Does Foreign Direct Investment Enhance or Inhibit Regional Innovation Efficiency?

— Evidence from China

Abstract

Purpose- The purpose of this paper is to examine whether FDI inflow impacts on regions innovation efficiency in China and whether the impacts of FDI are contingent on regional conditions that may maximize the effect of FDI on regional innovation efficiency.

Design/methodology/approach- Using panel data of 30 provinces from 2000 to 2010, we first employed data envelopment analysis (DEA) to measure regional innovation efficiency. We then used a spatial panel model to test our research hypotheses concerning the effect of FDI on regional innovation efficiency and the direct and moderating effects of regional characteristics such as regional innovation environment, regional absorptive capacity and regional complementary assets .

Findings- The paper finds that there are considerable inter-regional and intra-regional variations in innovation efficiency in China and that regional variations in innovation efficiency in China can firstly be explained by the differences in inflow FDI and then be accounted for by the direct and moderating effect of regional innovation environment, absorptive capacity, and complementary assets.

Research limitations/implications– Our research findings have three policy implications. First, governments should continue their efforts to increase the transparency and predictability of the framework for inward FDI and align FDI with the region's strategic priorities of development in order to improve innovation efficiency. Second, Governments should develop holistic and coherent policies that address the key aspects of regional conditions conducive to inflow of FDI. Third, Governments at the regional level should cultivate an open innovation environment and support the development of financial markets in order to maximize the positive effect of FDI technology spillover and externalities.

Originality/value–This paper fills a gap in research on the spatial heterogeneity characteristics of spillover effects of FDI on regional innovation efficiency.

Keywords: Regional Innovation, Innovative Efficiency, FDI, Spatial panel model

Paper type: Research paper

Introduction

Innovation activity has striking geographical characteristics in the contemporary economy (Asheim and Gertler, 2005). It is unevenly distributed across a country's geographical landscape, it tends to become more spatially concentrated over time, and the efficiency of innovation activities varies significantly between regions. Such characteristics of innovation activity have important implications for regional economic growth, job creation and competitive advantage. Regions will innovate more efficiently if they promote stronger interactions between innovators and the region's knowledge infrastructure. Regional innovation efficiency can be defined as a region's ability to "produce the possible maximum of innovative output from a given amount of innovative input" (Fritsch and Slavtchev, 2011, p.906).

It is commonly accepted that much strategic knowledge as a source of innovative input is sticky and thus learning processes tilt more to localization. This means that the firm's effectiveness of converting knowledge into economic value tends to depend on its access to important localized knowledge, innovation infrastructure, and close interaction with other co-locating organisations. It is also often considered true that firms need to access non-local sources of knowledge as an essential complement to the local sources of knowledge in order to stay innovative and avoid technological "lock-in". Global knowledge flows and spillovers have therefore become important sources of innovative ideas for economic activities (Qi and Li, 2008; Wu *et al*., 2015). Bathelts *et al*. (2004) refer to these phenomena as dual geography of innovation. It means that, in an open economic system, a region can raise its innovation efficiency endogenously by improving technological development and subsequent technological commercialization that draw resources from within the region's innovation system (Chen and Guan, 2012), and using spillover effects of foreign direct investment (FDI) from multinational corporations (MNCs) as a catalyst for enhancing regional innovation capability (Huang *et al*., 2012).

Eaton and Kortum's (1995) explored that spillovers of external (foreign) technology contributed to around half of all productivity in the United States. Region are more likely to be open to a greater extent to external technology flows and technology transfer, and technology spillovers are likely to be even more significant in terms of regional innovation and performance if spillovers of external (foreign) technology (Howells, 2005). So far as the effect of FDI is concerned, empirical research is inconclusive. Some have found evidence that FDI can significantly affect the innovation performance of domestic firms through positive knowledge spillover (Cheung and Lin, 2004; Liu and Buck, 2007) while others revealed that spillover effects of FDI are not unconditional and that FDI in a region will begin to produce positive spillover only when the level of regional innovation reaches the minimum innovation threshold (Huang *et al*., 2012). Contrarily, research has also found that FDI adversely affect the ex post innovation of local firms (García *et al*., 2013). Moreover, there is a dearth of studies that considers whether FDI may improve regional innovation efficiency.

After nearly four decades of economic reforms and opening to the outside world, China is at the crossroad of change. Recently, China has become the world's second-biggest economy in terms of purchasing power parity. Yet, the country's growth model stands on weak fundamentals including enormous and inefficient use of energy, too much dependent on exports and massive state spending. For long term economic sustainability, China has to find innovative solutions to these issues. For many years, China was the largest recipient of inward FDI in the world. Historically FDI played an important role in opening up China to the world and providing her with the latest technology and much needed finances. FDI still is instrumental in shaping the perception of innovation in local firms in China. Therefore, this paper investigates: Can FDI inflow help Chinese regions improve innovation efficiency? What are the contingent conditions that can maximize the effect of FDI on regional innovation efficiency? The aim of this paper is to address these two research questions and fill the gap in literature on FDI and innovation. Using panel data from 30 provinces over the period 2000-2010, we empirically examine the effect of FDI on regional innovation efficiency and the moderating effect of regional characteristics such as regional innovation environment, regional absorptive capacity and regional complementary assets on the relationship between FDI and regional innovation efficiency. We first employ data envelopment analysis (DEA) to measure regional innovation efficiency. We then use a spatial panel model to test our research hypotheses.

The paper proceeds as follows. In the next section we provide an overview of FDI policies and stylized facts in China in order to set the context for the research. Afterwards, we use multiple theoretical perspectives to develop a number of research hypotheses. We then establish the spatial panel model, discuss the data and estimation methods and present results. We finally discuss our findings and policy implications.

FDI in China: Policies and Stylized Facts

Overview of FDI policies in China

Attracting FDI has been an integral part of China's reform and open-door policies over the last few decades. Thanks to the effect of policies, China has seen the inflow FDI rise from a negligible level prior to 1978 to become the top global FDI destination for a sustained period. Over time, China's FDI policies changed from experimenting between the late 1970s and the early 1990s, then to encouraging between the early 1990s and early 2000s, and finally matured after the turn of the century to link FDI to domestic development priorities.

China's reform and opening up starting from 1978 signaled the change of FDI policies from restrictive before 1978 to experimenting in the early reform period. The first milestone of FDI policies was the enactment of the "Law of the People's Republic of China on Joint Ventures Using Chinese and Foreign Investment" in 1979. Soon afterward, the State Foreign Investment Commission was set up to oversee inward FDI. Additionally, numerous agencies at the national and provincial level were established to promote investment from overseas. The most noticeable development of policies in this period was the establishment of four special economic zones (SEZs) in four cities in 1980, namely Shenzhen, Zhuhai, and Shantou in Guangdong Province, and Xiamen in Fujian Province. SEZs were designated to test policies of opening up and build experiences and expertise through learning by doing and learning by experimenting (Ding and Li, 2015). Four years later, 14 more coastal cities were opened to foreign investment. In 1985, three more zones were opened to FDI, namely the Yangtze River delta, the Pearl River delta, and the Zhangzhou-Quanzhou-Xiamen region. Accordingly, FDI started spreading out from dots of SEZs to the much wider regions. In 1986, the Chinese government promulgated Law on Foreign Enterprises which formally granted legal rights to wholly-owned foreign enterprises. The State Council also issued the "Provisions for the Encouragement of Foreign Investment" that granted more freedom of independent operations to foreign invested enterprises (FIEs) and more tax incentives for foreign investment. In 1988, Hainan Province became another SEZ. In the meantime, the Chinese government further amended the joint venture laws which relaxed restrictions regarding repatriation of profits and dividends and allowed foreign nationals to be chairman of board of directors in FIEs (Sun *et al.*, 2002). In this period, China predominantly relied on preferential policies to attract FDI, such as tax incentives, foreign exchange provision, land use, and licensing procedures (Long *et al.*, 2015).

Deng Xiaoping's south China tour in 1992 injected a new lease of life into economic reform in general and FDI policies in particular. Since then, the pace of foreign capital inflows and utilization has increased. Significantly, FDI became the main form of China's use of foreign capital and constituted an important force in the economic development in China. By encouraging foreign investment, China gradually improved the mechanism of market competition, reduced the absolute preferential level of foreign investment, and abolished some "universal" preferential policies for FIEs (Fu, 2000). The State Planning Commission regularly updated, compiled and promulgated the Catalogues for Guiding Foreign Investment Industries which was to provide the basis for the assessment and approval of FDI projects in four categories: encouraged, restricted, prohibited and permitted. The catalogue of major industries, products and technologies encouraged for development in China that took effect in 1998 covered several hundreds of products and technologies in 29 industries (Lu, 2002).

Starting at the turn of the century, China had promulgated five landmark laws and sets of regulations (OECD 2008), namely expanded regulations on cross-border mergers and acquisitions, the Enterprise Income Tax Law that sets a single tax rate for domestic and foreign-owned enterprises, the Property Law giving equal protection to private and public property, the first Anti-Monopoly Law, and a third revision of the Catalogues for Guiding Foreign Investment Industries. The changes in FDI policies and regulations were to add essential building blocks to the regulatory structure within which businesses, including FIEs, operate in China. The unification of business tax rates increased the transparency of the tax regime for domestic and foreign investors (Ding *et al*., 2008). Subsequently, Chinese regions no longer relied on offering preferential policies to attract FDI. The emphasis had become to align inward FDI flows more closely with national priorities, including upgrading industrial sophistication, supporting innovation, setting up outsourcing industries and developing poorer hinterland regions (Davies, 2012). There were five essential changes in FDI policies (Davies 2012; Fung *et al*., 2004). First, more industries were opened to foreign investments. Second, the ceiling on provincial examination and approval authority over foreign investment projects in the "permitted catalogue" was raised. Third, restrictions on foreign shares were relaxed. Fourth, foreign investments were allowed in certain public utility sectors such as telecommunications, urban water supply and drainage, construction and operation of gas and heat distribution network. Fifth, the domestic service sector was gradually opened to foreign investment, including banking, insurance, and distribution, treading rights and tourism, telecommunications, transportation, accounting, auditing and legal services. More recently, a further revision of the Catalogue for Guiding Foreign Investment Industries was promulgated, effective in January 2012. This revision continues the trend of introducing more encouragement to FDI in "green" sub-sectors, while adjusting the incentives mix to current industrial needs, such as promoting higher-end manufacturing and new-generation IT (Davies, 2012).

Some stylised facts of FDI in China

Undoubtedly, China's FDI policies have underlined the country's success in attracting inward FDI. Four characteristics of FDI in China can be identified. First, the majority of FDI (e.g. 60% during 1993–1996) was in the form of EJVs, which have the potential to be particularly beneficial to the country, because of positive spillover effects (Chadee *et al*. 2003).

Second, the sectoral distribution of FDI has changed markedly since 1990. Traditionally, the primary sector (i.e. agriculture, mining and petroleum industries) recorded the largest share of inward FDI in China. For example, in 1984, 40% of FDI was in the primary sector while the secondary sector accounted for 27% and the tertiary sector accounted for 32.1% of inward FDI (Lin and Kwan, 2011). Starting in early 1990s, the majority of FDI in China has gone into the manufacturing industries. For example, between 1995 and 2005, FDI in the secondary sector accounted for 69.6% of the aggregated amount of FDI (Sharma *et al*. 2014).

Third, the geographical distribution of FDI in China has been uneven. FDI has been highly concentrated in coastal provinces. From 1992-2015, the eastern provinces received an average of 83% of FDI inflows while central and western regions received 17% of total FDI inflows. Within the coastal region itself, FDI in the south has declined due to the gradual opening of more regions to foreign investors. For example, Guangdong Province's share of FDI in coastal provinces declined from 38% in 1995 to 18% in 2015.

Fourth, as a result of recent government policies emphasizing the development of the central and western areas, the share of FDI in central and western China has experienced a gradual and steady increase (see Figure 1). For example, in 1997, FDI in the east constituted 83% of total FDI utilized in China, and FDI in central and western regions constituted 17% of the total. By 2008 the share of FDI in central and western China rose to 22%.

(insert Figure 1)

Theoretical development and hypothesis

Regions are recognized as the level at which innovation is produced through regional networks of innovators, local clusters and the cross-fertilizing effects of research institutions (Lundvall and Borrás, 1999). It is widely noted that regions differ considerably in innovation performance in terms of innovation output and innovation efficiency. Farrell (1957) defined technical efficiency as the generation of a maximum output from a given amount of resources. Research on regional innovation efficiency has commonly followed Farrell's (1957) concept of technical efficiency (Fritsch, 2003; Brenner and Broiekel, 2011; Fritsch and Slavtchev, 2011a; Bai, 2013). So, in the regional innovation context, regional innovation efficiency can be defined as the possible maximum of innovation output a region is able to produce from a given amount of innovation input (Fritsch and Slavtchev, 2011).

Knowledge spillovers from FDI can impact on regional innovation efficiency because regions are more open to external technology transfer and thus knowledge spillovers are likely to be even more significant (Howell, 2005). FDI, as a package of capital, technology and managerial skills, is an important source of both direct capital inputs and knowledge spillovers (Huang *et al*., 2012). Perri and Peruffo (2014) argue that FDI-related externalities differ from knowledge spillovers of FDI. The former occurs when FDI generates outcomes that become accessible to other agents at no cost, while the latter arises when the foreign firm has a sort of formal or informal relationship with the local firm. Regions can benefit from both FDI-induced externalities and spillovers.

There are two competing arguments concerning the effect of FDI on local firm performance (García *et al*., 2013). The first argument considers FDI to be a catalyst for local innovation. Three mechanisms through which FDI may act as a catalyst for innovation of local firms can be identified. First, local firms may enhance their innovation performance due to the opportunities arising from FDI-related knowledge spillovers, namely learning, state-of-the-art technologies and managerial know-how (Balasubramanyam *et al*., 1996). Second, local firms are forced to raise their stake in innovation in order to defend their markets when facing heightened competition pressure in the presence of better-endowed foreign entrants (Chung, 2001). Third, local firms may improve their innovation efficiency due to reduced cost of inputs because rise of FDI-induced demand for upstream supply allows for increased scale of economies that reduce costs for all firms (Kearns and Ruane, 2001). There is empirical evidence that supports this argument. For example, Aitken and Harrison

(1999) used the panel data on Venezuelan plants to examine the effect of technology spillovers from FDI on domestic firms. They found that foreign equity participation is positively correlated with plant productivity, particularly for small firms. Girma and Wakelin (2001) examine the regional impact of foreign-owned establishments on the performance of domestic establishments in the electronics sector in the UK, using establishment-level data taken from the UK Census of Production. The results indicate the existence of positive spillovers, but spillovers are mostly confined to the region in which the MNE is located and impacts are larger in more-developed regions. Similarly, after examining the effect of FDI on total factor productivity (TFP) in Russian regions between 1995 and 2011, Iwasaki and Suganuma (2015) find a positive effect of FDI on TFP increases in the regions that received larger amounts of foreign capital. Also, Cheung and Lin (2004) used provincial data from 1995 to 2000 and find positive effects of FDI on the number of domestic patent applications in China.

The alternative argument considers FDI a hindrance to innovation, suggesting that FDI may give rise to negative externalities. First, market-seeking FDI may hamper the growth of productivity in a host region due to its crowding-out effects through fierce competition between foreign and domestic firms (Konings, 2001). Under these circumstances, local firms may lose market share to better-endowed and more competitive foreign entrants, forcing them to reduce output. The local firm's shrinking market share leads to an increase in average costs and less capital to invest in new technologies, subsequently hampering innovation performance. Second, local firms may face increased labour costs when they have to pay higher wages for retaining and recruiting talents in order to fight off competition from foreign entrants (Spencer, 2008). Third, local firms may also endure pressure of reduced profit margin when upstream supply cannot match the increased FDI-induced demand in the short run, forcing factor input prices to go up (Hanson, 2001). Again, this leaves local firms with less capital to invest in new technologies. For all of these reasons, inward FDI may inhibit innovation of local firms or displace them to less-profitable and less-innovative segments of the market (Hanson, 2001). García *et al*. (2013) utilized data from 1799 Spanish manufacturing firms from 1990 to 2002 to investigate the relationships between industry-level and firm-level inward FDI and the innovative performance of host country firms. They find that FDI inflows into Spain are negatively associated with the ex post innovation of local firms. Considering the two competing arguments, we posit:

H1a: *FDI has a positive impact on regional innovation efficiency*

H1b: FDI has a negative impact on regional innovation efficiency

The innovation efficiency of a region to a large degree reflects its capability of transforming innovative input into innovative outputs. A region's innovation capability is related to the region's innovation environment, absorptive capacity, and complementary assets (Lundvall and Borrás, 1999). For regional innovation environment, regional competition and cultural characteristics such as trust, openness and risk-taking influence how firms use external actors and sources to help them achieve and sustain innovation. The literature on regional competitiveness (Porter, 1998, 2002) identifies the fundamental competitive forces that determines firms' competition behaviours and emphasizes the role of clusters as contexts for competition and cooperation and as centres of innovation. Companies in the highly competitive environment will have to raise their game and conduct innovation more efficiently, leading to higher regional innovation efficiency. The literature on regional advantage (Saxenian, 1994) emphasizes the influence of socio-cultural aspects on opening up innovation and engaging in networks. An open innovation culture in a region is conducive to collaboration, the mobility of highly qualified staff between firms, spin-offs and open information flow and learning. All this can contribute to regional innovation efficiency.

Consistent with Cohen and Levinthal (1990), regional absorptive capacity can be defined as regions' ability to assimilate knowledge from public and externally-conducted R&D. Regional absorptive capacity is influenced not only by the absorptive capacity of individual enterprises, but also by the capability of other knowledge creating organisations in the region and the extent of association between them (Roper and Love, 2006). This view of regional absorptive capacity suggests that, even given common access to technology, regional differences in absorptive capacity may lead to very different innovation efficiencies. In line with Teece (1986), regions need complementary assets to help firms to overcome the obstacles they face in exploiting opportunities arising from externalities and knowledge spillovers of FDI.

All in all, the region's innovation environment, absorptive capacity, and complementary assets shape regional characteristics that can influence flows of innovative activities and the effectiveness of innovation activities in the region (Brenner and Broiekel, 2011). Thus, we propose the following hypotheses:

H2a: Regional innovation environment has a positive impact on regional innovation efficiency

H2b: Regional absorptive capacity has a positive impact on regional innovation efficiency

H2c: Regional complementary assets have a positive impact on regional innovation efficiency

Furthermore, empirical evidence has suggested that spillovers are contingent on regional innovation environment, absorptive capacity, and complementary assets. For example, Iwasaki and Suganuma's (2015) research detects a positive synergistic effect between FDI and local R&D potential, indicating that the absorptive capability is essential for linking FDI and regional productivity in the country. Fu (2008) used a provincial-level panel dataset for 31 provincial regions in China over the period 1998–2004 to investigate the impact of FDI on the development of regional innovation capabilities. The research finds that the effect of FDI on regional innovation efficiency depends on the availability of the region's absorptive capacity and innovation complementary assets. More recently, Huang *et al*. (2012) used a dataset on twenty-nine Chinese provinces for the period 1985–2008 to analyse the relationship between spillover effects of FDI and regional innovation in China. They find double-threshold effects of regional innovation on productivity spillovers from

FDI. Specifically, FDI in the region will begin to produce positive productivity spillovers only when the level of regional innovation reaches the minimum innovation threshold. Furthermore, positive productivity spillovers from FDI will be substantial only when the level of regional innovation attains a higher threshold. Liu and Buck (2007) empirically investigate the impact of different channels for international technology spillover on the innovation performance of Chinese high-tech industries, using a panel of sub-sector level data from 1997 to 2002. They find the effect of FDI on innovation performance of firms is conditional on local firms' innovation capability. They argue that technology spillover from FDI will only produce significant and positive impact on the innovation performance of domestic firms when local firms are equipped with absorptive capacity. We therefore posit:

H3a: The positive relationship between FDI and regional innovation efficiency is moderated by regional innovation environment, such that a more innovation conducive regional environment will make the relationship stronger

H3b: The positive relationship between FDI and regional innovation efficiency is moderated by regional absorptive capacity, such that a greater regional absorptive capacity will make the relationship stronger

H3c: The positive relationship between FDI and regional innovation efficiency is moderated by regional complementary assets, such that better regional complementary assets will make the relationship stronger

Methods and data

Regional level panel data of Chinese provinces and municipalities is used to assess the moderated relationship between FDI and regional innovation efficiency. The panel consists of 30 provincial regions over the period 2000-2010. Tibet is excluded from the sample due to the availability of only very limited statistical information. The data are collected from various issues of *China Statistical Yearbook on Science and Technology* and *China Statistical Yearbook* published respectively by National Bureau of Statistics and Ministry of Science and Technology in China. We use a two-step approach to assessing the effect of FDI on regional innovation efficiency. We firstly used a Data Envelopment Analysis (DEA) approach to estimating regional innovation efficiency. We then used a GMM spatial panel model to assess the effect of FDI on regional innovation efficiency.

Dependent variable

In the current literature, regional innovation efficiency is often estimated using two main EDA approaches. One is the C^2R model proposed by Charnes *et al*. (1978) which is input-based and assumes constant return on scale; the other is BC^2 model proposed by Banker *et al*. (1984) which allows for variable return on scale. Coelli and Perelman (1999) show in their research that either input-based or output-based EDA estimation approach has only minor impact on the estimation results. In this paper, we use the BC^2 model in our estimation of regional innovation efficiency.

We measure innovation input in three ways. Following previous research (e.g., Fritsch and Slavtchev, 2011), we use two proxies, R&D investment and R&D employees, for innovation input in a region. We also consider the importance of imported advanced technology and add the third proxy for innovation input, namely average spending on purchase of domestic technology by large- and medium-sized industrial enterprises. These three measures of innovation input reflect innovation input in independent R&D and re-innovation of technology introduction and absorption in a region.

To measure innovation output, proxies used in the literature have included patents and sales of new products (e.g. Fu, 2008). In this paper, we use three proxies for regional innovation output. These include the number of invention patent applications per 10,000 population, high-tech per capita added value, and average transaction value of the technology market.

Independent variable

In this paper, FDI is measured as the total sum of foreign investment utilization in a region. It consists of a region’s inflow FDI and overseas borrowing.

Moderators

Regional innovation environment. It is measured by two indicators, namely regional Openness (OP) and Economic Competition (CO). OP is measured by FDI as a percentage of Gross Regional Product (GRP), and CO is measured by the capital of private enterprises as a percentage of industry total.

Absorptive capacity. It is measured by two indicators, namely Research and Development Input Density (RDI), and Human Resources Quality (HQ). RDI is the percentage of R&D input in GDP, and HQ is the ratio of college graduates in the total regional population.

Complementary assets. It is measured by four indicators, namely Regional Financial scale (FS), Industry Density (ID), Industry Conditions (IC) and System Conditions of Technology Transfer (TC). This paper measures regional financial scale as the percentage of financial output in gross regional product. Regional industry density provides a base for innovation development of enterprises. Following Weng (2009), we use the improved spatial Gini coefficient to measure the industrial concentration degree of a region. Also, we use the ratio of high-tech industry in the regional industrial output and the volume of technology transaction in regional technology market to measure regional industry condition and the institutional condition of technology transfer. The variable definitions can be seen in Table Ⅰ.

(insert Table I)

Spatial panel regression model

Empirical studies of spatial panel model normally adopt maximum likelihood estimation (MLE) to estimate model parameters. In the case of Large Cross Section (N), however, the simplest MLE can cause a serious calculation problem. Also, if random error is not normally distributed, the MLE of spatial panel will have a dubious effectiveness (Conley 1999). Comparing MLE and GMM of the spatial panel via Monte Carlo experiment, Kapoor *et al*. (2007) find that GMM has a low sample mean square error. Therefore, in this paper we use GMM.

Consider the following Panel Recession Model:

$$y_{it,N} = x_{it,N}^T \beta + u_{it,N}, \quad i = 1,\ldots,N; t = 1,\ldots,T \qquad (1)$$

In view of the contribution of Kapoor, Kelejian and Prucha (2007), N at each observation time can be stacked in the recession model as below:

$$y_N(t) = X_N(t)\beta + u_N(t), \quad t = 1,\ldots,T \qquad (2)$$

In the model, $y_N(t) = [y_{1t,N},\ldots,y_{Nt,N}]^T$, $X_N(t) = [X_{1t,N},\ldots,X_{Nt,N}]^T$, $u_N(t) = [u_{1t,N},\ldots,u_{Nt,N}]^T$. $u_N(t)$ follows the first-order spatial autoregressive process:

$$u_N(t) = \rho W_N u_N(t) + \varepsilon_N(t) \qquad (3)$$

In which, W_N is the spatial weight matrix of $N \times N$, ρ is the spatial autoregressive coefficient, $\varepsilon_N(t) = [\varepsilon_{1t,N},\ldots,\varepsilon_{Nt,N}]^T$ is the innovation vector of Time t and Cross Section $N \times 1$. With Formula (1) to (3), the error models above can be stacked into:

$$y_N = X_N \beta + u_N \qquad (4)$$

$$u_N = \rho(I_T \otimes W_N)u_N + \varepsilon_N \qquad (5)$$

In the equation, $y_N = [y_N^T(1),\ldots,y_N^T(T)]^T$, $X_N = [X_N^T(1),\ldots,X_N^T(T)]^T$, $u_N = [u_N^T(1),\ldots,u_N^T(T)]^T$, $\varepsilon_N = [\varepsilon_N^T(1),\ldots,\varepsilon_N^T(T)]^T$. Intertemporal correlation is allowed in the Innovation vector, so ε_N has the error structure as follows:

$$\varepsilon_N = (e_T \otimes I_N)\mu_N + v_N \qquad (6)$$

The design of the above spatial panel model is different from the basic model of Ansenlin（1988）in that it takes into consideration the spatial correlation of individual effect μ. By defining $\bar{u} = (I_T \otimes W)u$, $\bar{\bar{u}} = (I_T \otimes W)\bar{u}$ and $\bar{\varepsilon} = (I_T \otimes W)\varepsilon$, Kapoor *et al.*（2007）puts forward GMM on the basis of the six moment conditions below:

$$E[\varepsilon_N^T Q_{0,N} \varepsilon_N / N(T-1)] = \sigma_v^2 \qquad (7)$$

$$E[\bar{\varepsilon}_N^T Q_{0,N} \bar{\varepsilon}_N / N(T-1)] = \sigma_v^2 tr(W_N^T W_N)/N \qquad (8)$$

$$E[\bar{\varepsilon}_N^T Q_{0,N} \varepsilon_N / N(T-1)] = 0 \quad (9)$$

$$E(\varepsilon_N^T Q_{1,N} \varepsilon_N / N) = \sigma_1^2 \quad (10)$$

$$E(\bar{\varepsilon}_N^T Q_{1,N} \bar{\varepsilon}_N / N) = \sigma_1^2 tr(W_N^T W_N) / N \quad (11)$$

$$E(\bar{\varepsilon}_N^T Q_{1,N} \varepsilon_N / N) = 0 \quad (12)$$

in which, $Q_{0,N} = (I_T - \frac{e_T}{T}) \otimes I_N$, $Q_{1,N} = \frac{e_T}{T} \otimes I_N$.

Kapoor *et al*. (2007), based on the six conditions above, proposes three GMMs. The first is generally called initial GMM (GMM 1), which concerns Condition (7) to (9), not σ_1^2. The estimates of σ_v^2 and ρ can be obtained, with which σ_1^2 can be estimated from Formula (10). The second GMM is full weighted GMM (GMM 2), which is got by weighting moment equator. Weighted matrix is the inverse of variance-covariance in the strict normal sample of the actual parameters. In case of normal error assumption, a simple weighted matrix is possible. The third GMM is partial weighted GMM (GMM 3), and it is for the convenience of calculation and is the result of replacing weighted matrix in GMM 2 by identity matrix.

Choosing Spatial Weight Matrix

Spatial weight matrix plays an important role in the spatial stochastic process of spatial units. It reflects the spatial covariance structure between spatial units. Thus, a proper spatial weight matrix sets forth the basis for reflecting objectively variables' spatial correlation and spatial spillover effect. At present, there are two frequently-used construction methods:

The first is the distance-based spatial weight matrix, W_1. It can be further divided into spatial contiguity weight matrix (binary weight matrix) and geographical distance weight matrix (matrix elements are the reciprocal of squared distance between the two central points).

The simplest binary weight matrix W_{cont} is constructed by 1 or 0, in which 1 refers to the correlation between the two places and 0 irrelevance. After the final standardization, the sum of the elements is made 1.

$$w_{ij}=1\text{, when Area } i \text{ and } j \text{ are adjacent}$$

$$w_{ij}=0\text{, when } i=j \text{ or not adjacent}$$

W_{net} shows the geographical distance, and its setting is:

$$w_{ij}=\frac{N_{ij}}{\sum_j N_{ij}}$$

In the equator, N_{ij} is the distance between i and j. If i and j are not adjacent, w_{ij} is 0.

W_2, the second method, is based on the socio-economic weights, and is determined by the flux between the two spatial units. Its setting depends on the inter-industrial correlation, the interregional trade volume or population migration. Research in this aspect includes: Conley and Dupor (2003) set weight matrix with forward and backward linkage in Input and Output Format of the industrial linkage data; Verspagen (1997) expands concepts like technology exchange and R&D spillover, and set "technical flow matrix" with patent citation rate; Aten (1997) bases on the international trade volume (the percentage of the total import and export between the two countries in the trade volume) and sets up an unsymmetrical weight matrix; Eliste and Fredriksson (2004) get the compound weight matrix by taking export flow rate and distance in between as threshold value. W_{perpop} stands for population density spatial weight matrix and W_{pergdp} GDP per capita. These two matrixes can reveal the economic differences and therefore are chosen to fit the formula below:

$$w_{ij}=\frac{1/\left|X_i-X_j\right|}{\sum_j 1/\left|X_i-X_j\right|}$$

In W_{perpop}, X_i is the population density in Area i ; while in W_{pergdp}, X_i is the average GDP in Area i. Sum of elements are standardized to be 1 finally.

Anselin and Lozano-Gracia (2008) points out that in the coefficient estimation and inspection of the spatial econometrics, exogenous variables should be used. Besides, parameters that can determine weight matrix structure should be independent from and unrelated to the explanatory variables. Also, the disadvantage of the socio-economic weight matrix in application is that it cannot avoid the correlation with other variables in the model. In this paper, we focus on the spillover of FDI on the neighboring provinces, so in terms of geographical features, the adjacent standards are adopted to construct the weight matrix.

Global Spatial Autocorrelation Inspection

In establishing spatial econometric model, it is vital to check its spatial autocorrelation. The common inspecting methods are Moran I index, Geary C index and Global G index. Of all three methods, Moran I has been used more widely. The inspection is to find the dependency in the distribution of overall spatial data, that is, to examine whether the spatial joints have associated the observations of the spatial units with that of the adjacent units.

The calculating formula of Moran I is:

$$Moran \quad I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(U_i - \overline{U})(U_j - \overline{U})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(U_i - \overline{U})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(U_i - \overline{U})(U_j - \overline{U})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \qquad (13)$$

In it， $S^2 = \frac{1}{n}\sum_{i=1}^{n}(U_i - \overline{U})^2, \overline{U} = \frac{1}{n}\sum_{i=1}^{n} U_i$ ， U_i is the observation sample of the related index in Region i ， n is the number of regions, w_{ij} spatial weight matrix elements. In checking the supposed non-existent spatial autocorrelation, the standardized index of Moran I can be used, that is, $Z(I)$.

$$Z(I) = \frac{I - E(I)}{\sqrt{D(I)}} \qquad (14)$$

The standard Moran I bases on the average value of all the outcome measures and gets the result between 1 and -1. The more it approaches 1, the closer the spatial relation is, the more similar the inter-unit features. However, the closer it is to -1, the greater the inter-unit differences or the less concentrated the distribution.

With Moran I, the spatial autocorrelation inspection is made on the innovation efficiency of 30 provinces over 11 years, that is, checking the spatial dependency of innovation efficiency. As is shown in Table Ⅱ, the spatial distribution of innovation efficiency in 30 Chinese provinces has an obvious normal autocorrelation, namely spatial autocorrelation, suggesting that the spatial distribution of innovation efficiency is not random, but concentrated in areas with close innovation efficiency: high-efficiency provinces tend to stay close in space, while those with low innovation efficiency always adjoins with each other.

(insert Table II)

Moran I results show the obvious spatial correlation in the innovation efficiency of 30 Chinese provinces from 2000 to 2010. We then use the spatial panel data model to further analyze the impacts of FDI on regional innovation efficiency. Before that, the model setup should be first examined, the results of which can be seen in Table Ⅲ. According to Anselin's criteria (2004), if the Lagrange Multiplier (Lag) is more significant statistically than the Langrange Multiplier (Error), and if the Robust LM (Lag) is significant while the Robust LM (Error) is not, the use of spatial lag model is appropriate; otherwise, the use of spatial error model is more proper. It can be concluded from Table Ⅲ that Lagrange Multiplier (Error) and Robust LM (Error) are not as significant as the corresponding Lagrange Multiplier (Lag) and Robust LM (Lag). In addition, both Lagrange Multiplier (lag) and Robust LM (lag) pass the 1% significance level test, and both Lagrange Multiplier (Error) and Robust LM (error) are insignificant. Therefore, it can be fully justified that spatial autoregressive model should be chosen.

(insert Table III)

The result above leads to the Spatial Panel Model as follows:

$$IE_{it} = \alpha + W \cdot IE_{it} + \beta_1 FDI_{it} + \Sigma\beta_n X_{nt} + \Sigma\beta_j FDI_{it} X_{nt} + \varepsilon_{it} \qquad (15)$$

In Equation (15), the dependent variable (IE) denotes regional innovation efficiency, W represents a vector of Spatial Weight Matrix, regressive parameters $\beta_1 \ldots \beta_9$ measure the nine factors impacting on regional innovation efficiency: Regional FDI, Openness (OP), Economic Competition (CO), R&D Input density (RDI), Human Resource Quality (HQ), Financial Scale (FS), Industry Density (ID), Industrial Conditions (IC) and System Conditions of Technology Transfer (TC).

Results

(inset Table IV)

(insert Table V)

Table Ⅳ displays descriptive statistics and a correlation matrix for all variables. Table Ⅴ presents the results of DEA estimations of regional innovation efficiency.

The mean values of innovation efficiency in Table Ⅴ reveal that there is great spatial disparity of innovation efficiency. Nationally, Shanghai is the top performer with a mean value of 0.974, while Hebei is the worst performer with a mean value of 0.359. Across regions, innovation efficiency displays a diminishing trend from the eastern region to the central region and the western region. Within the 11 provinces of the eastern region, Beijing, Tianjin, Shanghai, Jiangsu, Hainan, and Guangdong had the highest innovation efficiency with the maximum value of 1. Surprisingly, economically developed provinces such as Shandong and Zhejiang performed less well in innovation efficiency with the mean values below the national average. For the eight Central provinces, only Hunan achieved an above national average of innovation efficiency. The cause of underperformance in many provinces appears to be the inconsistency over the period, as the deviation values suggest. In the western region, Chongqing had the highest innovation efficiency, to be followed by Guizhou, Xinjiang, Qinghai and Yunnan. The performance of innovation efficiency of many provinces in the region was highly inconsistent.

The results of spatial panel model estimations are reported in Table Ⅵ. We estimate Eq. (15) firstly by entering the FDI variable and eight variables of regional characteristics to assess the direct effect of FDI and regional characteristics on regional innovation efficiency. We then enter the interaction terms of FDI and individual regional characteristics variables in turn to assess the moderating effect of regional characteristics on the relationship between FDI and regional innovation efficiency.

(insert Table VI)

The results of model 1 suggest that FDI is statistically significant at 5% level, implying that FDI does enhance regional innovation efficiency. Thus, hypothesis H1a is supported. This result is consistent with findings of extant research (Fu, 2000). The results of model 1 also suggest that regional innovation environment and regional absorptive capacity are statistically significant at 1% level, implying that regional innovation environment and absorptive capacity have a significantly positive effect on regional innovation efficiency. Thus, hypotheses H2a and H2b are supported. Furthermore, the results of model 1 also suggest that financial scale and system conditions of technology transfer are statistically significant at 1% level, suggesting that hypothesis H2c is partially supported.

Models 2-9 test the moderating effect of regional innovation environment, absorptive capacity, and complementary assets on the relationship between FDI and regional innovation efficiency. The interaction terms between FDI and regional openness and FDI and financial scale are positively significant at 10% level. Thus, hypotheses H3a and H3c are partially supported. All other interaction terms are not statistically significant. The results suggest that in regions with a more open innovation environment, FDI will have a greater impact on regional innovation efficiency and that in regions with more developed financial markets, FDI will also have a greater impact on regional innovation efficiency.

Discussion and conclusions

Conclusions

This paper empirically examines the effect of FDI on regional innovation efficiency and the moderating effect of regional innovation environment, absorptive capacity, and complementary assets on the relationship between FDI and regional innovation efficiency. We first employ the DEA method to develop an index of regional innovation efficiency for 30 provincial regions in China over the period 2000-2010. We then test our hypotheses using spatial panel model. From the empirical results, we obtain four main research findings. First, the index of regional innovation efficiency from the estimation of DEA suggests that there are considerable inter-regional and intra-regional variations in innovation efficiency in China. Second, our GMM estimation of spatial panel model confirms the positive effect of FDI on regional innovation efficiency, suggesting FDI's catalytic role in the improvement of regional innovation efficiency. It implies that FDI is attributable to inter-regional and intra-regional variations in innovation efficiency. Third, our GMM estimation results also suggest that regional characteristics, namely innovation environment, absorptive capacity, and complementary assets, can also have a positive effect on regional innovation efficiency. This provides fresh empirical evidence to support the argument in the literature that regional characteristics can influence innovation performance (Bai, 2013; Brenner and Broiekel, 2011; Werker and Athreye, 2004). Finally, our empirical results provide some evidence that suggest that regional innovation environment in terms of regional openness and regional complementary assets in terms of the size of regional financial markets may have a moderating effect on the relationship between FDI and regional innovation efficiency. The more open the regional innovation environment, the greater the effect of FDI on regional innovation efficiency; the more developed the regional financial markets, the greater the effect of FDI on regional innovation efficiency. We thus conclude that inter-regional and intra-regional variations in innovation efficiency in China can firstly be explained by the differences in inflow FDI and then be accounted for by the direct and moderating effect of regional innovation environment, absorptive capacity, and complementary assets.

Theoretical contributions

In this paper we make a number of contributions to the FDI and innovation literature. First, we depict the spatial disparities of inter-regional and intra-regional innovation efficiency in China, using the DEA approach. This contributes to the understanding of the complexity of regional innovation in China. Second, we use more advanced spatial panel data econometric modelling to estimate the direct effect of FDI on regional innovation efficiency and hence provide new empirical evidence to the debate on FDI's catalytic and inhibiting effect on regional innovation. Third, we contribute to the literature by confirming that regional characteristics in terms of innovation environment, absorptive capacity, and complementary assets can have direct and moderating effect on regional innovation efficiency.

Policy implications

Our research findings can have policy implications. First, governments should continue their efforts to increase the transparency and predictability of the framework for inward FDI. It is important to align FDI with the region's strategic priorities of development in order to improve innovation efficiency. Second, our results suggest that foreign investors value the quality of regional conditions, in terms of innovation environment, absorptive capacity and complementary assets, as the most important factor in making their investment decisions. Governments should develop holistic and coherent policies that address the key aspects of those regional conditions. Third, regional openness and regional development of financial markets can magnify the effect of FDI on regional innovation efficiency. Governments at the regional level should cultivate an open innovation environment and support the development of financial markets in order to maximize the positive effect of FDI technology spillover and externalities.

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