological weights matrices while accounting for endogenous weights matrices.

The objective of this paper is to assess the contribution to the productivity of each element of "effective" R&D capital. More specifically, this paper takes both internal R&D input and knowledge externalities into consideration and further adds R&D collaboration as a firm's effective R&D capital (Griliches, 1979; Katz, 1986; Ahuja et al., 2008). Our results are based on a sample of 1018 Shanghai technological enterprises between 2009 and 2017. The results show positive, significant relationships between each element of effective R&D capital and total-factor productivity. Knowledge spillovers have greater effects on a firm's TFP than its internal R&D input and R&D collaboration. The contribution of R&D collaboration to TFP is less than that of internal R&D, which indicates that R&D collaboration is not fully internalized. This paper contributes to the current literature in two ways. First, this paper uses the framework of "effective" R&D capital, to assess its impact on TFP. We decompose a firm's R&D capital into internal R&D and R&D collaboration, and find a relatively large difference in their contribution to TFP, while the existing literature investigating the effect of R&D capital on corporate productivity does not distinguish between internal R&D capital and cooperative R&D capital. Second, we use spatial econometric models with time-varying endogenous weights matrices to estimate the production function. The spatial dynamic panel model better mitigates the problem of omitted variables, and we also take into account the endogeneity of the spatial weights matrices following Qu and Lee (2015) and Qu et al. (2017), resulting in more accurate estimates.

There are two main motivations behind this research. First, it is important to construct a firm's effective R&D capital stocks and evaluate its contribution to productivity. Assessing the contribution of each of its elements to TFP helps to inform the innovation decision-making of firms and government innovation policy. Second, it is important to alleviate the problem of omitted variables and the endogeneity of weights matrices to obtain more accurate estimations.

The remainder of this article is organized as follows. In Section 2, we build the theoretical framework. In Section 3 we discuss the models. Section 4 presents the data and variables. Empirical results and robustness checks are presented in Sections 5 and 6, respectively. We conclude the article in Section 7.

2. Theoretical framework

2.1. Internal R&D

R&D activities directly contribute to the accumulation of knowledge, which is an important source of technological progress and economic growth. Among developed countries, countries with higher levels of R&D investment and innovation have significantly higher economic growth rates than other countries (Samimi and Alerasoul, 2009). The contribution of a firm's own R&D investment to productivity has been extensively examined. Most empirical studies have found a positive relationship between internal R&D investment and productivity (Nadiri, 1993; Griffith et al., 2004; Higon, 2007). Higon (2007) reviewed the existing literature and concluded that the output elasticity of R&D to TFP is between 0.015 and 0.37. For example, Nadiri (1993) estimated that the output elasticity of R&D input to TFP is between 0.1 and 0.3. Although most studies have confirmed the contribution of R&D to productivity improvement, there are still situations in which R&D investment does not result in high productivity (Ejermo et al., 2011; Yu et al., 2021), which is known as the Swedish paradox, and some of which have not been clearly demonstrated. Existing literature also points out that the impact of R&D activities on a firm's productivity varies significantly depending on the type of industry. Griliches and Mairesse (1983) and Cuneo and Mairesse (1983) found that the output elasticity of R&D on scientific firms is significantly greater than on nonscientific firms. Tsai and Wang (2004) also found that the R&D output elasticity of high-tech enterprises is significantly greater than that of other types of enterprise. Although the impact of R&D investment on TFP is still debated, it is reasonable to assume that R&D directly stimulates productivity growth (Griffith et al., 2003). In line with prior findings, we propose the following hypothesis:

H1. A firm's internal R&D investment has a positive impact on its productivity.

2.2. R&D collaboration

The growing complexity and risk of innovative processes stimulates R&D collaborations through which firms acquire resources that are not available in-house (Miotti and Sachwald, 2003). Although there is not much research investigating the impact of R&D collaboration on total-factor productivity, there is evidence showing that R&D collaboration promotes the firm's innovation, including innovation input and innovation output. Czarnitzki et al. (2007) found that in Germany, R&D subsidies to individuals have no significant effect on R&D input and patent output, while incentives for collaboration can improve innovation performance. Becker and Dietz (2004) identified the significant positive effect of joint R&D on both innovative input and output, as measured by internal R&D intensity and the realization of product innovation. Belderbos et al. (2004) analyzed the influence of different types of partner and found that cooperation with competitors and suppliers can improve the productivity, while cooperation with competitors and universities can improve the revenue. However, R&D collaboration also has potential risks, one of which is free-riding (Veugelers and Kesteloot, 1994), which causes R&D investment to be lower than optimal (Katz, 1986). It is possible that the company only allocates relatively inefficient researchers to the cooperative R&D activities, making R&D cooperation not as efficient as internal R&D (Contractor et al., 1988). In addition, cross-organizational cooperation requires additional coordination, monitoring, and management costs (Harrigan, 1988; Mitchell and Singh, 1996). Therefore, part of these R&D resources will be allocated to cross-organization coordination tasks, reducing the actual R&D resources used for innovation. Therefore, we propose the following hypothesis:

H2. R&D collaboration has a positive impact on firm productivity and its contribution is less than that of internal R&D.

2.3. Knowledge spillovers

Griliches (1979) investigated the contribution of R&D capital to productivity growth and discussed the measurement of the stock of R&D capital. One firm's level of productivity depends not only on its own R&D efforts but also on the effect of “outside” knowledge capital. Most evidence has been shown with respect to the impact of knowledge spillovers on innovation or productivity across regions or countries (Coe and Helpman, 1995; Coe et al., 1997; Lumenga-Neso et al., 2005; Peri, 2005; Madsen, 2007; Fischer et al., 2009; Barasa et al., 2019; Sun et al., 2021a, b; Razzaq et al., 2021). For example, Fischer et al. (2009) used a spatial error model on a panel of 203 NUTS-2 areas and found that the elasticity of knowledge spillover to regions' TFP is 0.12. Madsen (2007) found that one of the important drivers of TFP convergence in OECD countries is technology spillovers between countries. Knowledge spillovers between firms or industries also have a positive impacts (Tsai and Wang, 2004; Moretti, 2004; Higon, 2007). Tsai and Wang (2004) used a panel of Taiwanese high-tech and traditional manufacturing firms and showed that the knowledge spillovers from the high-tech sector have a positive impact on the productivity of the traditional manufacturing sector. However, the flow of knowledge may also have a negative impact due to the competitive effect between firms (Branstetter, 2001; Higon, 2007; Zhang et al., 2021). The total effect of knowledge spillovers depends on which of the positive and negative effects is greater. Based on the above findings, it is reasonable to assume that positive effects may dominate and we formulate the following hypothesis:

H3. Knowledge spillovers have positive impacts on firm productivity.

Fig. 1 presents the theoretical framework of this article. We will empirically examine the relationship between each element of effective R&D capital and total-factor productivity.

3. Models

One approach to quantifying the return of R&D capital to total-factor productivity is the knowledge capital model introduced by Griliches (1979). We augment it so that the measurement of the stock of R&D capital includes not only the firm's own R&D efforts but also cooperative R&D capital and knowledge externalities. Following Griliches (1979), we assume a Cobb-Douglas production function:

$$Y_{it} = AC_{it}^{\alpha}L_{it}^{\beta}RD_{it}^{I\gamma_1}RD_{it}^{C\gamma_2}K_{it}^{\gamma_3}e^{v_{it}}, \tag{3.1}$$

where Y_{it} is some kind of output of firm i at time t, such as revenue; RD_{it}^{I} it represents the stock of internal R&D expenditures; RD_{it}^{C} represents the stock of cooperative R&D benefit; K_{it} represents the accessible knowledge pool; Cit represents the stock of physical capital; and Lit represents the stock of labor. A is a constant. Then, total-factor productivity is defined as follows:

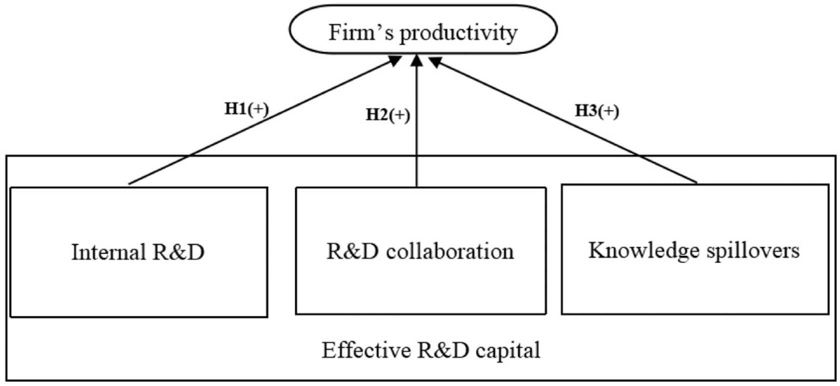

Fig. 1. Theoretical framework.

$$F_{it} = \frac{Y_{it}}{C_{it}^{\alpha} L_{it}^{\beta}} = ARD_{it}^{I\gamma_1} RD_{it}^{C\gamma_2} K_{it}^{\gamma_3} e^{v_{it}}. \tag{3.2}$$

We take the logarithm of both sides of (3.2) to obtain the following model and use lowercase to represent the variable after taking the logarithm:

$$f_{it} = a + \gamma_1 rd_{it}^{I} + \gamma_2 rd_{it}^{C} + \gamma_3 k_{it} + v_{it}. \tag{3.3}$$

Rewrite (3.3) in vector form:

$$f_{nt} = \boldsymbol{a} + \gamma_1 rd_{nt}^{I} + \gamma_2 rd_{nt}^{C} + \gamma_3 k_{nt} + v_{nt}, \tag{3.4}$$

where f_{nt}, rd_{nt}^{I}, rd_{nt}^{C}, $\boldsymbol{a}$ and v_{nt} are $n \times 1$ vectors. Following LeSage and Fischer (2012), we take the spatial dependence of productivity into account and rewrite the accessible knowledge pool as $W_{nt}k_{nt}$:

$$f_{nt} = \lambda_1 W_{nt} f_{nt} + \gamma_1 rd_{nt}^{I} + \gamma_2 rd_{nt}^{C} + \gamma_3 W_{nt} k_{nt} + x_{nt}\beta + \boldsymbol{c}_n + \alpha_t l_n + v_{nt}, \tag{3.5}$$

where W_{nt} is the spatial weight matrix; $\boldsymbol{c}_n$ is the individual fixed effect; $\alpha_t l_n$ represents the time fixed effect, where α_t is a scalar and l_n is an n-dimensional vector with all elements being 1; x_{nt} is an $n \times k_x$ matrix of control variables. If we consider the dynamic adjustment of productivity, then we specify a spatial dynamic panel data (SDPD) model:

$$\begin{aligned} f_{nt} = {} & \lambda_1 W_{nt} f_{nt} + \rho f_{n,t-1} + \lambda_2 W_{n,t-1} f_{n,t-1} + \gamma_1 rd_{nt}^{I} + \gamma_2 rd_{nt}^{C} + \gamma_3 W_{nt} k_{nt} + x_{nt}\beta \\ & + \boldsymbol{c}_n + \alpha_t l_n + v_{nt}. \end{aligned} \tag{3.6}$$

In spatial econometrics, spatial weights matrices are used to represent spatial dependence between economic units. Based on the knowledge capital stock or the technological position of each firm, there are various ways to calculate the technical proximity between firms (Jaffe, 1986; Rosenkopf and Almeida, 2003; Gilsing et al., 2008). In this article, we follow Jaffe (1986), classifying firm i's patent into m categories and constructing firm i's patent vectors $P_{i,t} = (p_{ik,t})_{k=1,\ldots,m}$, where $p_{ik,t}$ denotes the number of patents in category k. The patent vectors are eight-dimensional if the International Patent Classification (IPC) section[1] is used as the classification method (Parent and LeSage, 2008). Based on these patent vectors, we construct the spatial lag weights matrices $W_{nt} = (w_{ij,t})_{i,j=1,\ldots,n}$, where the (i, j)th entry is the correlation coefficient of firm i's and firm j's patent vectors:

$$w_{ij,t} = \frac{\sum_{k=1}^{m} \left(p_{ik,t} - \overline{p}_{i,t}\right)\left(p_{jk,t} - \overline{p}_{j,t}\right)}{\sqrt{\sum_{k=1}^{m} \left(p_{ik,t} - \overline{p}_{i,t}\right)^2} \sqrt{\sum_{k=1}^{m} \left(p_{jk,t} - \overline{p}_{j,t}\right)^2}}, \tag{3.7}$$

$w_{ij,t}$ is closer to unity if their technological types are more similar. W_{nt} is row-normalized and has zero diagonals. Therefore, each element in $W_{nt}k_{nt}$ represents the potential external knowledge pool accessible to the corresponding firm.

Since the weights are constructed based on the number of patents in different classifications, they can be time-varying and highly correlated with the unobservable disturbance v_{nt} that may affect productivity. Following Qu and Lee (2015) and Qu et al. (2017), we employ a control function approach to overcome the endogeneity problem. We allow the endogeneity of spatial weights matrices by the following equation:

$$p_{nt} = \Gamma_1 rd_{nt}^{I} + \Gamma_2 rd_{nt}^{O} + \Gamma_3 gov_{nt} + \Gamma_4 rl_{nt} + \boldsymbol{c}_{n2} + \alpha_{t2} l_n + \epsilon_{nt} - u_{nt}, \tag{3.8}$$

where p_{nt} is an $n \times 1$ vector, which represents the number of patents granted; rd_{nt}^{I} represents the internal R&D investment; rd_{nt}^{O} represents entrusted R&D investment to cooperative firms; govnt represents R&D subsidies from the government; and rl_{nt} represents employees engaged in R&D activities. u_{nt} is a one-sided term that captures inefficiency in the innovation process, and ϵ_{nt} is the specification error. To overcome the potential endogeneity problems that exist in some previous studies, the estimating equations are specified as follows:

$$f_{nt} = \lambda_1 W_{nt} f_{nt} + \gamma_1 rd_{nt}^{I} + \gamma_2 rd_{nt}^{C} + \gamma_3 W_{nt} k_{nt} + x_{nt}\beta + \boldsymbol{c}_n + \alpha_t l_n + \delta_1 \widehat{\epsilon}_{nt} + \delta_2 \widehat{u}_{nt} + \xi_{nt}, \tag{3.9}$$

$$\begin{aligned} f_{nt} = {} & \lambda_1 W_{nt} f_{nt} + \rho f_{n,t-1} + \lambda_2 W_{n,t-1} f_{n,t-1} + \gamma_1 rd_{nt}^{I} + \gamma_2 rd_{nt}^{C} + \gamma_3 W_{nt} k_{nt} + x_{nt}\beta \\ & + \boldsymbol{c}_n + \alpha_t l_n + \delta_1 \widehat{\epsilon}_{nt} + \delta_2 \widehat{u}_{nt} + \xi_{nt}. \end{aligned} \tag{3.10}$$

If $\delta_1 \neq 0$ or $\delta_2 \neq 0$, W_{nt} is endogenous. ξ_{nt} is independent with $\widehat{\epsilon}_{nt}$ and $\widehat{u}_{nt}$. The decomposition of the error term in the control function helps to specify the source of endogeneity.

In a nonspatial setting, the estimates of regression present the marginal effect of explanatory variables. However, in the spatial dependence setting, the marginal impacts involving weights matrices are more complex (LeSage and Pace, 2007). For instance, in spatial panel data model (SPD), take partial derivatives with respect to $W_{nt}k_{nt}$:

$$\frac{\partial f_{nt}}{\partial W_{nt} k_{nt}} = \gamma_3 (I - \lambda_1 W_{nt})^{-1}, \tag{3.11}$$

which is the impact matrix associated with the knowledge capital of neighbors. The marginal impact is also time-varying. The average total effects on productivity are given by:

$$E_{t,total} = \frac{\mathbf{1}' \gamma_3 (I - \lambda_1 W_{nt})^{-1} \mathbf{1}}{n}. \tag{3.12}$$

4. Data and variables

To better understand the development status of Shanghai's science and technology firms, the Science and Technology Commission of Shanghai Municipality (STCSM) has been conducting a yearly sample survey since 2008. The survey includes firms' information such as

[1] The codes are A–H (see Table 7).

revenues, taxation, profit, trade, innovation, R&D investment, personnel, etc. In this paper, we use a balanced panel of 9162 observations for the period between 2009 and 2017 constructed from the yearly sample survey. Because the surveys only include the total number of patents, without the classification of patents that is required in our study for measuring the technological proximity of firms, we retrieved the IPC classification of the patents from the incoPat database, which is a patent database that provides a global collection of patent information. We calculated the number of patents in each IPC classification and matched these two databases according to firms' names and constructed the firms' patent vectors. The summary statistics are reported in Table 1.

The general method of calculating TFP is using a fixed effect model to estimate the Solow surplus, but this approach fails to take into account the endogeneity problem caused by the correlation between unobservable productivity shocks and production factor inputs. The resulting endogeneity might lead to estimation bias. Olley and Pakes (1996) first proposed a two-step estimation method to overcome endogeneity and used firms' current investment as a proxy for unobservable productivity shocks. A similar approach is the LP method (Levinsohn and Petrin, 2003), which is more flexible in choosing proxy variables. This paper uses total revenue as output and uses total assets and labor as input. Fixed asset investment for scientific research is used as the proxy variable. RD^I represents the stock of internal R&D. RD^C represents the stock of cooperative R&D, which includes two components: entrusted R&D investments to cooperative firms and R&D service revenues. K is the stock of patents granted. Although there are useful technological inventions that are not patentable, and thus will be missed, those that are patented must meet minimum standards of novelty, originality, and potential use (Ho et al., 2018). To construct effective R&D capital stocks, the depreciation of R&D investment and patents granted need to be taken into account. We use the perpetual inventory approach to calculate R&D capital stocks:

$$RD^I_{t+1} = RD^I_t(1-r) + I_{1,t+1}, \tag{4.1}$$

$$RD^C_{t+1} = RD^C_t(1-r) + I_{2,t+1}, \tag{4.2}$$

$$K_{t+1} = K_t(1-r) + I_{3,t+1}, \tag{4.3}$$

where r is an exogenously given depreciation rate and we use a constant depreciation rate of 10 %. $I_{1,\ t+1}$, $I_{2,\ t+1}$ and $I_{3,\ t+1}$ are the internal R&D expenditures, R&D collaboration amount and patents granted during t + 1.

This article selects trade openness, education level, and government R&D subsidies as control variables. Trade can promote the accumulation of knowledge capital, and empirical studies show that there is a stable relationship between TFP and knowledge imports. In the past century, 93 % of TFP growth was due to knowledge imports and the import of knowledge also explains the convergence of TFP in OECD countries (Madsen, 2007). We use the total amount of foreign exchange earned from exports to represent the degree of trade openness of firms. Productivity is also affected by the level of individual education, which is correlated with R&D input in a firm. Moretti (2004) found that plants with a higher proportion of college graduates have a higher level of productivity. We use the proportion of employees with a bachelor's degree to represent the education level of a firm. Government R&D subsidies are also an important source of innovation input for firms, which affects productivity non-linearly (Bernini et al., 2017). This article uses the amount of government R&D subsidies to represent the R&D support from government.

5. Results

5.1. Moran's I test

Before a spatial econometric model is specified, the spatial correlation between economic units is usually tested. To test whether there is a spatial correlation of firms' productivity, the global Moran's I index is used to measure the degree of spatial dependence:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(f_i - \bar{f})(f_j - \bar{f})}{s^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}. \tag{5.1}$$

where I ranges from −1 to 1. $\bar{f}$ is the mean of f, and s^2 is the variance of f. w_{ij} is an element of the technological distance weight matrix. The null hypothesis of Moran's I test is that economic units are randomly distributed and have no interdependence. The alternative hypothesis is that economic units are interdependent. The closer the value of I is to unity, the stronger the positive spatial correlation, and vice versa. If $I = 0$, then there is no statistically significant evidence that the economic units are spatially dependent.

Fig. 2 show Moran's I scatter plots for 2009 and 2017. It can be seen from the figure that there is a positive spatial correlation between the firms' TFPs, indicating that firms have a positive mutual influence on productivity, accounting for technological proximity. Therefore, spatial econometric models must be used.

5.2. Spatial panel data models

Table 2 presents the results of the spatial panel data model and spatial dynamic panel data model regressions with their standard deviations shown in parentheses[2]. Columns 1–4 use the TFP calculated by the OP approach as the dependent variable, and Columns 5–8 use the TFP calculated by the LP approach as the dependent variable. Columns 1–2 and 5–6 are the results of the static spatial autoregressive model regression, and Columns 3–4 and 7–8 are the results of the spatial dynamic panel data model regression.

λ_1, λ_2, and ρ are positive and significant, which confirms the importance of a spatial dynamic panel data model specification. In line with H1 and with Higon (2007) and Cuneo and Mairesse (1983), the impact of internal R&D stock on productivity ranges from 0.094 to 0.123. It can be seen from the results that the omission of R&D collaboration will lead to inconsistent estimates of internal R&D and knowledge spillovers, which overestimates the return to internal R&D. The coefficient of collaborative R&D is positive and significant at the 1 % level, ranging from 0.026 to 0.033. From the magnitude of the coefficients, we can see that the return of cooperative R&D is smaller than the return of internal R&D, which is consistent with H2. This result is in line with the view that a unit of R&D done outside the firm may contribute less to the firm's knowledge base than a comparable unit conducted inside the firm (Ahuja et al., 2008). The coefficient of W k is positive and significant, which supports H3. Note that the magnitude of the spillover effects is larger than that of both internal R&D and R&D collaboration. The coefficients of u and ϵ are significant, which implies the endogeneity of the weights matrices. In addition, as mentioned above, we should keep in mind that these estimates cannot be interpreted as the elasticities of TFP with respect to internal R&D, R&D collaboration, and knowledge spillovers, respectively. Table 3 shows the total effects of each component in effective R&D on TFP.

For the static panel data model, a 10 % increase in the internal R&D, R&D collaboration and knowledge capital stocks of the technologically relevant neighbors would lead to 1.29 %, 0.36 %, and 1.76 % increases on average in a firm's TFP, respectively. For the dynamic panel data model, a 10 % increase in the internal R&D, R&D collaboration and knowledge capital stocks of the technologically relevant neighbors would lead to 1.37 %, 0.37 %, and 1.91 % increases on average in a

[2] The estimation methods are based on Zhang et al. (2021). Matlab codes are available from the second author.

Table 1
Descriptive statistics.

Variables	Descriptions	Obs	Mean	SD	Min	Max
OP	TFP calculated by OP approach	9162	3.681	0.741	−1.418	6.995
LP	TFP calculated by LP approach	9162	3.630	0.735	−1.454	6.956
RD^I	Internal R&D investment	9162	12,062	39,082	0	875,651
RD^C	R&D collaboration amount	9162	1769	19,052	0	1,348,405
K	Patent granted	9162	4.975	14.48	0	460
Gov	Government R&D subsidies	9162	1012	10,440	0	478,576
Edu	Proportion of employees with bachelor degree or above	9162	0.456	0.277	0	1
Open	Total foreign exchange earned from exports	9162	8349	61,288	0	2,260,643
RL	Labors engaged in R&D	9162	74.224	154.87	0	3796
RD^O	Entrusted R&D investment to cooperative firms	9162	605	6365	0	271,326

Notes: Prices are for yuan in 2009 prices.
RD^I, RD^C, *Gov*, *Open* and RD^O in nominal values are deflated by CPI of Shanghai based on 2009.

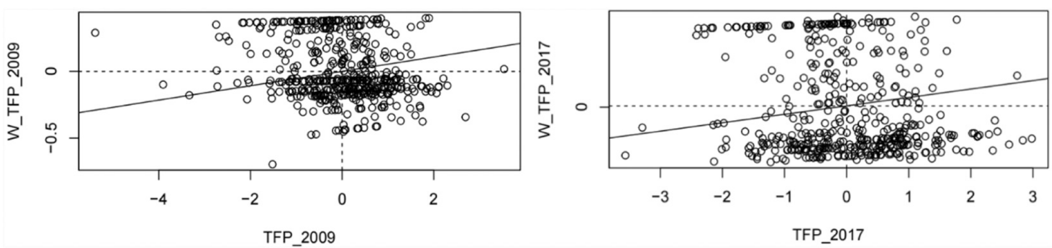

Fig. 2. Moran's I scatter plot of TFP in 2009 and 2017.

Table 2
Results: static and dynamic spatial panel data models.

TFP	OP				LP			
	Static	Static	Dynamic	Dynamic	Static	Static	Dynamic	Dynamic
λ_1	0.138*** (0.020)	0.146*** (0.022)	0.059** (0.028)	0.082*** (0.027)	0.141*** (0.021)	0.139*** (0.020)	0.065** (0.028)	0.087*** (0.029)
ρ			0.315*** (0.042)	0.306*** (0.040)			0.321*** (0.041)	0.309*** (0.041)
λ_2			0.083*** (0.008)	0.096*** (0.007)			0.081*** (0.010)	0.089*** (0.009)
rd^I	0.123*** (0.008)	0.120*** (0.008)	0.113*** (0.008)	0.094*** (0.008)	0.127*** (0.007)	0.122*** (0.008)	0.115*** (0.009)	0.096*** (0.009)
rd^C		0.033*** (0.003)		0.026*** (0.003)		0.032*** (0.002)		0.029*** (0.002)
Wk	0.128*** (0.036)	0.164*** (0.040)	0.171*** (0.050)	0.132*** (0.049)	0.121*** (0.037)	0.167*** (0.035)	0.173*** (0.050)	0.138*** (0.050)
u	−0.240*** (0.008)	−0.293*** (0.009)	−0.291*** (0.008)	−0.247*** (0.008)	−0.241*** (0.008)	−0.287*** (0.007)	−0.281*** (0.008)	−0.254*** (0.007)
ϵ	0.330*** (0.041)	0.388*** (0.045)	0.375*** (0.042)	0.331*** (0.041)	0.312*** (0.039)	0.371*** (0.042)	0.324*** (0.042)	0.322*** (0.040)
Controls	Yes							
Firm FE	Yes							
Time FE	Yes							
Obs	9162							

The standard deviations of the estimated values are reported in parentheses.
***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

firm's TFP, respectively, which are slightly higher than the estimates of the SPD. This result shows that the elasticity of TFP with respect to knowledge spillovers is the greatest, followed by internal R&D and R&D collaboration. The magnitudes of elasticities of knowledge spillovers and internal R&D are about 5 times and 4 times that of R&D collaboration, respectively.

6. Robustness checks

6.1. Aggregation on patents

Unlike geographical distance, technological distance is controversial and diverse. Benner and Waldfogel (2008) and Vom Stein et al. (2015) indicated that using the number of different types of patent each year to calculate technological distance might be imprecise because this calculation is based on a small number of patents. This problem can be mitigated by a larger sample size or coarser patent classification. Therefore, we follow Benner and Waldfogel (2008) in increasing the patent size by aggregating on years. We aggregate the number of patents every three years, and thus, the sample period changes from 2009–2017 to 2011–2017.

The results are presented in Table 4. Most estimates are consistent with the baseline regression, and thus, the conclusions presented in this study do not change.

6.2. Lagged explanatory variables

Considering the potential reverse causality between firms' productivity and effective R&D, we lag all explanatory variables by one period. The results are presented in Table 5. Most estimates are consistent with the baseline regression, proving the stability and reliability of the conclusion.

6.3. Pooled regression on the full sample

Since the sample is based on a balanced panel constructed from

Table 3
Results: total effects.

SPD	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
rd^I	0.129***	0.129***	0.130***	0.130***	0.130***	0.130***	0.129***	0.129***	0.129***	0.129
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	
rd^C	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	
Wk	0.175***	0.176***	0.177***	0.177***	0.177***	0.177***	0.176***	0.176***	0.175***	0.176
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	

SDPD	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
rd^I	–	0.154***	0.155***	0.155***	0.152***	0.147***	0.133***	0.098***	0.097***	0.137
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	
rd^C	–	0.042***	0.043***	0.042***	0.042***	0.040***	0.037***	0.027***	0.027***	0.037
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	
Wk	–	0.217***	0.218***	0.217***	0.214***	0.206***	0.187***	0.137***	0.136***	0.191
		(0.050)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.050)	

The standard deviations of the estimated values are reported in parentheses.
***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table 4
Results: aggregation on patents.

TFP	OP				LP			
	Static	Static	Dynamic	Dynamic	Static	Static	Dynamic	Dynamic
λ_1	0.129*** (0.028)	0.156*** (0.029)	0.101*** (0.033)	0.090*** (0.032)	0.122*** (0.027)	0.151*** (0.029)	0.113*** (0.031)	0.095*** (0.032)
ρ			0.323*** (0.055)	0.307*** (0.054)			0.320*** (0.051)	0.313*** (0.052)
λ_2			0.083*** (0.016)	0.099*** (0.013)			0.085*** (0.016)	0.102*** (0.013)
rd^I	0.116*** (0.009)	0.105*** (0.010)	0.108*** (0.012)	0.095*** (0.012)	0.119*** (0.009)	0.106*** (0.010)	0.094*** (0.011)	0.099*** (0.012)
rd^C		0.027*** (0.003)		0.022*** (0.003)		0.026*** (0.003)		0.023*** (0.003)
Wk	0.162*** (0.053)	0.161*** (0.056)	0.174*** (0.060)	0.136** (0.059)	0.153*** (0.051)	0.165*** (0.054)	0.167*** (0.056)	0.133** (0.058)s
u	−0.251*** (0.008)	−0.272*** (0.009)	−0.226*** (0.008)	−0.243*** (0.008)	−0.257*** (0.007)	−0.245*** (0.008)	−0.282*** (0.007)	−0.241*** (0.008)
ϵ	0.336*** (0.047)	0.323*** (0.050)	0.335*** (0.061)	0.336*** (0.060)	0.341*** (0.045)	0.328*** (0.048)	0.330*** (0.057)	0.326*** (0.060)
Controls	Yes							
Firm FE	Yes							
Time FE	Yes							
Obs	7126							

The standard deviations of the estimated values are reported in parentheses.
***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table 5
Results: lagged explanatory variables.

TFP	OP				LP			
	Static	Static	Dynamic	Dynamic	Static	Static	Dynamic	Dynamic
λ_1	0.138*** (0.019)	0.145*** (0.020)	0.096*** (0.025)	0.105*** (0.025)	0.136*** (0.020)	0.141*** (0.023)	0.099*** (0.024)	0.102*** (0.025)
ρ			0.328*** (0.045)	0.325 (0.044)			0.320*** (0.043)	0.324*** (0.044) s
λ_2			0.080*** (0.008)	0.079*** (0.009)			0.083*** (0.007)	0.077*** (0.008)
rd^I	0.119*** (0.008)	0.098*** (0.008)	0.100*** (0.010)	0.080*** (0.009)	0.125*** (0.008)	0.093*** (0.008)	0.109*** (0.007)	0.074*** (0.010)
rd^C		0.031*** (0.003)		0.021*** (0.005)		0.033*** (0.003)		0.026*** (0.003)
Wk	0.137*** (0.035)	0.140*** (0.036)	0.137*** (0.044)	0.126*** (0.045)	0.135*** (0.034)	0.139*** (0.036)	0.131*** (0.044)	0.122*** (0.046)
u	−0.233*** (0.010)	−0.254*** (0.009)	−0.223*** (0.008)	−0.236*** (0.008)	−0.237*** (0.009)	−0.244*** (0.011)	−0.235*** (0.011)	−0.241*** (0.010)
ϵ	0.366*** (0.043)	0.373*** (0.044)	0.342*** (0.038)	0.345*** (0.039)	0.360*** (0.041)	0.368*** (0.043)	0.337*** (0.038)	0.355*** (0.038)
Controls	Yes							
Firm FE	Yes							
Time FE	Yes							
Obs	8144							

The standard deviations of the estimated values are reported in parentheses.
***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

sample surveys of Shanghai technology firms, other observations are inevitably dropped. The advantage of using a balanced panel is that we can construct effective R&D capital stocks through the perpetual inventory method based on firms' R&D input each year, and we can control for individual fixed effects. However, the entry and exit of enterprises might influence the results. To test how this might affect the results, we consider a pooled regression on the full-sample.

The results are presented in Table 6. The direction and significance of the coefficients are still consistent with the baseline regression, indicating that the main conclusions are robust.

Table 6
Results: pooled regression on the full sample.

TFP	OP		LP	
	Static	Static	Static	Static
λ_1	0.262***	0.278***	0.264***	0.272***
	(0.097)	(0.102)	(0.095)	(0.100)
rd^I	0.188***	0.175***	0.181***	0.169***
	(0.016)	(0.021)	(0.018)	(0.022)
rd^C		0.041***		0.039***
		(0.008)		(0.009)
Wk	0.279***	0.267***	0.292***	0.264***
	(0.077)	(0.085)	(0.081)	(0.090)
u	−0.279***	−0.345***	−0.298***	−0.353***
	(0.060)	(0.068)	(0.065)	(0.070)
ϵ	0.371**	0.368**	0.370**	0.373**
	(0.151)	(0.145)	(0.160)	(0.155)
Controls	Yes			
Firm FE	Yes			
Time FE	Yes			
Obs	87,720			

The standard deviations of the estimated values are reported in parentheses.

7. Conclusions

China is undergoing an economic transition from a factor-driven to an innovation-driven economy and faces a series of challenges, such as the inefficiency of innovation investment. This paper uses internal R&D, R&D collaboration, and knowledge spillovers as the "effective" R&D capital stocks of firms and uses data from Shanghai science and technology firms to assess their contribution to productivity. We exploit spatial panel data models with time-varying weights matrices constructed based on technological distance to capture knowledge spillovers and use control function to deal with the endogeneity from weights.

The conclusion of this paper is that all components of effective R&D capital stocks have significant positive impacts on a firm's productivity. Knowledge spillovers have greater effects on a firm's TFP than its internal R&D input and R&D collaboration. For every 10 % increase in the knowledge capital of other technology-adjacent firms, the firm's productivity will increase by 1.91 %. In addition, we find that if cooperative R&D capital is omitted, the contribution of internal R&D will be overestimated. In our baseline result, the estimates of internal R&D drop from 0.113 to 0.094 after controlling the cooperative R&D capital. Although R&D cooperation between enterprises is seen as a more direct form of cooperation than knowledge spillovers are, its impact on productivity is much lower than that of knowledge spillovers. For every 10 % increase in the amount of R&D collaboration, TFP increases by about 0.37 %. This number is also lower than the contribution of the firm's internal R&D, which can increase TFP by about 1.37 %. This indicates that R&D collaboration among science and technology firms in Shanghai has not reached a high level of efficiency. As previously mentioned, there are many potential factors that restrict the efficiency of R&D collaboration. A possible explanation is that R&D across organizational boundaries requires many additional coordination, monitoring, and management costs. In addition, R&D cooperation has potential information asymmetry. For example, one partner may only send relatively inefficient employees, even though they could meet the minimum quality of the project (Pisano, 1990; Williamson, 1989; Becker and Dietz, 2004). It is also possible that the scale of enterprise R&D cooperation is not at the optimal level.

7.1. Policy implications

The results provide useful insights into the impact of firms' effective R&D capital on TFP. Although the Chinese government has been encouraging R&D collaboration between firms and between firms and universities, the amount of R&D collaboration in our data shows an annual downward trend from 2009 to 2017 (see Fig. 3). We do not discuss the reasons for this tendency in this article, but our empirical results indicate that the return of R&D collaboration is at a lower level than that of internal R&D and knowledge spillovers. One potential implication of this article is that firms should be more careful with R&D collaboration because the inefficiency problem may result in the cooperative output being less than expected.

Due to information asymmetry in R&D collaboration and coordination, monitoring, and management costs, firms cannot fully internalize R&D collaboration as effective R&D capital. Therefore, at firm level, a sound partner selection and evaluation mechanism should be established to review the partners' technological innovation capabilities and resources and willingness to cooperate; a sound supervision mechanism and a long-term cooperation management mechanism should be established. At government level, it is necessary to improve the legal system for corporate R&D collaboration, and to build a platform for cooperation and information sharing, to help the complementation of innovation resources of firms, and promote technological progress and economic growth.

In addition, the results imply that knowledge spillovers through technological proximity have positive impacts on TFP. The sharing of scientific and technological information and knowledge between firms, and the strengthening of communication with advanced technological neighboring firms will help improve firms' TFP. The government should play an active role in platform building and provide a superior environment for enterprises in technology exchange in terms of information sharing and policy support.

7.2. Limitations

One of the limitations of this article is the single source of the sample. Although Shanghai is one of the innovative pioneer cities in China and leads China's economic and technological development, due to the nature of knowledge as a public good, firms in other cities or regions, especially the Yangtze River Delta region, also affect firms in Shanghai; however, this was not considered in our research. We do not claim that our results hold for other regions of China, but our empirical method can be directly applied to assess the contribution of effective R&D capital stocks.

CRediT authorship contribution statement

Lu Dai: Conceptualization, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Jiajun Zhang:** Methodology, Software, Writing – review & editing. **Shougui Luo:** Supervision, Data curation, Funding acquisition.

Data availability

The authors do not have permission to share data.

Acknowledgements

We acknowledge support from the National Natural Science Foundation of China (Project no. 72174117) and the key program of Shanghai Soft Science Foundation (Project no. 21692181000). We thank the editor Scott Cunningham, and two anonymous reviewers for their helpful comments on an earlier draft of this paper. We also thank participants of the Annual Meeting of Young Econometricians in Asia-Pacific (YEAP 2022) for their comments.

Appendix I

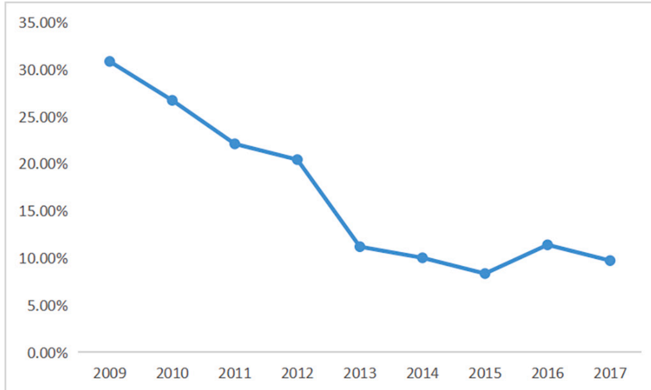

Fig. 3. The proportion of firms whose R&D amount accounts for >15 % of the total amount of scientific research.

Appendix II

Table 7
Number of patents in each IPC section of the sample.

IPC code	Section name	Number of patents
A	Human necessities	2045
B	Performing operations; transporting	9403
C	Chemistry; metallurgy	7631
D	Textiles; paper	793
E	Fixed constructions	2040
F	Mechanical engineering; lighting; heating; weapons; blasting	5730
G	Physics	10,403
H	Electricity	13,934

References

Ahuja, G., Lampert, C.M., Tandon, V., 2008. Moving beyond schumpeter: management research on the determinants of technological innovation. Acad. Manag. Ann. 2 (1), 1–98.
Barasa, L., Vermeulen, P., Knoben, J., Kinyanjui, B., Kimuyu, P., 2019. Innovation inputs and efficiency: manufacturing firms in sub-saharan africa. Eur. J. Innov. Manag. 22 (1), 59–83.
Becker, W., Dietz, J., 2004. R&D cooperation and innovation activities of firms—evidence for the German manufacturing industry. Res. Policy 33 (2), 209–223.
Belderbos, R., Carree, M., Lokshin, B., 2004. Cooperative R&D and firm performance. Res. Policy 33 (10), 1477–1492.
Benner, M., Waldfogel, J., 2008. Close to you? Bias and precision in patent-based measures of technological proximity. Res. Policy 37 (9), 1556–1567.
Bernini, C., Cerqua, A., Pellegrini, G., 2017. Public subsidies, TFP and efficiency: a tale of complex relationships. Res. Policy 46 (4), 751–767.
Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and investment dynamics. Rev. Econ. Stud. 74 (2), 391–415.
Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. Econometrica 81 (4), 1347–1393.
Branstetter, L.G., 2001. Are knowledge spillovers international or intranational in scope? Microeconometric evidence from the US and Japan. J. Int. Econ. 53 (1), 53–79.
Chesbrough, H.W., 2003. Open Innovation: The New Imperative for Creating and Profiting From Technology. Harvard Business Press.
Coe, D.T., Helpman, E., 1995. International R&D spillovers. Eur. Econ. Rev. 39 (5), 859–887.
Coe, D.T., Helpman, E., Hoffmaister, A.W., 1997. North-south R&D spillovers. Econ. J. 107 (440), 134–149.
Colombo, M.G., 1995. Firm size and cooperation: the determinants of cooperative agreements in information technology industries. Int. J. Econ. Bus. 2 (1), 3–30.
Contractor, F.J., Lorange, P., et al., 1988. Why should firms cooperate? The strategy and economics basis for cooperative ventures. In: Cooperative Strategies in International Business, 1, pp. 3–30.
Cuneo, P., Mairesse, J., 1983. Productivity and R&D at the firm level in French manufacturing. In: NBER Working Papers.
Czarnitzki, D., Ebersberger, B., Fier, A., 2007. The relationship between R&D collaboration, subsidies and R&D performance: Empirical evidence from Finland and Germany. J. Appl. Econ. 22 (7), 1347–1366.
Eberhardt, M., Helmers, C., Strauss, H., 2013. Do spillovers matter when estimating private returns to R&D? Rev. Econ. Stat. 95 (2), 436–448.
Ejermo, O., Kander, A., Henning, M.S., 2011. The R&D-growth paradox arises in fast-growing sectors. Res. Policy 40 (5), 664–672.
Fischer, M.M., Scherngell, T., Reismann, M., 2009. Knowledge spillovers and total factor productivity: evidence using a spatial panel data model. Geogr. Anal. 41 (2), 204–220.
Fujita, M., Thisse, J.-F., 1996. Economics of agglomeration. J. Jpn. Int. Econ. 10 (4), 339–378.
Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., Van Den Oord, A., 2008. Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. Res. Policy 37 (10), 1717–1731.
Griffith, R., Redding, S., Van Reenen, J., 2003. R&D and absorptive capacity: theory and empirical evidence. Scand. J. Econ. 105 (1), 99–118.
Griffith, R., Redding, S., Reenen, J.V., 2004. Mapping the two faces of R&D: Productivity growth in a panel of OECD industries. Rev. Econ. Stat. 86 (4), 883–895.
Griliches, Z., 1979. Issues in assessing the contribution of research and development to productivity growth. Bell J. Econ. 10 (1), 92–116.
Griliches, Z., Mairesse, J., 1983. Comparing productivity growth: An exploration of French and US industrial and firm data. Eur. Econ. Rev. 21 (1–2), 89–119.
Hagedoorn, J., 2002. Inter-firm R&D partnerships: An overview of major trends and patterns since 1960. Res. Policy 31 (4), 477–492.
Hall, B.H., Mairesse, J., 1995. Exploring the relationship between R&D and productivity in French manufacturing firms. J. Econ. 65 (1), 263–293.
Harrigan, K.R., 1988. Joint ventures and competitive strategy. Strateg. Manag. J. 9 (2), 141–158.
Higon, D.A., 2007. The impact of R&D spillovers on UK manufacturing TFP: a dynamic panel approach. Res. Policy 36 (7), 964–979.
Ho, C.-Y., Wang, W., Yu, J., 2018. International knowledge spillover through trade: A time-varying spatial panel data approach. Econ. Lett. 162, 30–33.
Ibrahim, S.E., Fallah, M.H., Reilly, R.R., 2009. Localized sources of knowledge and the effect of knowledge spillovers: an empirical study of inventors in the telecommunications industry. J. Econ. Geogr. 9 (3), 405–431.
Jaffe, A.B., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value. Am. Econ. Rev. 76 (5), 984–1001.
Katz, M.L., 1986. An analysis of cooperative research and development. RAND J. Econ. 17 (4), 527–543.

LeSage, J.P., Fischer, M.M., 2012. Estimates of the impact of static and dynamic knowledge spillovers on regional factor productivity. Int. Reg. Sci. Rev. 35 (1), 103–127.
LeSage, J.P., Pace, R.K., 2007. A matrix exponential spatial specification. J. Econ. 140 (1), 190–214.
Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Rev. Econ. Stud. 70 (2), 317–341.
Lumenga-Neso, O., Olarreaga, M., Schiff, M., 2005. On indirect trade-related R&D spillovers. Eur. Econ. Rev. 49 (7), 1785–1798.
Madsen, J.B., 2007. Technology spillover through trade and TFP convergence: 135 years of evidence for the OECD countries. J. Int. Econ. 72 (2), 464–480.
Minasian, J.R., 1969. Research and development, production functions, and rates of return. Am. Econ. Rev. 59 (2), 80–85.
Miotti, L., Sachwald, F., 2003. Co-operative R&D: Why and with whom? An integrated framework of analysis. Res. Policy 32 (8), 1481–1499.
Mitchell, W., Singh, K., 1996. Survival of businesses using collaborative relationships to commercialize complex goods. Strateg. Manag. J. 17 (3), 169–195.
Moretti, E., 2004. Workers' education, spillovers, and productivity: evidence from plant-level production functions. Am. Econ. Rev. 94 (3), 656–690.
Moretti, E., 2021. The effect of high-tech clusters on the productivity of top inventors. Am. Econ. Rev. 111 (10), 3328–3375.
Nadiri, M.I., 1993. Innovations and technological spillovers. In: NBER Working Papers.
Olley, G.S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64 (6), 1263–1297.
Parent, O., LeSage, J.P., 2008. Using the variance structure of the conditional autoregressive spatial specification to model knowledge spillovers. J. Appl. Econ. 23 (2), 235–256.
Peri, G., 2005. Determinants of knowledge flows and their effect on innovation. Rev. Econ. Stat. 87 (2), 308–322.
Pisano, G.P., 1990. The R&D boundaries of the firm: an empirical analysis. Adm. Sci. Q. 35 (1), 153–176.
Qu, X., Lee, L.-F., 2015. Estimating a spatial autoregressive model with an endogenous spatial weight matrix. J. Econ. 184 (2), 209–232.
Qu, X., Lee, L., Yu, J., 2017. QML estimation of spatial dynamic panel data models with endogenous time varying spatial weights matrices. J. Econ. 197 (2), 173–201.
Razzaq, A., An, H., Delpachitra, S., 2021. Does technology gap increase FDI spillovers on productivity growth? Evidence from Chinese outward FDI in Belt and Road host countries. Technol. Forecast. Soc. Chang. 172, 121050.
Rosenkopf, L., Almeida, P., 2003. Overcoming local search through alliances and mobility. Manag. Sci. 49 (6), 751–766.
Samimi, A.J., Alerasoul, S.M., 2009. R&D and economic growth: new evidence from some developing countries. Aust. J. Basic Appl. Sci. 3 (4), 3464–3469.
Solow, R.M., 1956. A contribution to the theory of economic growth. Q. J. Econ. 70 (1), 65–94.
Sun, H., Edziah, B.K., Kporsu, A.K., Sarkodie, S.A., Taghizadeh-Hesary, F., 2021. Energy efficiency: The role of technological innovation and knowledge spillover. Technol. Forecast. Soc. Chang. 167, 120659.
Sun, H., Edziah, B.K., Sun, C., Kporsu, A.K., 2021. Institutional quality and its spatial spillover effects on energy efficiency. Socio Econ. Plan. Sci. 101023.
Tsai, K.-H., Wang, J.-C., 2004. R&D productivity and the spillover effects of high-tech industry on the traditional manufacturing sector: the case of Taiwan. World Econ. 27 (10), 1555–1570.
Veugelers, R., 1998. Collaboration in R&D: an assessment of theoretical and empirical findings. De Economist 146 (3), 419–443.
Veugelers, R., Kesteloot, K., 1994. On the design of stable joint ventures. Eur. Econ. Rev. 38 (9), 1799–1815.
Vom Stein, N., Sick, N., Leker, J., 2015. How to measure technological distance in collaborations—The case of electric mobility. Technol. Forecast. Soc. Chang. 97, 154–167.
Williamson, O.E., 1989. Transaction cost economics. In: Handbook of Industrial Organization, 1, pp. 135–182.
Yu, H., Devece, C., Martinez, J.M.G., Xu, B., 2021. An analysis of the paradox in R&D. insight from a new spatial heterogeneity model. Technol. Forecast. Soc. Chang. 165, 120471.
Zhang, J., Qu, X., Yu, J., 2021. Spatial Dynamic Panel Data Models With High Order Time Varying Endogenous Weights Matrices. Elsevier. Available at SSRN 4163612.

Lu Dai is a PhD Candidate at Antai College of Economics & Management, Shanghai Jiao Tong University in China. He received his master degree in statistics from the School of mathematical science of Shanghai Jiao Tong University. His main research interest is in empirical studies of corporate innovation and urban economics.

Jiajun Zhang is a PhD Candidate at Antai College of Economics & Management, Shanghai Jiao Tong University in China. His main research interest is in the theory of the spatial panel data models.

Shougui Luo is a professor at Antai College of Economics & Management, Shanghai Jiao Tong University in China. He received his PhD degree from Nanjing University in 2001. He was once a visiting scholar at the University of Sheffield and California State University, Northridge. His major area of expertise is Urban and Regional Economy, Regional Industrial Development and Technological Innovation. He has hosted more than thirty research projects that are supported by the National Natural Science Foundation and the National Social Science Foundation of China and research funds in Shanghai.