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Do External or Internal Technology Spillovers Have a Stronger Influence on Innovation Efficiency in China?

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Abstract: In this study, we bridge an important gap in the literature by comparing the extent to which external technology spillovers, as indicated by foreign direct investment (FDI), and internal technology spillovers, as indicated by university-institute-industry cooperation (UIC), influence innovation efficiency in China. We divide the innovation process into two sequential stages, namely the knowledge creation and technology commercialization stages, and employ a network data envelopment analysis approach to measure innovation efficiency at each stage. The spatial analysis of the distribution of knowledge creation efficiency and technology commercialization efficiency reveals the heterogeneity of innovation efficiency at the provincial level. Then, a panel data regression is used to analyze the effect of FDI and UIC on innovation efficiency at each stage, using data from 2009 to 2015 for 30 provinces in China. By comparing FDI with UIC, we find that FDI has a higher coefficient and stronger significance level at the knowledge creation stage, while only industry-institute linkages exhibit a stronger association with innovation efficiency at the technology commercialization stage.

Keywords: foreign direct investment; university-institute-industry cooperation; innovation efficiency; external and internal technology spillover; network DEA; China

1. Introduction

In the knowledge era, innovation is recognized as a driving force of sustainable economic development and innovation-driven growth is no longer the prerogative of high-income countries alone [1,2]. As a developing country, China has raised expenditure on research and development (R&D) markedly while also designing policies to enhance the country's innovation performance. However, while China's output of publications and patents is impressive, there are very few genuine innovations [3]. Against the backdrop of the "Silicon Valley Miracle" and "Cambridge Phenomenon", the output and transformation of genuine innovations play a pivotal role in economic growth [4]. As China's economic expansion has fallen to the so-called "new normal" pace [5], the pattern of heavy R&D investment in the long term is unsustainable, placing greater focus on increasing the contribution of innovation outputs to economic growth by improving innovation efficiency rather than the blind expansion of R&D expenditure. Hence, improving innovation efficiency must be the focus of national efforts to allocate innovative resources reasonably and facilitate indigenous innovation in order to sustain economic growth.

Increasing regional innovation performance mainly depends on two technology spillover effects. On the one hand, to accelerate scientific and technological innovation, host regions could absorb international technology spillovers as indicated by foreign direct investment (FDI) through imitation, competition, and personnel flows. This mechanism is defined as "external technology spillovers" herein. On the other hand, local R&D activities fostered by university-institute-industry cooperation (UIC) can encourage indigenous innovation by exploiting innovators' resources and

sharing complementarities among universities, institutes, and industry [6–8]. This mechanism is defined as “internal technology spillovers” herein. However, the empirical question of whether external or internal technology spillovers are most adept at improving innovation efficiency remains largely unexplored. The present study aims to bridge this gap in the body of knowledge on this topic.

Since the start of its reform and opening up era, China has attracted substantial foreign capital because of the country’s low labor costs and preferential tax policies, which, to some extent, have promoted technological progress and innovation. However, in recent years, FDI flows have slowed because of the weakened demographic dividend and narrowing technical gap between domestic and foreign enterprises. These factors have gradually reduced the role of FDI in improving innovation efficiency. Meanwhile, the level of human resources has gradually increased because of China’s continuously rising educational level. Indigenous innovation fostered by the UIC has thus begun to play an increasingly prominent role in improving innovation efficiency. This reason makes it necessary to compare the influences of FDI and UIC on innovation efficiency and identify which mechanism has the stronger influence.

Most previous research has tended to regard the innovation process as a “black box”, ignoring the internal structure and operating mechanisms of the innovation system. However, innovation is a complex process involving the consumption of a range of inputs, development of a scientific process, and production of a series of outputs that demands cooperation among all the actors of the innovation system [9–13]. As a result, cooperation efforts and innovative inputs and outputs differ from stage to stage. Based on the foregoing, to represent innovation efficiency in the whole process accurately, we refer to the definition of the innovation value chain [14,15] and divide the innovation process into the knowledge creation and technology commercialization stages. This consecutive process may include both an upstream sub-process (knowledge creation) and a downstream sub-process (technology commercialization) [16]. This fact suggests that the outputs generated in an upstream sub-process may become intermediate inputs in a downstream sub-process. To determine the appropriate production process that best represents innovation production, we employ the network data envelopment analysis (DEA) approach to measure innovation efficiency. From this perspective, a panel dataset is then built to investigate and compare the influence of FDI with that of UIC on innovation efficiency in each stage, covering 30 provinces in China from 2009 to 2015. The presented analysis offers specific policy actions to improve the use of internal and external technology spillovers.

The remainder of this paper is organized as follows. Section 2 reviews the literature and develops the hypotheses of the study. Section 3 presents the methodology and data collection approaches. Section 4 presents the empirical results. Finally, Section 5 concludes.

2. Literature Review and Hypotheses Development

2.1. External and Internal Technology Spillovers in Regional Innovation

This study brings together two strands of the literature. One focuses on the influence of external technology spillovers, as indicated by FDI, on innovation efficiency, while another discusses fostering local innovation performance through UIC to achieve technological progress.

Within the former stream of the literature, a number of studies have analyzed the influence of FDI on innovation performance through three major effects: the promotion effect, inhibition effect, and threshold effect. In terms of the promotion effect on knowledge creation, Vahter [17] shows that FDI can promote the flow of knowledge from foreign countries to domestic enterprises. According to Fu [18], FDI has significantly positive effects on managerial knowledge spillovers to local firms, as demonstrated by the author’s empirical evidence of their effects through the diffusion of management practices. With regard to the promotion effect on technology commercialization, Li et al. [19] investigate the degree to which the presence of FDI influences technology commercialization by emerging market firms and find that the diversity of industries with a foreign presence contributes to technology commercialization by Chinese firms. Girma et al. [20] show

that FDI promotes new product sales by China's domestic firms provided that they have sufficiently high R&D intensity and good access to financial resources.

As for the inhibition effect, Hou et al. [21] show that FDI as a source of external knowledge has a significant negative impact on green innovation growth but with different constraints on R&D levels among industries. Elmawazini and Nwankwo [22] claim that FDI has had little impact on the industrial development and global competitiveness of countries in sub-Saharan Africa and has rather widened the gap between them and developed countries. However, Pan [23] finds a threshold effect on external technology spillovers in regional enterprises. FDI in western China has not crossed the threshold (i.e., it has not positively influenced innovation performance), while the spillover effect of FDI in the eastern region is decreasing and that in the central region is gradually increasing. Finally, by using the theory of competitive dynamics, Meyer and Sinani [24] suggest that the spillover effect of FDI is closely related to human capital, income, and the institutional framework.

Within the strand of the literature related to the impact of UIC on innovation, the rapid development of knowledge and technology has prevented any enterprise from forging a technological advantage in all sectors [25]. Maietta [9] examines whether university-firm R&D collaboration has positive effects on process innovation, finding that university policies that aim to commercialize R&D outputs negatively affect regional innovation. Indeed, among the linkages cultivated by universities, institutes, and industry, only contractual relationships have a direct and significant effect on innovation, whereas relational activities simply serve to promote and support contractual activities [26]. However, more studies confirm that UIC has a positive impact on innovative outputs. For example, in terms of industry-university linkages, George et al. [27] show that companies with university linkages have lower R&D expenses and higher levels of innovative output. Likewise, university-firm R&D cooperation affects process innovation in low-tech industries [9]. UIC-subsidized universities and the presence of a formal UIC management mechanism drive improvements in academic innovation performance [28]. As for the industry-institute relationship, the technology novelty of industrial innovation is positively related to the collaboration between industry and institutes; in other words, the greater the collaboration, the higher is the technology novelty of the innovation [29]. Referring to institute-university cooperation, Gemünden et al. [30] claim that technology-oriented external relationships such as linkages to universities and research institutes are a critical factor for the success of a firm's technological innovation, which in turn is the main determinant of commercial innovation success.

Summing up, relatively few studies have quantified the impact of FDI and UIC on innovation efficiency. Moreover, innovation has been characterized as a process from input to output [31] that combines knowledge creation and knowledge commercialization. As innovation activities and UIC could occur in the stages of knowledge creation and technology commercialization, it is necessary to employ different indicators to measure innovation efficiency in each stage. In addition, no study comparatively analyzes the impact of FDI and that of UIC on innovation efficiency from the perspective of multistage innovation. These are the considerations upon which the study relies to offer novel evidence in this field.

2.2. Hypotheses Development

2.2.1. FDI and Innovation Efficiency

A rising number of studies are exploring the FDI–innovation relation, mostly confirming the positive influence of FDI on innovation activities in the host country [32]. Multinational companies (MNCs), as the main providers of FDI, enter host countries and compete with domestic firms and other MNCs. To seek competitive advantage, the R&D institutions of MNCs are likely to increase their R&D investment and cooperate with the host country's R&D institutions to localize their R&D activities. In doing so, the development and application of high-technology products bring the host country a larger quantity of innovative outputs in the technology commercialization stage. Therefore, FDI has a

positive effect on innovative output in the technology commercialization stage through direct external technology spillover effect.

In addition, through its indirect external technology spillover effect, FDI could also positively influence innovative outputs in the knowledge creation stage. First, as technological innovation is passed through the innovation value chain, MNCs can spill technology into the knowledge creation stage through forward correlation spillovers in the innovation value chain [33]. More specifically, to better carry out R&D activities in the technology commercialization stage, MNCs would employ professional talents and obtain knowledge from the upstream actors in the value chain such as institutes and universities where the spillover occurs. To achieve the high requirements of MNCs in the technology commercialization stage, institutes and universities in the knowledge creation stage must then improve the quality of knowledge and innovative outputs and train superior technicians and R&D personnel for MNCs. In other words, FDI can positively influence innovative outputs in the knowledge creation through forward correlation spillovers in the innovation value chain. Hence, we propose the first set of hypotheses:

Hypothesis 1a (H1a). *FDI positively affects innovation efficiency in the knowledge creation stage.*

Hypothesis 1b (H1b). *FDI positively affects innovation efficiency in the technology commercialization stage.*

2.2.2. UIC and Innovation Efficiency

Few studies have explored the influence of UIC on innovation efficiency in the context of multistage innovation. While UIC can enhance innovation performance [27,34], the nature of knowledge flows among universities, institutes, and industry and the consequent innovation-related benefits may differ according to the interaction channel and innovation stage [9]. Furthermore, innovation actors either complement or substitute each other, in the latter case mostly because researchers in universities or institutes may be time constrained and less able to engage in technology and product transformation projects.

Industry-university cooperation and industry-institute cooperation enable enterprises to access the latest scientific inventions as well as the cutting-edge science and technology provided by universities and institutes [35]. Unlike enterprises that typically acquire external knowledge only through the publication of journal papers and purchase of patents, such cooperation can help the R&D personnel in the enterprise cooperate with the R&D experts in universities and institutes [36]. This degree of cooperation in diverse academic fields greatly increases the opportunity for innovation subjects to acquire tacit knowledge [37]. Further, some studies have pointed out that the motivation of enterprises to cooperate with universities and institutes is not only for the commercialization of innovative outputs, but also for the opportunity to access highly trained and talented students as well as emerging technologies [38,39]. In addition, as universities and institutes are characterized by a strong R&D capacity and abundant labor resources, respectively, cooperation between universities and institutes could complement their individual advantages when carrying out joint R&D projects. That is, university-institute cooperation, industry-university cooperation, and industry-institute cooperation may help improve innovation efficiency. Therefore, we hypothesize the following:

Hypothesis 2a (H2a). *UIC positively affects innovation efficiency in the knowledge creation stage.*

Hypothesis 2b (H2b). *UIC positively affects innovation efficiency in the technology commercialization stage.*

2.2.3. FDI and UIC

Finally, both external and internal technology spillovers can improve innovation performance in developing countries. Some studies confirm that the core technology of foreign countries does

not flow into the host country through FDI, because MNCs are likely to shift production to Chinese firms rather than transfer technology in order to maintain their technological superiority [40]. Thus, achieving genuine innovations should rely on indigenous innovation in the host country, namely internal technology spillovers through UIC. Hence, we put forward the following set of hypotheses:

Hypothesis 3a (H3a). *UIC shows a stronger influence on innovation efficiency than FDI in the knowledge creation stage.*

Hypothesis 3b (H3b). *UIC shows a stronger influence on innovation efficiency than FDI in the technology commercialization stage.*

3. Methods

3.1. Conceptual Framework for the Innovation Process

As indicated above, this study seeks to develop a two-step analytical procedure for measuring stages of innovation performance, for which it is necessary to construct a process-oriented conceptual framework of regional innovation processes. Innovation is a complex process, and it should be evaluated as such, rather than as a single input-output activity [41]. In this study, following the literature, we divide the innovation process into two stages: (1) the generation and development of innovation; and (2) the transformation and dissemination of innovation [14]. The popular definition of innovation proposed by Forrester has generally led researchers to explore the innovation process from a production perspective [42]. In this framework, innovation is considered to be an input-output production process that contains multiple stages and multiple factors in an innovative value chain. In this context, a multistage model divides the process into two sequential sub-processes (Figure 1).

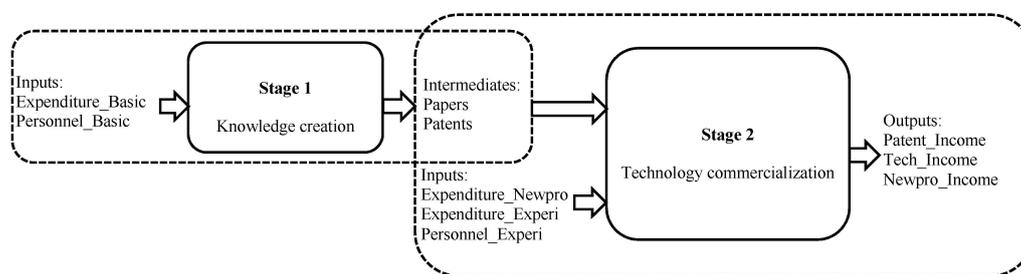


Figure 1. Two-stage chain process of innovation.

The upstream sub-process is the knowledge creation stage, which determines whether innovation actors can efficiently use funding and human resources to develop new research and academic outcomes. The downstream sub-process is the technology commercialization stage, which examines whether innovation actors can take advantage of its patents and technologies to develop new social and economic values. The input and output variables differ from stage to stage. The main purpose of the knowledge creation stage is to understand a phenomenon, grasp natural law, and obtain basic principles of knowledge to provide ways in which to solve problems. The significance of the multiple stages is to distinguish between direct outputs and intermediate outputs from innovation inputs and to consider possible intervening processes, which, to some extent, open the “black box” in regional innovation processes.

Network DEA was adopted, which considers a network of “divisions” or “sub-processes” to assess appropriately the divisional efficiencies and the overall efficiency of innovation (Figure 1). We specify the inputs in the knowledge creation stage as R&D expenditures on basic and applied research and R&D personnel engaged in basic and applied research (Expenditure_Basic and Personnel_Basic) and the outputs as the numbers of publications and patents. Inputs in the technology commercialization stage

not only include intermediate inputs (i.e., publications and patents), which result from the knowledge creation stage but also serve as the foundation for technology commercialization as manpower and material inputs (i.e., R&D expenditures on experimental development and new products development and R&D personnel engaged in experimental development (Expenditure_Experi, Expenditure_Newpro and Personnel_Experi)). The outputs in this stage are mainly in the form of economic benefits that include revenue from patent licensing and technology assignment and sales revenue of new product (Patent_Income, Tech_Income and Newpro_Income). We then calculate efficiency scores for each node and the whole process.

3.2. Network DEA

This study sets up an innovative chain process framework of cross-regions for regional innovation activities in 30 provinces in China. Each province is regarded as a decision making unit (DMU) that employs R&D expenditures and manpower as inputs to produce quantity and quality output indicators. Traditionally, DEA proposed by Charnes et al. [43] has treated each DMU as a “black box” by considering only the inputs consumed and final outputs produced, ignoring the links among sub-DMUs and, thus, making it hard to identify ways for the DMUs to improve their performances. In most real situations, DMUs can perform several functions and be separated into different components in series. In this case, some components play important roles in generating outputs by investing intermediate outputs obtained from their previous components. To open the “black box” of the innovation process, we propose a DEA network model that deals with the chain relationships among sub-DMUs and solves the problem of the standard DEA model in that it does not consider intermediate products [44,45].

Previous studies have proposed the network DEA model to utilize the radial measure of efficiency in the traditional DEA model [46,47]. Tone and Tsutsui [48] further introduce a non-radial network slacks-based measure (SBM) approach to evaluate efficiency. The advantage of the network SBM is that efficiency decreases strictly monotonically with the change in the degree of input and output slacks and it has stronger resolving power compared with traditional network DEA [49]. In this case, we employ the following objective function and define overall innovation efficiencies corresponding to the network SBM by

$$\min \rho_0^* = \frac{\sum_{k=1}^K w^k \left[1 - \frac{1}{m_k} \left(\sum_{i=1}^{m_k} \frac{s_{io}^{k-}}{x_{io}^k} \right) \right]}{\sum_{k=1}^K w^k \left[1 + \frac{1}{r_k} \left(\sum_{i=1}^{r_k} \frac{s_{ro}^{k+}}{y_{ro}^k} \right) \right]} \text{ s.t. } \begin{cases} \sum_{k=1}^K w^k = 1, w^k \geq 0 (\forall k) \\ x_0^k = X^k \lambda^k + s_0^{k-} \quad (k = 1, K, K) \\ y_0^k = Y^k \lambda^k - s_0^{k+} \quad (k = 1, K, K) \\ e\lambda^k = 1 \quad (k = 1, K, K) \\ S_0^{k+}, S_0^{k-}, \lambda^k \geq 0, (\forall k) \\ z_0^{(k,h)} = Z^{(k,h)} \lambda^h \quad (\forall (k, h)) \\ z_0^{(k,h)} = Z^{(k,h)} \lambda^k \quad (\forall (k, h)) \end{cases} \quad (1)$$

where X and Y are, respectively, the input vector and the output vector; m and r are the number of inputs and outputs; S are the slack variables of input and output; and w^k is the weight of sector k , whereby $e\lambda^k = 1$ indicates that the leading surface of production technology is constructed under the assumption of variable returns to scale. $z^{(k,h)}$ represents the linking inputs to DMU at division h from division k , and the linking outputs to DMU at division k from division h .

In this study, we define the divisional efficiency score of division k by

$$\rho_k = \frac{\sum_{i=1}^K 1 - \frac{1}{m_k} \left(\sum_{i=1}^{m_k} \frac{s_{io}^{k-*}}{x_{io}^k} \right)}{\sum_{i=1}^K 1 + \frac{1}{r_k} \left(\sum_{i=1}^{r_k} \frac{s_{ro}^{k+*}}{y_{ro}^k} \right)} \quad (k = 1, K, K) \quad (2)$$

where s^* are optimal input- and output-slacks for Equation (1). If $\rho_0^* = 1$, then DMU₀ is referred to as R&D “efficient”, which indicates that universities’ R&D efficiency is the highest. If $\rho_k = 1$, the division k in DMU₀ is R&D “efficient”.

3.3. Variables in the Panel Data Mode

3.3.1. Dependent Variables

Innovation is a multistage process that involves the transformation of the inputs of innovative elements into the outputs of innovative products. Innovative outputs are heterogeneous in value, with most worth little [50]. Therefore, rather than simply focusing on counts of innovative outputs, recent work has examined innovation efficiency to characterize genuine innovation. According to the concept of the innovation value chain [15], we employ a network SBM model to calculate innovation efficiency (dependent variables) in two stages, namely knowledge creation efficiency (*CRE_EFCY*) and technology commercialization efficiency (*COM_EFCY*).

3.3.2. Independent Variables

One important channel that contributes to innovation efficiency is FDI. First, one can expect external knowledge and technology spillovers to influence the innovative outputs and R&D activities of incumbents because of greater competition, which can increase the incentive to innovate and raise efforts to source external knowledge in order to overcome rivals [51]. In addition, technology transfer can drive external technology spillovers through FDI and thereby affect innovation efficiency. One example of technology transfer is the imitation of production processes used by foreign-owned firms, but new to incumbent firms [17].

UIC, as an indicator of measuring internal technology spillovers, is another channel that influences innovation efficiency. However, cooperation between different innovators exerts different influences on innovative outputs. For example, industry-university and industry-institute cooperation differ in their degree of interconnectedness as well as innovation goals [52]. Therefore, to investigate the role of internal technology spillovers in innovation efficiency, UIC can be divided into institute-university cooperation (*C_INS-UNI*), industry-university cooperation (*C_IND-UNI*), and industry-institute cooperation (*C_IND-INS*). Their cooperation can be expressed by mutually commissioned R&D projects. For example, industry-institute cooperation consists of R&D projects commissioned by industry to institutes and by institutes to industry. Therefore, we employ expenditure for R&D projects mutually commissioned between universities and institutes, institutes and industry, and universities and industry to measure the magnitude of *C_INS-UNI*, *C_IND-UNI* and *C_IND-INS*, respectively. Institute-university cooperation dominates the knowledge creation stage. In the technology commercialization stage, industry-university and industry-institute cooperation are more common. Therefore, the type of UIC differs by innovation stage.

3.3.3. Control Variables

As is typical in province-level analyses, the model controls for a set of factors likely to relate to innovation efficiency. Expenditure on R&D (*R&D investment*) is an important factor determining one's ability to absorb technology, which may lead technology spillovers to significantly affect innovation efficiency [53]. This variable thus captures the notion of absorptive capacity [54] in that innovative objects that produce their own innovative outputs are better able to use the externally available resources.

In addition, the quality of a university might affect knowledge creation efficiency. Based on global university rankings in Shanghai ranking list, we employ a dummy variable to measure the quality of a university (*Q_UNIVERSITY*) according to a four-point scale (0 = no university in the top 500 list; 1 = only one university in the top 500 list; 2 = two universities in the top 500 list; and 3 = more than two universities in the top 500 list). We also control for average firm size (*AVE_FIRMSIZE*), as this may affect the efficiency of technology commercialization. *AVE_FIRMSIZE* is expressed as total average assets. The other two factors are selected as proxies of the external environment. The first variable considered is the Internet penetration rate (i.e., the proportion of the population using the Internet relative to the total population). This variable is used as a proxy of information

technology infrastructure (*INFRASTRUCTURE*) [55]. Government support (*GOVERN_SUP*), measured by the proportion of government expenditure on science and technology relative to total government expenditure, which partly reflects the government's promotion of innovation activities by enhancing the innovative environment and providing funding, is the other proxy used.

Our analysis also uses two control variables: per-capita GDP (*per-capita GDP*) and the quality of R&D personnel (*Q_PERSONNEL*). First, technology transfer is highly positively correlated with per-capita GDP [56] and thus per-capita GDP is used as a proxy of market demand (i.e., a short-term increase in innovative products raises demand for new technologies). This will have promotional effects on the quantity of R&D personnel, equipment, and accumulation of knowledge stock and therefore it facilitates a country's innovation infrastructure and environment [57]. Second, the quality of R&D personnel (*Q_PERSONNEL*) reflects the innovative level of R&D labor.

3.4. Data

This study is based on a balanced panel dataset of 30 provinces in China observed over 2009 to 2015. It regards a region as the research object and focuses on the interaction among industry, institutes, and universities within that region. The above variables related to nominal prices are measured in constant 2009 prices after deflation by a GDP deflator. The GDP deflator P was obtained as the ratio of GDP in current prices to an index of GDP in constant 2009 prices. Data were obtained from the China Statistical Yearbook on Science [58] and the China Statistical Yearbook [59]. Tibet is excluded from this study because of a lack of relevant data. Data compiled by the National Bureau of Statistics are used to generate official innovation statistics for China, which have been used extensively to analyze the fields of management studies [60] and economic geography [61].

4. Results

4.1. Evaluation of Innovation Efficiency

The estimated innovation efficiency scores are briefly presented before their relations with FDI and UIC are analyzed. We employ a network SBM model to calculate the *CRE_EFCY*, *COM_EFCY*, and overall innovation efficiency (*INN_EFCY*) in 30 provinces in China from 2009 to 2015 (Figure 2).

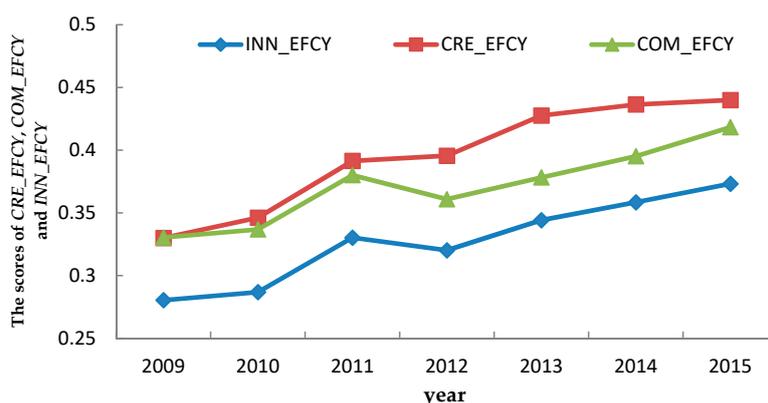


Figure 2. Changing trends of *CRE_EFCY*, *COM_EFCY*, and overall *INN_EFCY* in China during 2009–2015. The vertical coordinates denote the evaluation scores of *CRE_EFCY*, *COM_EFCY* and *INN_EFCY*, and the evaluation scores range from 0 to 1.

Generally, average *INN_EFCY* over the period is 0.328, which is still a relatively low level. However, *INN_EFCY* shows a gradual upward trend, rising from 0.280 in 2009 to 0.373 in 2015, a 9.3% increase. This finding reveals that there has been a significant improvement in regional *INN_EFCY* in recent years. Furthermore, the average scores of *CRE_EFCY* and *COM_EFCY*, which are based on the

network relationship, are 0.395 and 0.371, respectively. As for the decomposition of overall *INN_EFCY*, *CRE_EFCY* has a higher average score and more efficient processes than *COM_EFCY*.

Based on the average score of *INN_EFCY*, the *INN_EFCY*s of the 30 provinces are divided into four grades (high, medium, low, and very low) using the classification method of natural breaks (Figure 3) [62]. As shown in Figure 3, provinces with low or very low *INN_EFCY* are mainly located in northwestern China, while provinces with medium or high *INN_EFCY* are mainly located in coastal provinces and central areas. One explanation for this could be that coastal provinces have easier access to internationalization strategies that enable them to absorb advanced knowledge and technologies through scientific and technological exchanges and cooperation with foreigners [63]. In addition, innovative actors in coastal provinces are more open than those in inland areas and face fiercer international competition, which could help them gain advanced technology and managerial experience through technological spillovers or the “learning effect” [64], resulting in *INN_EFCY* that is better than that of the central regions [65]. Further, the scores of *CRE_EFCY* are higher than those of *COM_EFCY*, mainly in southeastern provinces (Figure 3). By contrast, provinces with higher values of *COM_EFCY* are located in northwestern China. The spatial distribution of *CRE_EFCY* and *COM_EFCY* reflects the heterogeneity of innovation efficiency at the provincial level. This finding clearly suggests that the econometric model should be based on provincial panel data. The empirical analysis is presented in the next subsection.

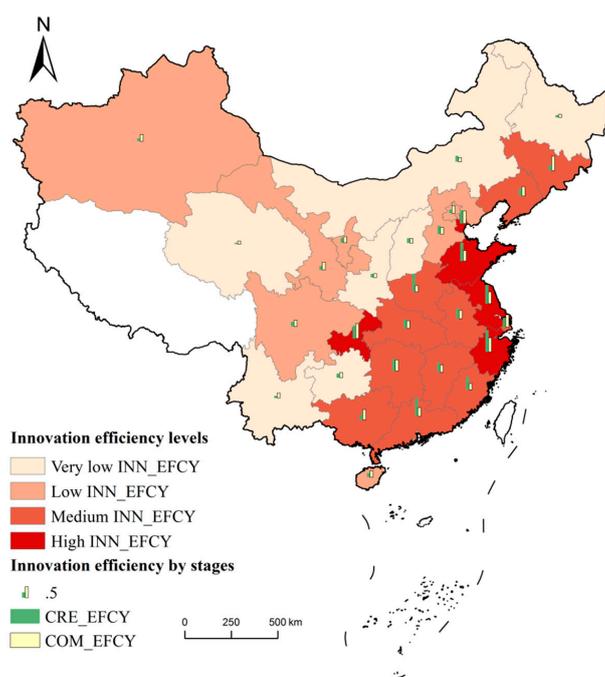


Figure 3. Spatial patterns of *INN_EFCY* in China.

4.2. Econometric Analysis

Table 1 presents the descriptive statistics and correlation matrix, confirming that innovation efficiency is significantly associated with UIC. The means of *CRE_EFCY* and *COM_EFCY* are 0.395 and 0.371 and their standard deviations are relatively large. Similarly, the provinces have means of 7837.8 for *C_INS-UNI* and 56884.4 for *C_IND-INS*, but with considerably larger standard deviations (15374.2 and 70784.7, respectively), which reflects the heterogeneity of innovation activities and UIC at the province level. We calculated the variance inflation factor (VIF) scores for each term to ensure that our models are not confounded by multicollinearity. The VIF for each variable is below 10 (the highest VIF value is 5.66), suggesting low multicollinearity among the parameters [66].

Table 1. Descriptive statistics and correlation matrix.

| | N | Mean | SD | Correlation | | | | | | | | | | | | | |
|-------------------|-----|-----------|-----------|-------------|----------|----------|---------|----------|----------|---------|---------|---------|--------|--------|--------|---|--|
| | | | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | | |
| 1. CRE_EFCY | 210 | 0.395 | 0.272 | 1 | | | | | | | | | | | | | |
| 2. COM_EFCY | 210 | 0.371 | 0.175 | 0.539 * | 1 | | | | | | | | | | | | |
| 3. FDI | 210 | 785,464.8 | 807,681.2 | 0.671 * | 0.380 * | 1 | | | | | | | | | | | |
| 4. C_INS-UNI | 210 | 7837.8 | 15,337.5 | 0.025 | 0.086 | 0.256 * | 1 | | | | | | | | | | |
| 5. C_IND-INS | 210 | 56,884.4 | 70,615.9 | 0.486 * | 0.256 * | 0.571 * | 0.539 * | 1 | | | | | | | | | |
| 6. C-IND-UNI | 210 | 30,586.9 | 33,438.0 | 0.494 * | 0.206 * | 0.559 * | 0.512 * | 0.749 * | 1 | | | | | | | | |
| 7. R&D investment | 210 | 4.227 | 5.982 | 0.133 * | 0.234 * | 0.396 * | 0.837 * | 0.524 * | 0.486 * | 1 | | | | | | | |
| 8. Q_PERSONNEL | 210 | 1.713 | 0.434 | −0.155 * | −0.058 | −0.058 | 0.025 | −0.104 | −0.088 | 0.080 | 1 | | | | | | |
| 9. per-capita GDP | 210 | 4.267 | 2.119 | −0.043 | −0.042 | 0.066 | 0.119 * | 0.058 | 0.120 * | 0.241 * | 0.175 * | 1 | | | | | |
| 10. GOVERN_SUP | 210 | 0.245 | 0.137 | −0.690 * | −0.273 * | −0.364 * | 0.370 * | −0.136 * | −0.149 * | 0.228 * | 0.131 | 0.014 | 1 | | | | |
| 11. INFRATRUCTURE | 210 | 42.609 | 13.628 | 0.328 * | 0.306 * | 0.448 * | 0.493 * | 0.445 * | 0.283 * | 0.638 * | −0.010 | −0.073 | −0.064 | 1 | | | |
| 12. Q_UNIVERSITY | 210 | 1.605 | 1.226 | −0.068 | 0.020 | 0.099 | 0.075 | 0.012 | 0.074 | 0.216 * | 0.392 * | 0.639 * | 0.033 | −0.009 | 1 | | |
| 13. AVE_FIRMSIZE | 210 | 32,640.8 | 20,849.0 | −0.062 | 0.022 | −0.095 | −0.035 | −0.058 | −0.123 * | −0.053 | 0.404 * | 0.138 * | 0.084 | −0.014 | −0.060 | 1 | |

SD—standard deviation, * $p < 0.1$.

The hypotheses proposed in Section 2 are evaluated by using panel regression analyses. Following the majority of previous studies [67,68], the variables are expressed either in logarithm form or in ratios. This strategy aims to make the estimation less sensitive to outliers and allow for the easy interpretation of the estimated coefficients [69]. Note that for all six models below we also carried out Hausman tests [70] to test the null hypothesis H_0 of random effects against the alternative H_a of fixed effects, which is used to test for systematic differences between the RE and FE models. If the null hypothesis of no significant differences is rejected, then there is unobserved heterogeneity and the FE estimator is preferred. Otherwise, the RE estimator leads to unbiased results.

First, we examine the association between FDI and innovation efficiency. In Model 1, the Hausman test with a p -value less than 0.05 shows that there is significant unobserved heterogeneity, so that the FE specification is preferred. As shown in Table 2, FDI has a significant influence on *CRE_EFCY* and *COM_EFCY*, confirming that external technology spillovers to some extent positively affect innovation efficiency. These findings support H1a and H1b. The R-squared value is 0.702 in Model 1, indicating the satisfactory explanatory power of the model.

Table 2. Estimation results of the effects of FDI on innovation efficiency.

| Independent Variables | <i>CRE_EFCY</i> (1) | | <i>COM_EFCY</i> (2) | |
|------------------------------|---------------------|-------|---------------------|-------|
| | Coefficient | S.E | Coefficient | S.E |
| <i>R&D investment</i> | 0.3381 | 0.233 | 0.4360 | 0.281 |
| <i>Q_PERSONNEL</i> | −0.0003 | 0.028 | −0.0195 | 0.028 |
| <i>per-capita GDP</i> | 0.0138 | 0.029 | −0.0251 | 0.026 |
| <i>GOVERN_SUP</i> | −0.3114 *** | 0.020 | −0.0666 *** | 0.024 |
| <i>R&D_INFRATRUCTURE</i> | 0.0471 | 0.040 | 0.0602 | 0.045 |
| <i>Q_UNIVERSITY</i> | −0.0249 | 0.017 | | |
| <i>AVE_FIRMSIZE</i> | | | 0.0292 | 0.020 |
| <i>FDI</i> | 0.0577 *** | 0.008 | 0.0204 ** | 0.009 |
| <i>CONSTANT</i> | −0.9962 *** | 0.176 | −0.4601 * | 0.266 |
| Number of obs | 210 | | 210 | |
| Hausman χ^2 Test | 103.03, $p < 0.01$ | | 4.93, $p > 0.05$ | |
| Model effects | fixed effect | | random effect | |

Note: Level of statistical significance: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

For the second set of hypotheses, the results of Model 3 show that *C_INS-UNI* has a significant influence on *CRE_EFCY* ($\beta = 0.0314$, $p < 0.01$), supporting H2a (Table 3). This finding indicates that R&D cooperation between universities and institutes tends to be more profound in the knowledge creation stage. For example, universities are able to use the advanced equipment of institutes to carry out scientific research, while universities can share their basic research achievements with institutes. Consequently, their cooperation can improve the efficiency and quality of knowledge innovation. *GOVERN_SUP* in the models has a negative effect on innovation efficiency. Indeed, the government formulates specific policies and provides R&D funding to promote innovation activities. For example, government statistics show that R&D institutes and universities receive 10 times more funding from the government than from enterprises [58]. However, the excessive interference of government tends to see UIC deviate from market guidance, leading to a lack of effective incentives and negatively affecting innovation performance.

In relation to *COM_EFCY* in Model 4, only *C_IND-INS* exerts a significant effect on innovation efficiency ($\beta = 0.0499$, $p < 0.05$), whereas the effect of *C_INS-UNI* ($\beta = -0.0221$, n.s.) is non-significant. The results of this model reveal that innovation efficiency in the technology commercialization stage is to some extent influenced by internal technology spillovers, where *C_IND-INS* has a stronger and more significant influence than *C_INS-UNI*. This finding might occur because, compared with the universities who are more engaged in basic research, the institute's emphasis is on applied research,

where their research orientation and R&D capability are able to better meet the needs of the industries. Therefore, *C_IND-INS* facilitates *COM_EFCY* more effectively.

Table 3. Estimation results of the effects of UIC on innovation efficiency.

| Independent Variables | CRE_EFCY (3) | | COM_EFCY (4) | |
|-------------------------------|-------------------|-------|------------------|-------|
| | Coefficient | S.E | Coefficient | S.E |
| <i>R&D investment</i> | 0.4339 | 0.304 | 0.4244 | 0.297 |
| <i>Q_PERSONNEL</i> | −0.0551 | 0.099 | −0.0110 | 0.029 |
| <i>per-capita GDP</i> | 0.0566 | 0.055 | −0.0206 | 0.026 |
| <i>GOVERN_SUP</i> | −0.3293 *** | 0.023 | −0.0768 *** | 0.024 |
| <i>R&D_INFRASTRUCTURE</i> | 0.0788 | 0.055 | 0.0508 | 0.046 |
| <i>Q_UNIVERSITY</i> | −0.0034 | 0.044 | | |
| <i>AVE_FIRMSIZE</i> | | | 0.0264 | 0.020 |
| <i>C_INS-UNI</i> | 0.0314 *** | 0.007 | | |
| <i>C_IND-INS</i> | | | 0.0499 ** | 0.020 |
| <i>C-IND-UNI</i> | | | −0.0221 | 0.017 |
| CONSTANT | −0.6401 *** | 0.234 | −0.4718 * | 0.279 |
| Number of obs | 210 | | 210 | |
| Hausman chi ² Test | 81.09, $p < 0.01$ | | 4.09, $p > 0.05$ | |
| Model effects | fixed effect | | random effect | |

Level of statistical significance: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

Third, we added FDI and UIC into Models 5 and 6 to compare the effect of FDI with that of UIC on innovation efficiency (Table 4). In Model 5, the coefficients of FDI and *C_INS-UNI* are 0.0498 ($p < 0.01$) and 0.0085 ($p > 0.1$), respectively. The regression coefficient estimate for FDI in Model 5 implies that a one standard deviation (SD = 1.585) increase in FDI leads to a 0.0789 increase in the value of *CRE_EFCY*, while the coefficient estimate for *C_INS-UNI* is non-significant. Thus, FDI has a higher coefficient and stronger significance in Model 5 than *C_INS-UNI*, rejecting H3a. One possible reason is that, compared with developed countries, China's basic research is still lagging [3]. Most basic research takes place in the knowledge creation stage and relies more on frontier knowledge, high-tech technology, and advanced equipment obtained from abroad. As a result, external knowledge spillovers facilitate basic research in the knowledge creation stage, thereby promoting an improvement in innovation efficiency to a higher extent.

Table 4. Estimation results of comparing the effect of FDI with that of UIC on innovation efficiency.

| Independent Variables | CRE_EFCY (5) | | COM_EFCY (6) | |
|-------------------------------|--------------------|-------|------------------|-------|
| | Coefficient | S.E | Coefficient | S.E |
| <i>R&D investment</i> | 0.3948 | 0.287 | 0.3731 | 0.300 |
| <i>Q_PERSONNEL</i> | 0.0002 | 0.094 | −0.0124 | 0.028 |
| <i>per-capita GDP</i> | 0.0420 | 0.052 | −0.0186 | 0.026 |
| <i>GOVERN_SUP</i> | −0.3086 *** | 0.022 | −0.0677 * | 0.025 |
| <i>R&D_INFRASTRUCTURE</i> | 0.0420 | 0.053 | 0.0513 | 0.046 |
| <i>Q_UNIVERSITY</i> | −0.0031 | 0.041 | | |
| <i>AVE_FIRMSIZE</i> | | | 0.0271 | 0.020 |
| <i>C_INS-UNI</i> | 0.0085 | 0.008 | | |
| <i>C_IND-INS</i> | | | 0.0393 * | 0.022 |
| <i>C-IND-UNI</i> | | | −0.0227 | 0.017 |
| FDI | 0.0498 *** | 0.010 | 0.0132 | 0.011 |
| CONSTANT | −0.9959 *** | 0.232 | −0.5168 * | 0.281 |
| Number of obs | 210 | | 210 | |
| Hausman chi ² Test | 282.06, $p < 0.01$ | | 5.10, $p > 0.05$ | |
| Model effects | fixed effect | | random effect | |

Note: Level of statistical significance: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

According to Model 6, *C_IND-INS* exerts a significant effect on *COM_EFCY*, whereas the effect of FDI is not significant, supporting H3b. The regression coefficient of FDI is 0.0393 ($p < 0.1$); hence, a one standard deviation ($SD = 1.119$) increase in FDI means that *COM_EFCY* increases by 0.0440. The reason for this phenomenon may depend on the following aspects. Regarding the protection of core technology, foreign enterprises, to maintain their monopoly positions and competitive advantage relative to domestic enterprises, would not transfer genuine technology to the host country in case domestic enterprises absorb and commercialize these technologies. Therefore, to improve *COM_EFCY*, China could only foster genuine technological innovation through the internal technology spillovers generated by UIC.

5. Conclusions

This study divided the innovation process into two sequential stages, namely knowledge creation and technology commercialization, and then employed a network DEA approach to measure innovation efficiency in each stage. Panel econometric models were applied to compare the influence of FDI with that of UIC on innovation efficiency in each stage, based on a dataset of 30 provinces in China from 2009 to 2015. The presented analysis allowed us to draw three main findings.

First, average innovation efficiency across all provinces was still fairly low, but it showed a gradual upward trend from 2009 to 2015. When we analyze the decomposition of innovation efficiency in each stage, knowledge creation efficiency (*CRE_EFCY*) shows a higher average score and more efficient processes than technology commercialization efficiency (*COM_EFCY*). The spatial pattern for the 30 provinces shows that provinces with higher values of *COM_EFCY* are located in northwestern China, which indicates the spatial heterogeneity of innovation efficiency.

Second, external technology spillovers, as represented by FDI, have a significant influence on *CRE_EFCY* and *COM_EFCY*. In Model 3, we find that UIC, specifically institute-university cooperation (*C_INS-UNI*), has a significant influence on innovation efficiency in the knowledge creation stage. However, only industry–institute cooperation (*C_IND-INS*) shows a significant and positive impact on *COM_EFCY*.

Finally, in comparison with UIC, FDI has a greater positive influence on innovation efficiency in the knowledge creation stage, while between the two examined types of cooperation, only industry-institute linkages exhibit a stronger association with innovation efficiency in the technology commercialization stage.

Based on these results, several implications and strategies can be discussed. First, both internal and external technology spillovers in China have a positive impact on innovation efficiency and the mechanism of their impact is a complex process. The goal of China's regional innovation strategy should thus be to combine internal and external technology spillovers, not only introducing foreign technology through FDI, but also using internal UIC to nurture indigenous innovation.

Second, in the process of UIC, industry should gradually become the main funder of R&D investment and technological innovation, strengthening its connectivity with universities and institutes by funding R&D activities and fostering R&D talent. This approach could maximize the positive effects of internal technology spillovers, laying the foundation for the absorption of external knowledge and offering endogenous impetus for regional innovation.

Third, in terms of FDI, the choice of introducing external technology should be based on whether it will enhance indigenous innovation. Further, it is necessary to encourage foreign enterprises to set up R&D institutions in China to allow them to forge innovative cooperation with universities, institutes, and domestic enterprises.

The study has several limitations to overcome in further research. As innovation is a complex process, it is biased only to employ manpower and R&D expenditure as the input indicators to measure the innovation efficiency. In addition, the intangible (hardly quantifiable) outputs during two-stage innovation process also trouble the accurate measurement of inputs' contributions. One kind of potential study in this context is to incorporate important innovative elements into the present network

DEA model from the systems perspective. The second limitation, which is common for the comparative studies of cross-region innovation performance, is that the obtained observations (that is, provinces in this study) cannot be completely independent in terms of the innovative input–output correspondence. It must be recognized that there would be spatial spillover effect or spatial correlation in innovative activities among 30 provinces. The third limitation is attributable to the deterministic property of the network DEA model. As indicated by the diagnostic analysis for the influences of outliers and statistical noise on innovation efficiency estimations, efficiency estimates in the context of deterministic DEA models may be biased. As such, it is necessary to construct the empirical distribution of the scores by means of bootstrapping methods [71] for the current network DEA model in the future study.

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