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International R&D Spillovers and Innovation Efficiency

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Abstract: The objective of this study is to examine the impact of international research and development (R&D) spillovers on innovation efficiency of specific R&D outcomes, employing the country-level panel data for 44 countries in the 1996–2013 period. Fully considering the heterogeneity of different R&D outputs, scientific papers, PCT (Patent Cooperation Treaty) patents, US patents, and domestic patents are observed separately, which enriches the angles of measuring international R&D spillovers. By applying a stochastic frontier analysis to knowledge production function, we find that foreign R&D capital stock positively contributes to the innovation efficiency of scientific papers, but suppresses the productivity of domestic patents, whereas it does not really matter for PCT or US patents. These results are robust to control for a set of institutional factors and also in sensitivity analyses. Hence, dependence on international R&D spillovers seems neither to be the right way for emerging economies to catch up, nor to be a sustainable model for developing countries to fill the technical gap. Local R&D capital stock, instead, keeps an essential contributor to all four R&D outputs, so raising internal R&D expenditure is actually the key to improving innovation level and sustainable development ability.

Keywords: international R&D spillovers; innovation efficiency; SFA; patents; scientific papers

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1. Introduction

Having gotten rid of the yoke of neoclassical theory which viewed technology development as an exogenous process, the development of endogenous growth theory by Romer, Grossman and Aghion [1–3] underlies the burgeoning literature attaching great importance to knowledge, innovation, and research and development (R&D). Based on the accumulation of knowledge, innovation plays an increasingly crucial role in the growth strategies of both nations and enterprises. Aggressive R&D activities, which prove to be effective and efficient as the backbone of innovation, by Griliches and Coe [4–6] are, therefore, looked upon as the source of enhancing total factor productivity (TFP) and an open sesame to long-term economic growth by governments, entrepreneurs, and academics.

When R&D causes differences in the productivity of countries and regions [7], it is improving the global technological level and production efficiency via knowledge transfer or spillovers. Knowledge spillover effects are perceived differently by lots of experts in this field so we can find no one fixed definition [8]. The OECD defines spillover as unintentional transmission of knowledge, while knowledge transfer is identified as intentional knowledge exchange. It is often difficult to recognize intention in the real world, in particular for country-level spillovers. As such, we tend to define spillovers as all forms of bilateral knowledge flow in this country-level analysis.

Empirically, the pioneering paper of Coe and Helpman [9] identified R&D efforts of trade partners as favorable to country-level TFP, namely the international R&D spillover effect which is generally characterized afterwards by the international transfer of technology by means of bilateral trade [10,11], foreign direct investment [12,13], foreign technology payments [14,15], international R&D collaboration [16,17], publications in scientific and technical field, and migration of scientists and skilled labor forces [18]. Henceforth, investigations about international R&D spillovers and productivity are flourishing with topics concerning different nations [13,19], sectors [20,21], industries [22,23], and firms [24].

Despite the large volume of work that has been done, there still remains some imperfections which need exploring in depth. For example, our economic growth theories put much emphasis on how foreign R&D inputs matter for the growth of productivity, however, little light is shed on their part in the direct R&D production process. In addition, most studies limit their scope to OECD countries, neglecting those emerging economies where campaigns of technological catch-up are happening, and substantial money and manpower are being expended, for example, China which had the second-highest R&D expenditure in 2015.

By applying a stochastic frontier analysis (SFA) to knowledge production function (KPF), we introduce foreign R&D capital stock, together with domestic R&D capital stock, and domestic R&D personnel input into the right-side of the function in the interest of figuring out the direction and magnitude of the influence of international R&D spillovers on a country's innovation efficiency. Meanwhile, following the idea of Coe et al. [19], a series of external economic and institutional factors, namely environmental variables, including Internet coverage, human capital, service industry development level, high-tech industry development level, intensity of R&D expenditure, structure of R&D expenditure sources, language distance and a dummy variable, are taken into account for the sake of both completing the function and figuring out their impact on innovation efficiency. Our data set of cross-country analysis is updated to 2013 and expanded to 44 countries from the 24 in Coe et al. [19], covering traditional OECD countries, BRICS, and several other emerging or developing nations. Furthermore, we adopt numbers of scientific papers, PCT patents, US patents, and domestic patents respectively, as output variables of the left-side in substitution for TFP in Coe and Helpman [9], to detect the role of international R&D spillovers from various angles. It deserves to be mentioned here that PCT patents are those which enjoy patent protection in different countries according to the Patent Cooperation Treaty, while US patents are those granted by the United States Patent Office.

Our empirical results provide robust evidence that international R&D spillovers are surprisingly negative or insignificant when domestic patents, PCT patents, US patents are taken as output variables, respectively, whereas it is significantly positive when the number of scientific papers is considered as an R&D output. While it is commonly acknowledged that international R&D spillovers contribute positively to productivity growth, our results catch sight of their impeditive impact on direct innovative gains. In addition, we also find that macro environmental factors, such as Internet coverage, human capital, intensity of R&D expenditure, and high economic development level, are favorable to the efficient transformation from R&D inputs to outputs. These results are valuable for policymakers who are looking forward to improving technological and innovative competitiveness.

This paper makes an important contribution to three streams of literature. First, it shows a different way of examining the international R&D spillovers, by focusing on specific R&D outputs like patents and publications rather than TFP which is determined by many other key explanatory variables. Second, that foreign R&D activities and a set of environmental variables are introduced into the model to complete the function and attenuate the potential bias caused by omitted variables. Third, it expands the research scope to those emerging and developing economies so as to respond to the new global situation in the field of R&D.

The remainder of the paper is as following. Section 2 reviews the literature on international R&D spillovers and innovation efficiency both theoretically and empirically. Section 3 elaborates the econometric framework including the knowledge production function model and the stochastic frontier analysis method. Section 4 is devoted to variable selection, data sources, and descriptive statistics. Section 5 reports empirical results. Conclusions and discussion are located in Section 6.

2. Literature Review

2.1. International R&D Spillovers

Because R&D is the primary activity for the creation of new technologies, international R&D spillovers are regarded as a powerful driver of productivity growth. As argued by Keller [25], 90 percent of productivity growth can be attributable to foreign technologies in many countries, especially for those followers weak in technology and R&D. International R&D spillovers are, therefore, fundamental to research into economic development and productivity growth in the actual globalized economic system.

Despite the long history in the consideration of R&D spillovers or externalities, which dates back at least to Schultz [26] where public investments in agricultural research proved to be profitable via technological upgrading and then resource saving, the branch of international R&D spillovers originates from Coe and Helpman [9] (CH, hereafter) where they found that a country's TFP depended not only on accumulative domestic R&D capital but also on accumulative foreign R&D capital. After that, a group of followers continued to re-examine the results of CH through improved econometric methods or different data sets, and in the process, progress has been made although unstable results are yielded sometimes, but most of the time, the main conclusions remain unchanged.

When Lichtenberg [27] re-examined the econometric model of CH with both an alternate weighting scheme that is much less biased theoretically and a correction of "indexation bias", which helps generalize CH's empirical framework, one of CH's core standpoints is confirmed—that open countries benefit more from foreign R&D. What is more, based on panel cointegration techniques newly-developed by Kao and Chiang [28], Kao et al. [29] redid the analysis of CH, and their empirical results support for the linkage between TFP and domestic R&D capital stock but dispute the existence of trade-related international R&D spillovers.

It is undeniable that R&D capital alone is not enough to completely explain the whole innovation production process. That is exactly why more and more other factors are being added to the right-side of CH's model. A general human capital variable is taken into consideration by Englebrecht [30] as a direct factor of production, and as expected, it proves to be highly statistically significant whereas the coefficient estimates for domestic R&D capital and international R&D spillovers turn out to be somewhat smaller. This practice continues to exist in Coe et al. [19] where several institutional factors are included as well as addressing the issue of parameter heterogeneity. It emerges that the institutional environment, such as ease of doing business, quality of tertiary education, strength of intellectual property rights, and origin of legal systems, exerts a substantial influence on the efficiency of both one's own R&D efforts and international R&D spillovers.

In the specification of CH's model, by means of weighting, the transfer of international R&D is attributable to bilateral trade. Nevertheless, doubt is cast on this claim by Keller [31] and Kao et al. [29]. In fact, as far as channels of international R&D spillovers are concerned, no consensus can be reached. Various channels have been mentioned in a number of papers, including trade, FDI (Foreign Direct Investment), migration, technology purchasing, international development aid, and so forth [32–37]. However, in practice, international trade is undoubtedly a good dummy for cross-border economic communication. That explains why, in this paper, special treatment is given to the number of imports, even though we admit that technological transfer is supposed to happen through a variety of channels.

Thus, we find theoretical foundation and empirical support for our three explanatory variables, along with a trace of environmental factors. Our development along this stream of literature is substituting TFP with directly correlated R&D output variables to take a closer look at the effect of foreign R&D capital stock on the country-level innovation production process.

2.2. Innovation Efficiency

Innovation efficiency is related to the concept of productivity which is improved when more innovation outputs are generated with the same amount of innovation inputs or when fewer innovation inputs are needed for certain amount of innovation outputs [38]. Output efficiency of R&D inputs is not a new topic. Based on the knowledge production function originating from Griliches [4], three kinds of techniques are employed to judge innovation efficiency; indexation [39,40], data envelopment analysis (DEA) [41–46], and SFA [47,48]. For a review of the methodology of Hollanders and Celikel-Esser Reference [38] is recommended. Based on sound economic theory, the SFA method not only estimates innovation efficiency but also analyses the impact of relevant factors, including both input and environmental variables quantitatively [49]. This advantage leads to the adoption of SFA in this study.

Consistent with Coe et al. [19], a series of economic and institutional factors are embraced in this framework, however, in a different way. Rather than forming interactions with input variables, these factors are observed independently as environmental variables. The collection of environmental factors, such as the proportion of highly educated population, Internet coverage, and academic English proficiency by Wang and Huang [50], government's special role by Hsu and Hsueh [51] and Guo et al. [52], product market regulation by Franco et al. [53], and collaboration network structure by Guan et al. [17], outline the recent reawakening of interest in the socio-economic environment.

Even if domestic R&D inputs and increasing environmental variables endow the model with greater explanatory power, the foreign R&D situation is always absent. Following CH, we fill this gap by focusing on the influence of international R&D spillovers on innovation efficiency by adding foreign R&D capital stock into knowledge production function as an R&D input.

3. Econometric Strategy

3.1. Knowledge Production Function (KPF)

Analogous to product production function, KPF proposed by Pakes and Griliches [54,55] is extensively applied to R&D measurement and provides a way to evaluate knowledge production and innovative activities. R&D output (Y) is assumed to depend on R&D expenditure (R) and R&D personnel (L), and the model can be expressed as follows:

$$\mathrm{Y} = \mathrm{f}\,(\mathrm{R}, \mathrm{L}) \tag{1}$$

The existent studies commonly take it for granted that KPF is the case of a closed economy so that Y is supposed to be the consequence of merely domestic R&D inputs [45,47,50]. The acquaintance with international R&D spillovers motivates us to enter into the case of an open economy, and consequently following CH, Lichtenberg and Pottelsberghe de la Potterie [27], López-Pueyo et al. [56] and Coe et al. [19], R&D capital stock is determined by domestic R&D capital stock (R^d) jointly with foreign R&D capital stock (R^f), to be written as:

$$R = \left(R_{it}^{d}\right)^{\alpha_1}\left(R_{it}^{f}\right)^{\alpha_2} \tag{2}$$

i denotes countries, t time, α_1, α_2 coefficients respectively. Furthermore, we convert Equation (1) into a Cobb-Douglas form:

$$\log Y_{it} = \alpha_0 + \alpha_1 \log R_{it}^{d} + \alpha_2 \log R_{it}^{f} + \alpha_3 \log L_{it} \tag{3}$$

3.2. Stochastic Frontier Analysis (SFA)

Innovation efficiency can be quantified by structuring an efficiency frontier and then measuring a country's distance to that frontier. Actually, when all R&D inputs and outputs are plotted in a multidimensional space, the most efficient countries form a frontier, and a country's distance to that frontier represents its degree of innovation inefficiency. Data envelopment analysis (DEA) and stochastic frontier analysis are designed to fulfil the task of computation. The former is non-parametric, while the latter is parametric.

This paper aims to explore the impact of international R&D spillovers on innovation efficiency. Non-parametric DEA method reports just efficiency values without paying attention to specific influential factors, just like a "black box". Fortunately, parametric SFA possesses inherent superiority in accounting for factors that may influence the innovation efficiency by setting a concrete function. Kumbhakar and Lovell [57] have proposed a general form of SFA model with the spirit of KPF:

$$\log Y_{it} = \alpha_0 + \alpha_1 \log R^d_{it} + \alpha_2 \log R^f_{it} + \alpha_3 \log L_{it} + v_{it} - u_{it} \tag{4}$$

where Y_{it} is the innovation output of country i in year t, R^d_{it}, R^f_{it}, L_{it} represent three kinds of innovation inputs, $(\alpha_0, \alpha_1, \alpha_2, \alpha_3)$ is the vector of coefficients. To construct the knowledge production frontier which is defined as the maximum attainable output by a given amount of inputs, the stochastic component is projected with a two-part composed error item $v_{it} - u_{it}$ [58,59] v_{it} is a random variable which is assumed to be iid$N(0, \sigma^2_v)$ and independent of u_{it} which accounts for technical inefficiency and is a half-normally distributed term truncated at zero, namely:

$$u_i \sim \text{iid}N^+\left(\mu, \sigma^2_u\right) \tag{5}$$

According to Equation (5), technical inefficiency term can be described as:

$$u_{it} = u_i \exp[-\eta(t-T)] \tag{6}$$

where η is an unknown scalar parameter to be estimated which manifests the fluctuate trend of technical inefficiency u_i over time t. $\eta > 0$, $\eta = 0$, $\eta < 0$ signify improved, constant or degressive technical efficiency respectively.

For the purpose of estimation, Battese and Coelli [60] replace the parameters σ^2_v and σ^2_u with $\sigma^2 = \sigma^2_v + \sigma^2_u$ and $\gamma = \frac{\sigma^2_u}{\sigma^2_v + \sigma^2_u}$, which can be calculated from the maximum likelihood (ML) estimates.

Afterwards, for dealing with the influence of environmental factors, Battese and Coelli [61] put forward a renewed frontier model where technical inefficiency function is created and subject to $u_{it} \sim N^+(m_{it}, \sigma^2_u)$ distribution which is iid as truncated at zero. The expectation of technical inefficiency term is dependent on external environmental factors and may be specified in this paper as:

$$m_{it} = \delta_0 + \delta_1 \ln IT + \delta_2 \ln HK + \delta_3 \ln Srv + \delta_4 \ln Htec + \delta_5 \ln Gerd + \delta_6 \ln Govrd + \delta_7 \ln Lang + \delta_8 G8 + \omega_{it} \tag{7}$$

where IT, HK, Srv, $Htec$, $Gerd$, $Govrd$, $Lang$, and $G8$ are agents of Internet coverage, human capital, tertiary industry development level, high-tech industry development level, intensity of R&D expenditure, structure of R&D expenditure sources, language distance, and a dummy variable respectively, $(\delta_0, \delta_1, \ldots, \delta_8)$ is a vector of parameters where negative values imply positive effect and vice versa, and ω_{it} is the random error which is not necessarily subject to identical distribution.

4. Variable Selection and Data Sources

4.1. Variable Selection

4.1.1. Input Variables

The principal inputs in R&D production activities are manpower and physical resources [47]. Thus, R&D input variables can be divided primarily into personnel input and expenditure input.

1. Domestic R&D capital stock (RDD). Country-level annual R&D expenditure data can be obtained from Science, Technology and Innovation of UNESCO's database and Research and Development Statistics of OECD database, by the name of gross domestic expenditure on R&D (GERD). Data in current American dollars from these two official publications are rendered comparable by being converted into data at 2005 constant price based on the Purchasing Power Parities (PPP)

method. Moreover, instead of expenditure, R&D capital stock should be used in the context of the knowledge production function. Accordingly, the data on annual R&D expenditure are transformed into R&D capital stock applying the perpetual inventory method as suggested by OECD [62], which can be specified as:

$$R_{it} = (1-\sigma)R_{it-1} + I_{it} \tag{8}$$

where R_{it} is the R&D capital stock of country i in year t, I_{it} is the R&D expenditure of country i in year t, σ is the R&D capital depreciation rate which is generally deemed to be 15% [53,63]. As for the base-period R&D capital stock R_0, we learn from Coe et al. [19], to be set as:

$$R_0 = \frac{I_0}{g+\sigma} \tag{9}$$

where I_0 is the R&D expenditure in 1996, g is the average annual growth rate of R&D expenditure, σ is the R&D capital depreciation rate.

2. Foreign R&D capital stock (RDF). The pioneering proposition about the measurement of foreign R&D capital stock appears in CH which constructs the foreign R&D capital stock R_i^{fCH} as a weighted sum of the other countries' domestic R&D capital stocks R_j^d,

$$R_i^{fCH} = \sum_{j\neq i} \frac{M_{ij}}{\sum\limits_{j\neq i} M_{ij}} R_j^d \tag{10}$$

where M_{ij} is the import of country i from country j. Then, this method is amended by Lichtenberg and Pottelsbergh de la Potterie [27], to be computed as follows:

$$R_i^{fLP} = \sum_{j\neq i} \frac{M_{ij}}{Y_j} R_j^d \tag{11}$$

where Y_j is the GDP of country j. This updated method is employed in our research.

3. R&D personnel (L). Two major norms are used to measure R&D personnel, researchers (L1) and total R&D personnel (L2) [47,50]. Researchers are those who are both engaged in R&D activities and equipped with intermediate or above titles or a doctor's degree, while total R&D personnel covers all those who are involved in the concept formation or creation of new knowledge, new product, new processes, new methods or new systems, and those related professionals in project management, even Ph.D. candidates in R&D field (ISCED97, level 6). It is evident that the number of researchers is less than that of total R&D personnel. However, the data of the latter are missing for some countries, such as the USA and Columbia, so that the former is taken as a substitute.

4.1.2. Output Variables

There are primarily two measures of innovation outputs which involve two major stages of the innovative process. One is the intermediate output, such as inventions which have been patented. The other is the final innovation output indicators, for example, sampling the new product sections of trade and technical journals. The latter is advantageous because it focuses on the aim or the end of innovation: commercialization. But these innovation output indicators are so expensive to generate that they are only available for a few countries in limited years. As such patents and scientific papers are very commonly used to measure innovative outputs as the second-best solution. In fact, Acs et al. [64] have found powerful evidence which supports the reliability of patents as the proxy of innovation output. We select patents and scientific papers as R&D outputs because they are found to fit very well the technological change and are sensitive enough to R&D inputs.

1. Patents (PAT). Patents are probably the most typical and important R&D fruit. The Patents Statistics of OECD database and the United States Patent Office offer the access to four types of patent indicators: domestic patents (DPAT), PCT patents (PCTPAT), triadic patents (TPAT) and US Patents (USPAT). In terms of quantity, DPAT generally far outweighs PCTPAT and TPAT, and it seems that TPAT is the least. Without doubt, TPAT is an efficacious indicator of advanced technologies, but it is not applicable to a cross-country research because many countries only achieve a few TPAT, or even have no record of this item, especially for underdeveloped countries. As a consequence, TPAT is excluded while the other three are selected.
2. Scientific papers (PAP). Scientific papers, as a kind of academic publication, are also the most common outcome of R&D activities, which play an exceptional role in delivering and sharing new ideas and laying a solid theoretical foundation for R&D practices. The source of this indicator is the S&E (Science & Engineering) Article from Science and Engineering Indicators, which collects and sorts global papers, books and conference publications, primarily including the papers published on the journals on the lists of Science Citation Index (SCI) or Social Sciences Citation Index (SSCI).

4.1.3. Environmental Variables

Based on previous literature and their observations, eight macro socio-economic factors are selected as environmental variables which are supposed to influence innovation efficiency to some extent.

1. Internet coverage (IT). The Internet, as a vital vehicle of information spreading and knowledge sharing, is essential to the function of international R&D spillovers. The ratio of Internet users in the last 12 months per 100 residents, an indicator released by WDI (World Development Indicators), is used to reflect the Internet coverage of each country. It is hypothesized that the broader the Internet coverage is, the easier it is to approach and share foreign R&D fruits and the higher the innovation efficiency may be.
2. Human capital (HK). The average educational level (years) of employees is the most popular measurement of human capital [65]. However, the average value is not necessarily accurate in evaluating R&D activities which, to a great extent, are the game of those intellectuals. Hence, the enrollment rate of tertiary education serves as the proxy, which is supposed to benefit the absorption of international R&D spillovers and the improvement of innovation efficiency.
3. Service industry development level (Srv). The ratio of value added by the service industry to GDP is included to identify the industrial structure of each country. Then, the service industry consists of several totally different sub-industries, like information technology and tourism. In practice, the former is beneficial to innovation and R&D spillovers, such as the case of Japan, while the latter is not, as is the case for Thailand.
4. High-tech industry development level (Hightec). On one hand, the level of high-tech industry, indicated by the ratio of value added by this industry to GDP, does rest with the R&D capacity. On the other hand, it is believed that the well-installed R&D infrastructure is accompanied by enhanced absorptive capability and innovation efficiency.
5. Intensity of R&D expenditure (Gerd). In terms of the ratio of total R&D expenditure to GDP, this indicator comes directly from WDI, letting us know the importance attached to R&D by both the government and firms of each country. It seems that this factor should strengthen innovation enthusiasm and efficiency.
6. Structure of R&D expenditure sources (Govrd). Defined as the part of the government in the total R&D expenditure, this variable will give us the idea about the heterogeneity of public and private R&D inputs.
7. Language distance (Lang). Referring to the data of West and Graham [66], language distance measures the degree of difficulty of learning English for different countries. As the global language, English fills the gap in international communication and is used for paper writing and

information diffusion, globally speaking. It is assumed that a closer language distance leads to a higher level of international R&D spillovers.

8. Country dummy variable (G8). Following CH and its followers, a country dummy variable is introduced into our model so as to distinguish those most powerful and R&D-intensive countries, namely G8 nations.

Table 1 displays the sources of variables.

Table 1. Variable selection and sources.

Variable Type	Abbreviation	Source
Output variable	DPAT	Domestic patents: Patents Statistics of OECD database
	USPAT	US patents: the United States Patent Office
	PCTPAT	PCT patents: Patents Statistics of OECD database
	PAP	Scientific papers: Science and Engineering Indicators
Input variable	RDD	Domestic R&D capital stock: Science, Technology and Innovation of UNESCO's database
	RDF	Foreign R&D capital stock: Science, Technology and Innovation of UNESCO's database
	L1	Full-time equivalent of researchers: WDI and UNESCO's database
	L2	Full-time equivalent of R&D personnel: WDI and UNESCO's database
Environmental variable	IT	Internet coverage: WDI
	HK	Human capital: UNESCO's database
	Srv	Service industry development level: WDI
	Hightec	High-tech industry development level: WDI
	Gerd	Intensity of R&D expenditure: WDI
	Govrd	Structure of R&D expenditure sources: WDI
	Lang	Language distance: West and Graham (2004)
	G8	Country dummy variable: G8 countries (1) or not (0)

4.2. Data Sources

We use country-level data for 44 countries observed between 1996 and 2013, which are collected primarily from Research and Development Statistics of OECD database, the United Nations Patent Office, Science, Technology and Innovation of UNESCO's database, World Development Indicators online database and Science and Engineering Indicators, as mentioned in Table 1. Data of exchange rate and PPP are from Prices and Purchasing Power Parities of OECD database.

The descriptive statistics are summarized in Table 2.

Table 2. Descriptive statistics of variables.

Variable	Unit	Mean	Standard Deviation	Minimum	Maximum
DPAT	number	27,920.05	59,352.89	17.90	414,758.50
USPAT	number	2882.26	7823.08	1.25	57,265.88
PCTPAT	number	3950.69	14,832.05	0.17	104,182.90
PAP	number	22,155.19	70,348.78	15.00	704,936.00
RDD	USD at 2005 constant price	116,000,000	304,000,000	571,762	2,340,000,000
RDF	USD at 2005 constant price	18,100,000	26,100,000	213,116	180,000,000
L1	Full-time equivalent	124,709.60	245,326.40	1271.32	1,592,420.00
L2	Full-time equivalent	172,195.70	337,957.40	2034.10	3,532,817.00
IT	percent	39.99	29.77	0.01	96.55
HK	percent	54.42	22.31	5.00	127.24
Srv	percent	65.38	8.30	33.57	87.99
Hightec	percent	0.04	0.10	0	0.84
Gerd	percent	1.43	0.89	0.11	4.15
Govrd	percent	41.55	14.12	3.20	89.37
Lang	Non-dimensional	2.06	1.66	0	6

5. Empirical Results

Different from data envelopment analysis, stochastic frontier analysis can include only one variable as output at a time. However, intermediate R&D outputs comprise primarily patents and scientific papers, and patents can be further classified into domestic patents, PCT patents, and US patents in the statistical scheme. In fact, the majority of patent applicants just seek domestic patent protection, so that the number of domestic patents is considered to be the most explanatory and consequential patent indicator. Then, PCT patents and US patents are more related to those multinational corporations which are supposed to play an important role in international knowledge transfer and R&D spillovers. So, if international R&D spillovers really exist in the field of innovation, PCT patents and US patents could be more sensitive indicators to observe their effects. That is why special attention is also paid to these two kinds of patents. In this paper, we evaluate the effect of international R&D spillovers on innovation efficiency, by observing these four R&D outputs respectively.

Having concern for the negative influence of multicollinearity on the robustness of our estimation when a set of environmental variables are taken into account, we undertook a test of variance inflation factors (VIF) as the first step of our empirical procedure. The result is reported in Table 3, as follows.

Table 3. Test of multicollinearity (variance inflation factors (VIF) test).

Variable	RDD	RDF	L1	IT	HK	Srv	Hightec	Gerd	Govrd	Lang	Mean
VIF value 1	26.70	12.25	15.67	4.22	2.72	2.46	2.19	2.00	1.86	1.34	7.14
VIF value 2	13.60	5.38	7.90								8.97

The mean of VIF values of explanatory variables is 7.14, less than 10. Thus, we can exclude the botheration of collinearity and continue the estimation using maximum likelihood method by FRONTIER 4.1 based on the efficiency model of Battese and Coelli [60,61].

5.1. Scientific Papers as Output

The estimation result is reported as following in Table 4 when the number of scientific papers is viewed as output variable.

In Table 4, column (1) reports the estimation result based on the model of Battese and Coelli [60] which excludes the existence of technical inefficiency while supposing innovation efficiency is not time-varying. In columns (2)–(9), we re-estimate the innovation equations based on the model of Battese and Coelli [61], considering the influence of technical inefficiency. As it turns out, there is a large consensus among the nine regression results. What is more, both LR test values and log-likelihood values are so large that $\sigma_u^2 = 0$ is significantly rejected, which proves the model specification is reasonable. In addition, all ML estimates for σ^2 and γ are different from zero significantly at 1% level, which means the impact of technical inefficiency is substantial across the observed countries. γ is distributed between 0.665–0.991, which indicates the variance of technical inefficiency is the main source of the total variance from both technical inefficiency and random shocks and further backs our model specification. The sum of the coefficients of RDD, RDF, and L1 is located at 1.011–1.049, which is consistent with the assumption that returns to scale are marginally increasing in current R&D production.

The upper panel of Table 4 displays the regression result of knowledge production function, from which some sensible conclusions are obtained. First, domestic R&D capital stock plays a significantly positive role in the production of scientific papers. Second, foreign R&D capital stock makes an even larger contribution than domestic R&D capital stock. This conclusion can be explained to some extent by occurrent academia globalization characterized by international student flows [34,67], brain circulation [36], international coauthorship [68,69] and so on. Scientific papers are communications of new research achievements which underlie the precedent fruits of other scholars all around the world. For those emerging and developing countries, learning from outside is the most convenient way to equip themselves with innovation capacity so that more and more developing countries are becoming involved in international coauthorship [69]. Third, more researchers lead to more scientific papers, while researchers are the indispensable factor of innovation production.

Table 4. Estimation result when the number of scientific papers published is considered as an output variable.

R&D Output (PAP)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RDD	0.445 *** (6.972)	0.061 * (1.659)	0.181 *** (5.267)	0.097 ** (2.392)	0.157 *** (4.345)	0.095 *** (2.687)	0.232 *** (6.521)	0.119 *** (3.364)	0.166 *** (4.281)
L1	0.692 *** (18.644)	0.287 *** (9.038)	0.429 *** (15.180)	0.413 *** (14.864)	0.464 *** (15.837)	0.443 *** (14.458)	0.454 *** (15.490)	0.444 *** (14.825)	0.494 *** (14.025)
RDF	0.525 *** (9.119)	0.676 *** (15.631)	0.403 *** (11.663)	0.514 *** (10.456)	0.394 *** (11.020)	0.485 *** (12.849)	0.325 *** (9.024)	0.482 *** (12.790)	0.389 *** (9.981)
Constant (1)	−13.251 *** (−28.660)	−3.168 *** (−11.071)	−4.695 *** (−19.690)	−4.127 *** (−14.678)	−4.719 *** (−17.868)	−4.299 *** (−17.075)	−5.146 *** (−21.513)	−4.693 *** (−17.673)	−5.364 *** (−21.631)
IT		−0.590 *** (−7.385)							−0.372 *** (−9.743)
HK			−4.482 *** (−3.144)						−0.137 * (−1.651)
Srv				−16.21 *** (−3.658)					2.397 *** (6.154)
Hightec					0.645 *** (9.981)				0.313 *** (6.599)
Gerd						−3.386 *** (−4.424)			−0.750 *** (−7.261)
Govrd							−4.004 *** (−5.761)		−1.263 *** (−11.468)
Lang								1.586 *** (4.911)	0.129 *** (4.604)
G8	−2.164 *** (−15.380)	−0.314 (−1.083)	−5.222 ** (−2.073)	−6.506 *** (−2.581)	−9.365 *** (−15.777)	−4.873 *** (−2.780)	−6.644 *** (−3.474)	−5.943 *** (−3.576)	−0.362 * (−1.835)
Constant (2)		0.972 *** (5.508)	9.161 *** (4.444)	54.962 *** (3.668)	−5.067 *** (−9.220)	−7.007 *** (−3.316)	9.423 *** (8.081)	−12.620 *** (−4.026)	−2.739 * (−1.828)
σ2	2.939 *** (4.267)	0.925 *** (5.974)	4.121 *** (2.736)	7.536 *** (3.743)	4.998 *** (17.125)	3.907 *** (4.124)	3.090 *** (4.428)	5.173 *** (4.389)	0.286 *** (7.683)
γ	0.975 *** (161.448)	0.940 *** (76.539)	0.981 *** (135.351)	0.991 *** (377.559)	0.986 *** (697.989)	0.981 *** (210.443)	0.972 *** (126.906)	0.985 *** (256.267)	0.665 *** (10.664)
Log-likelihood	−200.129	−514.501	−541.130	−581.974	−588.151	−562.817	−559.468	−574.134	−385.824
LR test value	1006.031	385.640	332.382	250.692	238.340	289.007	295.706	266.373	642.993
Observations	792	792	792	792	792	792	792	792	792

Note: The t-statistics in parentheses are below the coefficient estimates. ***, **, * indicate the significance at 1%, 5%, 10% level, respectively. Constant (1) and (2) are for the knowledge production function (KPF) and technological inefficiency function respectively. In column (1), G8 is added into the KPF as a control variable.

As discussed above, international R&D spillovers really exist and are even more important than domestic R&D expenditure in the field of the publication of scientific papers.

Turning to the middle panel of Table 4, the result of technical inefficiency function can be found. In accordance with our expectation and assumption, Internet coverage, the enrollment rate of tertiary education, the ratio of total R&D expenditure to GDP, and the part of the government in the total R&D expenditure positively influence innovation efficiency. The Internet is the vehicle of information, which makes it convenient for R&D employees to search, acquire, and share R&D results, therefore, promoting the absorption of international R&D spillovers and improving innovation efficiency [70]. Being in possession of tertiary education is completely necessary for scientific paper writing and publication, even if a large part of papers is merely based on the graduation thesis. The higher the ratio of total R&D expenditure to GDP, the more resources are devoted to R&D, which incurs R&D economies of scale. In addition, the R&D investment of government is more efficient than that of the private sector in scientific papers. Indeed, most universities and other academic institutes in charge of research are supported totally or partly by governments. Inconsistent with our supposition, high-tech industry and service industry development levels restrain the production efficiency of scientific papers. A plausible reason is that scientific papers are born mostly in universities and other research institutes which are independent of high-tech industry and service industry which pay more attention to the practicability and profitability of R&D outcome. By the way, language distance causes innovation inefficiency while G8 countries benefit more from a certain amount of R&D inputs.

5.2. PCT Patents as Output

Then, we substitute the number of scientific papers published with the number of PCT patents granted as an output variable, as reported in Table 5.

As revealed in Table 5, domestic R&D capital stock remains a substantial contributor to PCT patents, whereas the number of domestic R&D personnel does not really matter as seen in column (9), and even becomes significantly negative as seen in columns (2)–(8). We attempt to disentangle this confusing conclusion from two angles. On one hand, not all researchers in our data set take part in patents' R&D which is out of reach of professors in social sciences. On the other hand, it is the quality rather than quantity of researchers that determines the position in the fierce global competition of PCT patents. Similarly, there is no evidence that international R&D spillovers exist in the country-level production of PCT patents. In fact, although foreign technologies can be introduced and absorbed by learning and imitating as the consequence of international trade and investment, the exclusiveness of core knowledge requested in the process of R&D of PCT patents cannot be ignored. Furthermore, extreme dependence on foreign technological transfer is somewhat of a chronic killer of innovativeness for those countries lagging in technology, especially considering that most of the multinational corporations who are inclined to apply for PCT patents are from the developed countries.

As to innovation inefficiency function, wider Internet coverage, a larger amount of human capital, more intensive R&D expenditure, and closer language distance continue to be favorable to innovation efficiency as seen in Table 4. Then, two differences are found yet: First, the development of high-tech industry tends to boost the innovation efficiency of PCT patents. It makes sense when we are aware of the fact that most PCT patents are granted to the high-and-new-tech enterprises instead of universities or academic institutes. Second, the government's R&D investment is less powerful than that of private actors, which gives guidance to policymakers of governments about how to allocate R&D resources and subsidy, fully considering the stronger innovative motivation of private sector. In fact, those developed countries, especially G8 countries, are characterized by a higher ratio of private R&D investment, while less developed nations are more dependent on public R&D activities.

Table 5. Estimation result when the number of PCT patents is considered as an output variable.

R&D Output (PCTPAT)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RDD	0.842 *** (9.957)	1.537 *** (25.266)	1.709 *** (34.157)	1.601 *** (28.145)	1.695 *** (34.505)	0.878 *** (15.322)	1.375 *** (17.881)	1.579 *** (27.233)	0.979 *** (14.574)
L1	0.082 (1.059)	−0.487 *** (−8.725)	−0.752 *** (−18.973)	−0.621 *** (−12.431)	−0.638 *** (−14.659)	−0.237 *** (−5.208)	−0.451 *** (−7.369)	−0.664 *** (−14.996)	−0.073 (−1.163)
RDF	0.518 *** (10.647)	−0.177 *** (−4.014)	−0.093 ** (−2.143)	−0.080 * (−1.701)	−0.209 *** (−4.917)	0.313 *** (6.887)	0.035 (0.668)	0.000 (−0.003)	0.036 (0.715)
Constant (1)	−15.707 *** (−27.726)	−11.336 *** (−29.324)	−12.948 *** (−43.517)	−12.749 *** (−38.090)	−12.063 *** (−35.684)	−10.020 *** (−27.873)	−12.548 *** (−33.406)	−13.218 *** (−37.930)	−9.215 *** (−24.826)
IT		−0.497 *** (−12.184)							−0.214 *** (−9.077)
HK			−1.515 *** (−6.834)						−0.145 ** (−2.360)
Srv				−7.494 *** (−3.200)					0.362 (1.246)
Hightec					−1.208 *** (−5.098)				−0.076 ** (−2.441)
Gerd						−0.987 *** (−21.446)			−0.548 *** (−8.872)
Govrd							3.448 *** (5.235)		0.364 *** (3.836)
Lang								0.639 ** (2.227)	0.113 *** (6.270)
G8	−1.526 *** (−5.232)	−0.919 *** (−3.719)	−1.961 *** (−2.916)	−4.431 ** (−2.204)	−2.460 *** (−3.767)	−0.326 *** (−3.447)	−2.204 *** (−3.116)	−6.988 *** (−1.783)	−0.259 *** (−2.642)
Constant (2)		2.080 *** (17.598)	5.472 *** (10.028)	28.877 *** (3.414)	−5.918 *** (−3.927)	1.608 *** (14.993)	−13.290 *** (−4.535)	−4.243 (−1.518)	−0.828 (−0.748)
σ2	3.373 *** (4.242)	0.769 *** (8.221)	1.469 *** (5.430)	3.130 *** (2.970)	1.879 *** (5.830)	0.400 *** (14.437)	1.440 *** (4.154)	3.602 ** (2.164)	0.348 *** (13.645)
γ	0.961 *** (99.653)	0.903 *** (44.775)	0.928 *** (54.037)	0.961 *** (69.997)	0.948 *** (89.669)	0.927 *** (26.955)	0.885 *** (24.016)	0.962 *** (54.494)	0.953 *** (43.927)
Log-likelihood	−425.422	−722.500	−778.561	−827.348	−776.670	−680.170	−809.728	−832.885	−580.927
LR test value	998.697	414.038	301.916	204.341	305.698	498.699	239.582	193.268	697.184
Observations	792	792	792	792	792	792	792	792	792

Note: The t-statistics in parentheses are below the coefficient estimates. ***, **, * indicate the significance at 1%, 5%, 10% level, respectively. Constant (1) and (2) are for the knowledge production function and technological inefficiency function respectively. In column (1), G8 is added into the KPF as a control variable.

5.3. US Patents as Output

Next, the number of US patents is treated as the output variable in the following regressions, the result of which is presented in Table A1 located in Appendix B.

Overall, the regression result of Table A1 corresponds to that of Table 5, which further corroborates the steadiness of the empirical analysis. Here, no strong and robust proof can be obtained to support the existence of positive international R&D spillovers on the innovation process when US patents are taken as an output.

5.4. Domestic Patents as Output

Finally, we focus on the influence of international R&D spillovers on the innovation efficiency of domestic patents. Table 6 shows the regression result of the re-examination.

In Table 6, the empirical result of KPF panel is far more stable than that of Tables 5 and A1. In addition, we detect the positive effect of the number of researchers on the outcome of domestic patents, while no statistically robust proof is found in this point in Tables 5 and A1. As documented in literature review, compared to PCT patents and US patents, domestic patents are more accessible and obtainable because of its lower cost and threshold. Actually, as in Table 2, the average amount of domestic patents is ten times larger than that of US patents, seven times than that of PCT patents, and the gap is substantially wider in BRICS than in OECD countries. Then, the significantly negative international R&D spillovers are eye-catching here. However, this discovery is never groundbreaking. Trace back to Reference [71] which extends CH's model and allows for country-specific spillover effects by using interactive dummy variables, international R&D spillovers seem to have a negative impact on TFP for a group of countries, like the USA, Canada, and West Germany. What explains this result by the author is that the leading knowledge producers who focus on a large amount of domestic R&D seem to be poor at taking advantage of relatively small foreign R&D spillovers. In addition, from the point of international patent competition, our result supports the conclusion of Porter and Stern [72] that idea production by other countries raises the bar for producing new patents, outweighing the positive effect of international R&D spillovers. And of course, purchasing foreign patent license is somehow more attractive than independent R&D for some benefit-seeking firms, which enlarges the worldwide R&D disparity.

Switching to the environmental factors, the obvious change happens in language distance, while other variables are relatively constant. In fact, language barrier, which is removed when applying for domestic patents, is just one of the thresholds that applicants from non-English-speaking regions are faced with in the process of dealing with PCT patents and US patents.

Table 7 presents the summarized result of above regressions.

When we take a closer look at the impact of international R&D spillovers on four R&D output variables, detailed and noteworthy conclusions are reached. First, domestic R&D expenditure is always important no matter which output variable is chosen as the final R&D outcome, while the quantity of domestic researchers contributes positively to only scientific papers and domestic patents, instead of PCT patents or US patents. Second, international R&D spillovers do exist in terms of the production of scientific papers, but they are negative when it comes to domestic patents while there is no significant evidence of spillover effect for PCT patents or US patents. Finally, wider Internet coverage, larger human capital, and more intensive R&D expenditure are generally advantageous to the improvement of innovation efficiency.

Table 6. Estimation result when the number of domestic patents is considered as an output variable.

R&D Output (DPAT)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RDD	0.762 *** (10.262)	0.627 *** (11.091)	0.716 *** (12.106)	0.647 *** (0.936)	0.648 *** (11.260)	0.525 *** (7.927)	0.386 *** (5.941)	0.692 *** (13.349)	0.889 *** (13.371)
L1	0.277 *** (3.973)	0.875 *** (38.562)	0.788 *** (16.029)	0.809 *** (11.790)	0.901 *** (17.966)	0.859 *** (16.220)	1.019 *** (19.303)	0.697 *** (14.414)	0.571 *** (7.591)
RDF	−0.131 *** (−3.010)	−0.373 *** (−11.376)	−0.428 *** (−8.809)	−0.342 *** (−8.814)	−0.573 *** (−11.875)	−0.329 *** (−6.898)	−0.336 *** (−7.066)	−0.385 *** (−7.661)	−0.511 *** (−7.557)
Constant (1)	−3.962 *** (−5.873)	−6.427 *** (−12.182)	−6.010 *** (−13.001)	−6.595 *** (−6.745)	−3.344 *** (−7.915)	−2.843 *** (−7.300)	−4.246 *** (−10.024)	−5.054 *** (−12.502)	−4.632 *** (−8.237)
IT		−0.232 *** (−48.695)							0.035 (1.073)
HK			−0.583 *** (−6.968)						−0.661 *** (−11.804)
Srv				0.017 (0.019)					2.358 *** (4.987)
Hightec					−0.275 *** (−9.868)				−0.167 *** (−4.686)
Gerd						−0.124 ** (−2.474)			0.300 *** (4.622)
Govrd							0.657 *** (11.348)		0.673 *** (7.732)
Lang								−0.065 ** (−2.000)	−0.011 (−0.710)
G8	−0.153 (−0.919)	−0.038 (−0.118)	−0.877 *** (−2.767)	−0.178 (−0.184)	−0.553 *** (−4.830)	−0.390 *** (−4.222)	−0.395 *** (−12.542)	−1.800 *** (−14.541)	−0.613 *** (−4.714)
Constant (2)		0.080 (0.822)	2.223 *** (8.438)	−0.017 (−0.033)	−0.481 ** (−2.426)	2.495 *** (7.131)	−2.106 *** (−11.394)	0.710 *** (6.016)	−9.555 *** (−5.335)
σ2	6.130 *** (4.265)	0.606 *** (26.198)	0.577 *** (14.043)	0.613 (1.253)	0.519 *** (18.616)	0.591 *** (38.256)	0.539 *** (23.373)	0.550 *** (25.369)	0.405 *** (18.456)
γ	0.984 *** (245.386)	0.024 (1.424)	0.045 (0.527)	0.000 (0.066)	0.005 (0.151)	1.000 *** (12.250)	0.000 (1.089)	0.049 *** (15.980)	0.000 (0.022)
Log-likelihood	−338.866	−915.952	−889.779	−915.701	−874.625	−908.679	−879.048	−890.409	−765.449
LR test value	1147.901	11.094	63.440	11.596	93.746	25.640	84.901	62.180	312.100
Observations	792	792	792	792	792	792	792	792	792

Note: The t-statistics in parentheses are below the coefficient estimates. ***, ** indicate the significance at 1%, 5% level, respectively. Constant (1) and (2) are for the knowledge production function and technological inefficiency function respectively. In column (1), G8 is added into the KPF as a control variable.

Table 7. Summarized result of above regressions.

Output Variable		Scientific Papers	PCT Patents	US Patents	Domestic Patents
Input variable	RDD	+	+	+	+
	L1	+	/	/	+
	RDF	+	/	/	—
Environmental variable	IT	+	+	+	+
	HK	+	+	+	+
	Srv	/	/	+	—
	Hightec	—	+	+	+
	Gerd	+	+	+	+
	Govrd	+	—	—	—
	Lang	—	—	—	+
	G8	+	+	+	+

Note: +, — and / represent positive, negative and uncertain influence, respectively.

5.5. Robustness Checks

To gauge the robustness of the finding, we perform sensitivity analysis from four aspects.

1. Adoption of alternative lag periods. It is believed that there exists a time lag from R&D input to output. A two-year lag is proved to be appropriate by conducting a correlation and regression analysis and used extensively in precedent researches [72,73], although no attention is paid to time lag in numerous papers [47,74]. Our one-year and two-year lag models both conclude results similar to those reported above.
2. Re-examination using different depreciation rates of R&D capital. In spite of the popularity of 15% depreciation rate, 20% [9,70], and 5% [19] are employed as well in practice. Depreciation which levels directly influences the R&D capital stock, further our regressions. Our re-examinations with those two alternative depreciation rates do not change the interpretation of primary conclusions.
3. Variable substitution. Given the inherent complexity, foreign R&D capital stocks have no widely accepted measure [18]. Returning to CH, we operate, once again, the regressions following their way of measurement of foreign R&D capital stock. Moreover, L1 is substituted with L2, ceteris paribus. Then, the key points remain unchanged, although some variables turn out to be less statistically robust.
4. Considering that knowledge is a basket of heterogeneous and sequential layers and referring to the two-factor knowledge production function put forward by Jaffe [75] and Acs et al. [64], which relates knowledge output to two parts, namely R&D performed by industry and research conducted by universities, we use the number of scientific papers as a proxy of research by universities and then add it into the KPFs of PCT patents, US patents, and domestic patents respectively as a complementary input. The results are presented in Tables A2–A4 located in Appendix B. We find our empirical results and conclusions are very robust to different forms of KPF.

6. Conclusions and Discussion

Drawing inspiration from historical studies that have shown a country's total factor productivity depends on not only its own R&D capital stock but also the R&D capital stocks of its trade partners, the main aim of this paper is to examine whether positive international R&D spillovers also exist in the direct innovation production process. In other words, we would like to explore whether foreign R&D input contributes to a country's innovation efficiency. Our country-level panel data set covers 44 countries during 1996–2013. Fully considering the heterogeneity of different R&D outcomes, four output variables are observed separately, namely scientific papers, PCT patents, US patents, and domestic patents.

Our econometric analysis clearly suggests that positive international R&D spillovers really exist in the production of scientific papers. However, when we take PCT patents or US patents as R&D

output, we cannot observe the same effect. Furthermore, strong evidence supports that increased foreign R&D input makes it more difficult for a country to produce domestic patents. Then, relative to scientific papers, patents are undoubtedly more related to a country's innovative and technological level. Hence, we are convinced that depending on R&D spillovers from advanced nations is neither the right way for emerging economies to catch up in innovative competitiveness nor a sustainable model for developing countries to fill the technical gap. Local R&D capital stock, instead, is an essential contributor to all four R&D outputs, so raising internal R&D expenditure is actually the key to improving innovation level and sustainable development ability.

We address the issue of parameter heterogeneity by introducing a large array of institutional sources of heterogeneity as environmental variables. There is abundant evidence that environmental factors play important roles in innovation efficiency. For instance, countries with wider Internet coverage, larger human capital, and more intensive R&D expenditure always benefit more from their own and foreign R&D inputs, while language distance is a barrier to innovation production, except for domestic patents. G8 countries take advantage of their front-runner status, while private investment is more efficient in patent R&D. It is necessary for policymakers to build a favorable institutional framework to improve a country's innovation efficiency.

Coe and Helpman [9] in 1995 already proved the existence of the effect of international R&D spillovers on a country's productivity based on the data of OECD countries. As mentioned in the literature review, their conclusion has been reaffirmed again and again by different data and methods. Until recently, Nortin et al. [11] emphasized in their research the importance of imports to the productivity growth of ASEAN countries through international R&D spillovers. It seems that the whole world is benefitting from the R&D inputs of advanced countries. However, while international R&D spillovers are helping countries to improve technologies, the worldwide technological gap still exists, and is even enlarging. In fact, Cherif [76] built a model and found powerful cross-country evidence that less technologically advanced countries are more vulnerable to Dutch disease and it is a self-reinforcing process. Our research reaches a similar conclusion that there is fierce cross-country innovation competition, and dependence of foreign R&D spillovers can weaken a country's innovation capacity. It is also a self-reinforced process. So only if developing countries raise the R&D inputs and develop their own R&D activities, they can fill the technological gap.

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Appendix A

The 44 countries observed in our empirical section are: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, China, Columbia, Croatia, Czech, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, India, Ireland, Italy, Kazakhstan, Lithuania, Japan, Luxembourg, Mexico, The Netherlands, New Zealand, Norway, Poland, Portugal, South Korea, Romania, Russia, Singapore, Slovakia, Slovenia, South Africa, Spain, Sweden, Turkey, Ukraine, the United Kingdom, and the United States.

Appendix B

Table A1. Estimation result when the number of US patents is considered as an output variable.

R&D Output (USPAT)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RDD	0.639 *** (5.417)	1.993 *** (22.227)	2.168 *** (30.582)	1.937 *** (17.185)	2.056 *** (28.396)	1.281 *** (27.669)	1.575 *** (14.810)	1.979 *** (24.885)	1.321 *** (12.855)
L1	−0.401 *** (−3.691)	−0.739 *** (−7.605)	−1.017 *** (−16.067)	−0.726 *** (−5.376)	−0.719 *** (−9.921)	−0.495 *** (−8.662)	−0.358 *** (−3.136)	−0.863 *** (−11.941)	0.011 (0.103)
RDF	0.289 *** (4.209)	−0.345 *** (−5.935)	−0.245 *** (−4.158)	−0.237 *** (−3.903)	−0.494 *** (−9.384)	0.163 *** (4.236)	−0.200 *** (−3.686)	−0.122 * (−1.923)	−0.306 *** (−6.322)
Constant (1)	−3.296 *** (−3.065)	−13.996 *** (−21.483)	−15.840 *** (−32.400)	−14.988 *** (−19.172)	−12.824 *** (−24.564)	−11.567 *** (−23.643)	−13.019 *** (−20.631)	−16.214 *** (−30.896)	−10.800 *** (−22.801)
IT		−0.389 *** (−7.412)							−0.039 (−1.045)
HK			−1.004 *** (−5.294)						−0.104 (−0.973)
Srv				−3.744 *** (−4.808)					−1.721 *** (−3.462)
Hightec					−0.801 *** (−10.982)				−0.466 *** (−8.901)
Gerd						−1.057 *** (−20.406)			−0.411 *** (−4.430)
Govrd							2.218 *** (6.901)		0.754 *** (3.845)
Lang								0.303 *** (4.323)	0.208 *** (6.461)
G8	1.421 *** (5.784)	−1.752 *** (−4.050)	−2.551 *** (−3.152)	−1.775 ** (−2.276)	−1.391 *** (−5.786)	−0.691 *** (−7.696)	−1.172 *** (−4.510)	−2.704 *** (−2.851)	−0.470 *** (−2.848)
Constant (2)		2.120 *** (9.016)	4.304 *** (8.667)	16.157 *** (5.153)	−2.095 *** (−5.017)	2.557 *** (59.744)	−7.000 *** (−5.452)	−0.369 (−0.599)	4.034 ** (2.261)
σ2	10.607 *** (4.144)	1.682 *** (7.422)	1.965 *** (5.687)	2.046 *** (5.373)	1.239 *** (10.611)	0.705 *** (25.248)	1.611 *** (8.997)	2.203 *** (4.820)	0.925 *** (12.603)
γ	0.977 *** (168.445)	0.918 *** (36.197)	0.879 *** (31.869)	0.913 *** (34.884)	0.919 *** (44.258)	1.000 *** (29.135)	0.957 *** (60.498)	0.888 *** (33.710)	0.966 *** (85.136)
Log-likelihood	−683.313	−1040.753	−1047.858	−1064.306	−964.183	−946.042	−1040.582	−1063.644	−874.109
LR test value	873.995	189.752	175.544	142.646	342.893	379.175	190.095	143.970	523.041
Observations	792	792	792	792	792	792	792	792	792

Note: The t-statistics in parentheses are below the coefficient estimates. ***, **, * indicate the significance at 1%, 5%, 10% level, respectively. Constant (1) and (2) are for the knowledge production function and technological inefficiency function respectively. In column (1), G8 is added into the KPF as a control variable.

Table A2. Estimation result taking PCT patents as R&D output with adding scientific papers into knowledge production function (KPF).

R&D Output (PCTPAT)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RDD	0.622 *** (7.968)	1.544 *** (30.968)	1.621 *** (34.687)	1.548 *** (31.279)	1.595 *** (36.410)	0.761 *** (17.648)	1.144 *** (15.340)	1.532 *** (29.535)	0.875 *** (14.298)
L1	−0.182 *** (−2.738)	−0.710 *** (−12.997)	−0.916 *** (−22.710)	−0.872 *** (−19.371)	−0.912 *** (−23.515)	−0.458 *** (−12.355)	−0.690 *** (−12.258)	−0.898 *** (−20.637)	−0.235 *** (−3.874)
RDF	0.112 ** (2.363)	−0.265 *** (−6.251)	−0.264 *** (−5.790)	−0.281 *** (−6.112)	−0.447 *** (−11.210)	0.189 *** (5.139)	−0.179 *** (−4.059)	−0.233 *** (−4.643)	−0.105 ** (−2.198)
PAP	0.576 *** (14.354)	0.289 *** (6.120)	0.414 *** (9.929)	0.468 *** (12.321)	0.566 *** (16.920)	0.415 *** (12.913)	0.600 *** (16.829)	0.473 *** (11.897)	0.390 *** (10.291)
Constant (1)	−8.430 *** (−10.975)	−10.448 *** (−28.675)	−10.821 *** (−28.797)	−10.297 *** (−26.869)	−8.850 *** (−23.748)	−7.014 *** (−18.784)	−7.957 *** (−15.282)	−10.578 *** (−26.163)	−7.056 *** (−15.715)
IT		−0.474 *** (−8.722)							−0.120 *** (−4.997)
HK			−1.519 *** (−4.370)						−0.081 (−1.417)
Srv				−6.975 ** (−2.277)					−0.044 (−0.168)
Hightec					−0.977 *** (−7.264)				−0.111 *** (−3.795)
Gerd						−0.867 *** (−25.301)			−0.424 *** (−7.315)
Govrd							2.172 *** (9.143)		0.771 *** (7.624)
Lang								0.538 * (1.720)	0.087 *** (4.807)
G8	−0.335 ** (−2.021)	−1.296 *** (−3.192)	−2.725 ** (−2.331)	−5.702 * (−1.834)	−1.493 *** (−3.827)	−0.368 *** (−5.496)	−1.072 *** (−3.872)	−9.171 (−1.587)	−0.234 ** (−2.463)
Constant (2)		1.656 *** (10.896)	4.796 *** (6.963)	26.079 ** (2.425)	−4.211 *** (−5.064)	2.101 *** (27.208)	−7.349 *** (−7.193)	−5.336 (−1.320)	−1.288 (−1.278)
σ2	2.267 *** (5.057)	0.884 *** (6.325)	1.733 *** (3.882)	3.193 ** (2.264)	1.007 *** (6.512)	0.289 *** (18.557)	0.562 *** (7.612)	4.120 * (1.836)	0.296 *** (14.290)
γ	0.954 *** (97.616)	0.899 *** (40.669)	0.934 *** (51.801)	0.962 *** (60.885)	0.910 *** (45.380)	1.000 *** (7079.120)	0.799 *** (16.405)	0.968 *** (61.151)	0.906 *** (23.382)
Log-likelihood	−334.059	−706.451	−744.031	−771.882	−676.359	−612.709	−686.694	−779.513	−539.632
LR test value	1036.657	313.293	238.133	182.431	373.477	500.777	352.806	167.169	646.930
Observations	792	792	792	792	792	792	792	792	792

Note: The t-statistics in parentheses are below the coefficient estimates. ***, **, * indicate the significance at 1%, 5%, 10% level, respectively. Constant (1) and (2) are for the knowledge production function and technological inefficiency function respectively. In column (1), G8 is added into the KPF as a control variable. The number of scientific papers is added into the knowledge production function as an input.

Table A3. Estimation result taking US patents as R&D output and adding scientific papers into KPF.

R&D Output (USPAT)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RDD	0.427 *** (3.397)	1.978 *** (23.250)	2.164 *** (29.538)	1.962 *** (20.010)	2.020 *** (29.628)	1.256 *** (26.190)	1.531 *** (16.964)	1.974 *** (24.576)	1.318 *** (13.253)
L1	−0.618 *** (−5.324)	−0.636 *** (−5.918)	−1.026 *** (−14.209)	−0.846 *** (−6.687)	−0.902 *** (−11.742)	−0.524 *** (−8.970)	−0.579 *** (−5.957)	−0.940 *** (−11.099)	−0.048 (−0.445)
RDF	0.055 (0.695)	−0.316 *** (−5.383)	−0.252 *** (−3.906)	−0.272 *** (−4.250)	−0.659 *** (−10.551)	0.107 ** (2.396)	−0.324 *** (−4.757)	−0.174 ** (−2.510)	−0.343 *** (−6.202)
PAP	0.370 *** (5.735)	−0.108 (−1.548)	0.020 (0.291)	0.112 * (1.761)	0.326 *** (5.804)	0.078 *** (2.763)	0.339 *** (6.142)	0.119 * (1.849)	0.086 (1.461)
Constant (1)	3.571 ** (2.263)	−14.269 *** (−22.203)	−15.739 *** (−26.312)	−14.650 *** (−20.693)	−10.489 *** (−14.770)	−10.593 *** (−19.079)	−10.900 *** (−15.340)	−15.582 *** (−24.418)	−10.306 *** (−17.633)
IT		−0.425 *** (−6.865)							−0.018 (−0.444)
HK			−0.990 *** (−5.055)						−0.094 (−0.880)
Srv				−3.324 *** (−4.107)					−1.730 *** (−3.632)
Hightec					−0.725 *** (−12.311)				−0.468 *** (−8.993)
Gerd						−1.041 *** (−18.314)			−0.382 *** (−3.097)
Govrd							2.002 *** (8.296)		0.822 *** (4.086)
Lang								0.275 *** (3.573)	0.196 *** (5.862)
G8	1.790 *** (5.740)	−1.693 *** (−4.567)	−2.559 *** (−3.082)	−2.002 ** (−2.336)	−1.232 *** (−6.394)	−0.775 *** (8.549)	−0.954 *** (−4.933)	−2.731 *** (−2.882)	−0.477 *** (−2.937)
Constant (2)		2.268 *** (10.257)	4.249 *** (8.016)	14.347 *** (4.459)	−1.509 *** (−4.258)	2.615 *** (46.566)	−5.840 *** (−5.916)	−0.292 (−0.436)	3.773 ** (2.167)
σ2	15.415 *** (4.173)	1.690 *** (7.858)	1.959 *** (5.616)	2.036 *** (5.022)	1.007 *** (11.326)	0.705 *** (18.260)	1.222 *** (10.071)	2.140 *** (4.488)	0.898 *** (12.569)
γ	0.985 *** (263.329)	0.929 *** (42.901)	0.877 *** (30.764)	0.899 *** (34.568)	0.903 *** (32.449)	1.000 *** (18.547)	0.947 *** (48.389)	0.879 *** (28.897)	0.965 *** (74.646)
Log-likelihood	−668.416	−1039.598	−1047.815	−1062.816	−948.065	−944.168	−1021.913	−1061.881	−872.961
LR test value	882.944	176.989	160.555	130.553	360.056	367.850	212.360	132.425	510.263
Observations	792	792	792	792	792	792	792	792	792

Note: The t-statistics in parentheses are below the coefficient estimates. ***, **, * indicate the significance at 1%, 5%, 10% level, respectively. Constant (1) and (2) are for the knowledge production function and technological inefficiency function respectively. In column (1), G8 is added into the KPF as a control variable. The number of scientific papers is added into the knowledge production function as an input.

Table A4. Estimation result taking domestic patents as R&D output and adding scientific papers into KPF.

R&D Output (DPAT)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RDD	0.744 *** (9.604)	0.661 *** (9.995)	0.794 *** (12.325)	0.738 *** (14.408)	0.643 *** (10.616)	0.555 *** (8.118)	0.384 *** (5.578)	0.657 *** (11.547)	0.881 *** (12.322)
L1	0.257 *** (3.388)	1.005 *** (14.061)	0.934 *** (16.163)	0.611 *** (9.522)	0.944 *** (14.263)	0.927 *** (14.478)	1.025 *** (16.854)	0.815 *** (13.647)	0.554 *** (7.844)
RDF	−0.153 *** (−2.939)	−0.325 *** (−5.984)	−0.289 *** (−5.333)	−0.247 *** (−4.779)	−0.527 *** (−8.341)	−0.244 *** (−4.508)	−0.336 *** (−6.456)	−0.321 *** (−5.668)	−0.524 *** (−7.939)
PAP	0.033 (0.789)	−0.241 *** (−4.445)	−0.328 *** (−6.509)	−0.058 (−1.195)	−0.057 (−0.634)	−0.156 *** (−3.390)	−0.001 (−0.016)	−0.096 ** (−2.071)	0.032 (0.581)
Constant (1)	−3.366 *** (−3.312)	−6.587 *** (−8.219)	−8.142 *** (−11.511)	−6.684 *** (−13.458)	−3.946 *** (−4.181)	−3.917 *** (−6.564)	−4.109 *** (−6.219)	−5.935 *** (−10.575)	−3.978 *** (−6.267)
IT		−0.139 (−1.418)							0.041 (1.447)
HK			−0.876 *** (−8.277)						−0.660 *** (−11.060)
Srv				1.716 *** (7.044)					2.354 *** (8.751)
Hightec					−0.264 *** (−5.341)				−0.169 *** (−5.540)
Gerd						−0.131 *** (−2.613)			0.303 *** (4.356)
Govrd							0.670 *** (8.683)		0.696 *** (6.653)
Lang								−0.048 * (−1.906)	−0.014 (−0.791)
G8	−0.130 (−0.674)	−0.820 (−0.724)	−0.582 ** (−2.311)	−0.622 *** (−7.840)	−0.510 *** (−3.558)	−0.415 *** (−4.268)	−0.383 *** (−5.061)	−1.724 *** (−13.708)	−0.621 *** (−6.959)
Constant (2)		0.739 ** (2.049)	3.181 *** (9.724)	−6.683 *** (−6.953)	−0.446 (−0.970)	2.583 *** (5.237)	−2.017 *** (−8.778)	0.556 *** (4.799)	−9.227 *** (−8.778)
σ2	6.395 *** (4.286)	0.633 *** (5.581)	0.539 *** (6.637)	0.554 *** (19.916)	0.529 *** (12.258)	0.573 *** (19.817)	0.537 *** (20.236)	0.583 *** (22.842)	0.404 *** (19.466)
γ	0.984 *** (256.878)	0.203 (1.629)	0.054 (0.320)	0.000 (0.149)	0.004 (0.064)	1.000 (1.319)	0.000 (0.374)	0.047 *** (35.135)	0.000 (0.304)
Log-likelihood	−338.574	−900.587	−867.713	−889.761	−873.706	−903.980	−878.944	−888.420	−765.263
LR test value	1140.122	31.107	96.854	52.760	84.869	24.321	74.393	55.441	301.755
Observations	792	792	792	792	792	792	792	792	792

Note: The t-statistics in parentheses are below the coefficient estimates. ***, **, * indicate the significance at 1%, 5%, 10% level, respectively. Constant (1) and (2) are for the knowledge production function and technological inefficiency function respectively. In column (1), G8 is added into the KPF as a control variable. The number of scientific papers is added into the knowledge production function as an input.

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