The Knowledge Spillover Effects of FDI on The Productivity and Efficiency of Research Activities in China

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published in *China Economic Review*

Abstract

As China is moving toward an innovation-driven economy, this paper offers new insights for both policymakers and investors to optimize the effectiveness of investment performance. This paper studies China's provincial research activities with a focus on the spillover-induced productivity and efficiency change. The results show that spillovers as a result of inflow of foreign investment contribute positively to the performance of overall research activities, however, the productivity effects vary across regions. Our analysis also indicates that highly skewed distribution of FDI leads to a less improved innovation efficiency in FDI-rich provinces. Future innovation policy should adjust the investment profiles based on the preferential innovation output on one hand, and optimize the complementary policy for FDI on the other hand to reduce inefficiency and the potential negative effects of knowledge spillovers. Inter-provincial governmental cooperation is necessary to resolve the uneven distribution of FDI and improve the innovation efficiency in both FDI-poor and rich regions.

Keywords: Patent application; Spillover; Productivity; Efficiency; Poisson model; DEA.

JEL Classification: C2; D2; F19; F29; O3

Please cite as follows:

Lin Zhang (2017): The knowledge spillover effects of FDI on the productivity and efficiency of research activities in China. China Economic Review, 42, 1-14.

DOI: https://doi.org/10.1016/j.chieco.2016.11.001

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1 Introduction

China sets a target in the 12th Five Year Plan (2011-2015) to spend 2.2% of its GDP on R&D by 2015. To achieve the goal of building an innovation-driven economy by 2020, China needs to address many resource, environmental and institutional challenges. Therefore, a clear understanding of the status-quo of the research sector in China is necessary for both policymakers and investors to optimize the development strategy and to improve the effectiveness of investment performance.

In this paper, we study the *productivity* which is defined as the ratio of transforming inputs into output in the frontier, and *efficiency* which refers to the ratio between real output and the best-practice output in Chinese provincial research sector by using data from 2004 to 2012. We investigate particularly the impacts of knowledge spillovers through FDI on the innovation output, mainly the domestic patent application. The reason is as follows. Although knowledge is a non-rival public good, there exists social and political barriers which prohibit free dissemination of information across countries. The use of knowledge and its positive externalities can be limited and geographically localized (Jaffe et al. 1993; Audretsch and Feldman,1996). The most important channels of breaking the geographic restrictions is FDI. Therefore, it is expected that spillovers induced from FDI not only contribute to the regional economic growth (Kuo and Yang, 2008), but also impact the productivity and efficiency of regional innovation production. According to the World Bank statistics, China has overtaken the U.S. as the top destination for FDI in the world market since 2009. This implies that an accurate measurement of the performance of China's research activities should take into account the spillover effects of FDI.

We first develop a theoretical framework to disintangle the *productivity* and *efficiency* effects. We then investigate the two effects empirically for Chinese provinces in the period of 2004-2012 by employing both parametric and non-parametric approaches for this study. Specifically, we use Poisson model to estimate the productivity effect due to FDI-induced spillovers. Our results illustrate that spillovers as externalities of inflow of foreign investment contribute positively to the productivity improvement of China's overall research performance. The data envelopment analysis is then applied to study the efficiency effect of FDI. We have observed from statistics the regional heterogeneity in terms of FDI, R&D expenditures, and the innovation output. Our analysis confirms that heterogeneous effects of FDI on productivity and efficiency across regions. East region with high level of FDI benefits largely from productivity improvement, while the efficiency effects are small. In the central and west regions, the spillover effects of FDI contribute mostly to the efficiency improvement rather than the increase in productivity. Such differences vary across different types of innovation output as well. This study concludes that future policy of promoting innovation at the provincial level should adjust the investment profiles based on the preferential innovation output on the one hand, and optimize the complementary policy for FDI on the other hand to avoid the inefficient use of resources and reduce the potential crowding-out effects of knowledge spillovers. Regional or inter-provincial governmental cooperation for resolving the uneven distribution of FDI is necessary for the improvement of innovation efficiency in both FDI-poor and rich regions.

Our paper is related to several strings of literature. In addition to the knowledge spillover and innovation literatures (e.g., Jaffe 1986; Coe and Helpman 1995), there are now several complementary frameworks for studying knowledge spillover effects of FDI in China. The first includes studies trying to identify the types of FDI spillovers. For example, Lin et al. (2009) provide with evidence of horizontal and vertical spillover effects from FDI in China. Ito et al. (2012) further examine how the horizontal and vertical spillover effect of FDI is different according to outcome by estimating both production function and patent production function. The second group includes a series of papers focusing on the analysis of FDI spillovers in selected firms or industry. Jeon et al. (2013) find that FDI spillover effects vary depending on industries and technological level of indigenous firms. Zhang (2014) report that FDI has large positive effects on China's industrial performance and the effects are much greater on low-tech manufacturing than medium- and high-tech industries. These studies have focused on the complexity of inter-industry spillovers from FDI according to firm or industry characteristics. The final group discovers the connections between FDI and the innovation capacity. Fu (2008) studies the relationship between FDI and regional innovation capabilities using data between 1998 and 2003. Li (2009) and Fu (2008) focus on the innovation capacity using data up to the year 2005. Hu and Jefferson (2009) find the growth of foreign direct investment in China is one of the major factors resulting in the patent surge in recent years. Chen and Guan (2011) use a structural approach with partial least squares to detect and untangle the periodically operating state of China's regional innovation systems

Our emphasis on the heterogeneous effects of different channels of FDI spillover effects across regions, is different from, though complementary to, all the above mentioned groups of papers.[1] The strength of this paper is that, first, we have developed an analytical framework to integrate the innovation efficiency into the knowledge production function, and thus both *productivity* and *efficiency* effects are identified accordingly. This means that our analytical framework makes it true to empirically investigate innovation performance by assessing the resources devoted for research activities across regions in China. Second, inspired by Cheung and Lin (2004) where they study the research sector in China from 1995 to 2000, our study fills the gap where the available studies in the literature are outdated in terms of data periods and the development phase of China's research sector. In fact, China's R&D activities started to take off from the year 2004. According to the statistics from World Intellectual Property

[1]Different from this study where we focus on the regional differences of FDI spillovers, Bai et al. (2012), Shang et al. (2012), Scherngell et al. (2014) investigate the general spillover effects between regions.

Organization[2], the number of patent application in China grows at an annual rate of around 30% from 26 thousand patent applications in 2000, less than a tenth of patent applications of the U.S., to more than 700 thousand in 2013 which is 46% larger than the cases of the U.S. Moreover, China's continued strong economic growth fuels further increase of its R&D investments. In fact, China surpassed Japan in terms of overall research spending in 2011 after a few decades of global R&D investment was dominated by Europe, the U.S. and Japan. It is expected that China's research expenditures will soon surpass those of Europe and the U.S. in absolute terms. With such aggressive investment, China is experiencing a tremendous change in its research profiles. To be competent and take its place among global R&D leaders, China has to recognize its own competitive advantages and restructure the weaknesses which have long existed in current innovation system. The study by Cheung and Lin (2004) is not enough to illustrate the fast developing trend of the research activities in China. For this purpose, an updated empirical study on the performance of China's research sector at the provincial level is necessary for both the central government and local authorities to optimize their policy preferences and investment strategies in order to maximize the innovation output. Finally, our empirical model specifications provide more reliable results for the investigation of the determinants of innovation performance. Our model differs from Cheung and Lin (2004) in several aspects. We utilize the Poisson estimation featuring count data for a panel model. The R&D stock is constructed for knowledge production function and the FDI stock is developed for the proxy of spillovers. We also address the endogeneity issues by using lagged variables and generalized method of moments (GMM) estimator. Accordingly, our findings in the empirical investigations guided by the theoretical framework with most recent data source provide systematic evidences for the specificities of China's innovation activities.

This paper is organized as follows. Section 2 provides the theoretical framework for this study. Section 3 describes the econometric specification for the estimation of productivity effects. The data description is also presented. Section 4 presents the estimation results. Section 5 is a detailed description of the regional heterogeneity on China's research sector and its development over time. We then re-estimate our model by taking into account the regional differences. Section 6 reveals the effects of spillovers on the innovation efficiency by using a non-parametric method. Finally section 7 concludes the paper.

2 Theoretical predictions

In this section we develop theoretical predictions which will guide our empirical analysis. We consider a one-period production model where research unit maximizes the intellectual output. The creation of new knowledge dependents on the level of research activities (H),

[2]Data source is available from `http://ipstats.wipo.int/ipstatv2/ipsDistributionchart`.

own knowledge (A_0) and external knowledge (S) according to the following functional form:[3]

$$Y = F(A_0, H, S). \tag{1}$$

Nation-wide knowledge accumulation, international trade or foreign investment are typical sources for the external knowledge. In this paper, we focus on the external knowledge spillovers as a result of FDI. Knowledge spillovers may contribute to the overall regional innovation performance directly by expanding the knowledge base. In addition, spillovers bring in advanced practices and experiences in innovation performance. Successful innovation requires not only brilliant scientists and greater R&D investment, but also high-quality decision-making, long-term development strategy, management techniques, coordination and so on. Such "soft" factors, together with "hard" factors such as R&D manpower and investment, determine the productivity and efficiency of regional innovation performance. In general, the knowledge (innovation output) production is affected by spillovers via two channels: (i) by entering the production as an additional input for productivity improvement; spillovers affect the relative price of inputs, thus leading to induced innovation through input augmentation (e.g.: Binswanger, 1974; Hayami and Ruttan, 1970). (ii) it affects the knowledge output by impacting the innovation efficiency levels. Therefore, external knowledge S affects not only the innovation efficiency E, but also the activity level H.

To introduce innovation efficiency into the knowledge production function, we follow the suggestions by Afriat (1972) and Richmond (1974)[4] by letting

$$Y = A_0 \cdot H(L, K, S) \cdot E(S). \tag{2}$$

L and K are the research labor and R&D capital used for research activities. Accordingly, $A_0 \cdot H(L, K, S)$ represents the production frontier, showing the maximum output that may be obtained from given inputs when the inputs are used in the most efficient manner. $E(S)$ is a multiplicative random error taking values between 0 and 1 representing the innovation efficiency.

The level of research activity H depends on how much research labor L and R&D capital stock K are involved in the researching process. The accumulation of R&D stock is determined by the purposeful research investments, $K = K(I)$. Based on the Frascati definition (OECD 2002), which is the internationally recognized methodology for collecting and using research and experimental development (R&D) statistics, research covers three types of activities: basic research, applied research and experimental development. Basic research

[3]Time subscript is omitted in this section.

[4]In Afriat (1972), he discussed the problem of estimating a production function and introduced a multiplicative error u to represent the inefficiency of production. This random variable takes values between 0 and 1. Richmond (1974) agreed with the separable feature and complements to Afriat (1972) by assuming that $u = \exp(-z)$, where z has a Gamma distribution. Based on the count data feature, we will use the Poisson error structure for this analysis.

is experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundation of phenomena and observable facts, without any particular application or use in view. Applied research is also original investigation undertaken in order to acquire new knowledge. It is, however, directed primarily towards a specific practical aim or objective. Experimental development is systematic work, drawing on existing knowledge gained from research and/or practical experience, which is directed to producing new materials, products or devices, to installing new processes, systems and services, or to improving substantially those already produced or installed.

We thus formulate that H is a function of three types of research investment:

$$H \equiv H[L, K(I^B, I^A, I^D), S] = H[L, K(I, \alpha^B, \alpha^A, \alpha^D), S]\,, \tag{3}$$

where I^B, I^A, and I^D are the R&D investment on basic research, applied research and experimental development, respectively. α^B, α^A and α^D are the shares of each investment type in total R&D expenditure I, respectively. The marginal effect of each type of investment is defined as:

$$\frac{\partial Y}{\partial \alpha^n} = A_0 \cdot \frac{\partial H(L, K, S)}{\partial K} \frac{\partial K}{\partial \alpha^n} \cdot E(S)\,, \tag{4}$$

where $n \in \{B, A, E\}$ representing the research investment type, namely basic research (B), applied research (A), and experimental research (E). In this framework, we can derive following predictions:

Prediction 1: *Output in R&D is affected not only by factor input increase (L and K), but also by the structure of the investment (α^B, α^A and α^D). In addition, knowledge spillovers induced from FDI tend to increase the output through input augmentation.*

From eq. (2), the marginal effect of external knowledge is given by:

$$\frac{\partial Y}{\partial S} = A_0 \cdot \frac{\partial H}{\partial S} \cdot E + A_0 \cdot H \cdot \frac{\partial E}{\partial S}\,. \tag{5}$$

We then define the elasticity of innovation frontier with respect to knowledge spillover as $\epsilon = \frac{\partial H}{\partial S}\frac{S}{H}$, the elasticity of innovation efficiency with respect to knowledge spillover as $\lambda = \frac{\partial E}{\partial S}\frac{S}{E}$, equation (5) can be re-written as follows:

$$\frac{\partial Y}{\partial S} = \frac{A_0\, H\, E}{S} \cdot (\epsilon + \lambda) \begin{cases} > 0, & \text{if } \lambda > -\epsilon\,; \\ = 0, & \text{if } \lambda = -\epsilon\,; \\ < 0, & \text{if } \lambda < -\epsilon\,. \end{cases} \tag{6}$$

The sign of ϵ is always positive as the knowledge spillover contributes to input augmentation and final higher output. We label this as the *productivity effects*, as it implicitly increases the productivity of labor and R&D capital by shifting the production frontier outwards. The sign of λ is not clear. In general, an open economy may benefit from international knowledge spillover which can improve the efficiency of innovation. However, as discovered in literature, effects of FDI are double-edged. On the one hand, the newly invested foreign enterprises will drive technology progress of indigenous firms through intensified competition and demonstration (Thompson 2002). Lack of competition in a market will give rise to inefficiency and result in sluggish innovative activities (Fu 2008). On the other hand, intensive foreign invested firms will result in "extrusion effects" on indigenous firms by crowding out local innovation as foreign-invested firms possess both technology and cost advantages (Zeng et al. 2009). There is empirical evidence in the literature supporting the negative effects of spillovers (Aghion et al. 2005; Aitken and Harrison 1999; Kathuria 2000; Konings 2001; Hu and Jafferson 2002; Reganati and Sica 2007; Zeng et al. 2009). The effects indicated by λ is labeled as *efficiency effects*. The sign of (6) is determined by the relatively size of the two effects.

Based on the facts discussed above, we can further derive following prediction in the case of China:

Prediction 2: *The spillover effect can be either positive or negative, which is determined by the relative magnitude of two effects: the productivity effects indicated by ϵ, and the efficiency effects reflected by λ. In particular, provinces with lagged innovation development can benefit from FDI with positive externality ($\frac{\partial Y}{\partial S} > 0$) through demonstration and intensified competition, indicating higher or positive value of λ. Provinces with advanced innovation level can suffer from lower or negative effects of spillovers ($\frac{\partial Y}{\partial S} < 0$) as international competition discourages local innovation through crowding out effect, reflecting by lower or negative value of λ.*

Following our theoretical framework, we will conduct empirical analysis to study the productivity and efficiency effects respectively in the next sections.

3 Econometrics

3.1 Econometric specification

In the literature of statistical models of count data, the Poisson and negative binomial models have been suggested for the estimation of the number of occurrences of event counts. Similar to Hausman et al. (1984)[5], we consider the following Poisson specification for the

[5]Hausman et al. (1984) develop a Poisson model to analyze the relationship between patents and R&D expenditures.

determination of province innovation in this paper:

$$PAT_{i,t} = \exp(\beta_l \ln L_{i,t} + \beta_k \ln K_{i,t} + \beta_b SB_{i,t} + \beta_d SD_{i,t} + \beta_y PY_{i,t} + \beta_f \ln FDI_{i,t} + \beta_{Dt} D_t) + u_{i,t} \tag{7}$$

with $u_{i,t}$ is an error term; $\exp(\cdot)$ is the exponential operator. $L_{i,t}$ is the number of personnels working in the research sector in province i at time t; $K_{i,t}$ is the R&D stock in province i at time t. Both variables are the key inputs and are expected to have positive impacts on research output. Taking the applied research expenses as benchmark, we introduce two share variables to reflect the investment structure. $SB_{i,t}$ and $SD_{i,t}$ are the share of expenses on basic research and experiment research, respectively. The effects of the investment structure are unclear as one type of patents may prefer a specific research investment to others. $PY_{i,t}$ is the per capita real GDP in province i at time t, which accounts for the fact that provinces are at different stage of economic development as well as different level of research frontier. A higher level of per capita GDP indicates that the respective province is at the research frontier, and hence it becomes relatively difficult to innovate. $PY_{i,t}$ also reflects the absorptive capacity of a province. A higher level of per capital income indicates that a high level of absorptive capacity of knowledge and spillovers, contributing positively to the innovation. $FDI_{i,t}$ is the stock of FDI in province i at time t which shows the degree of spillover effect of FDI. D_t is the time dummies capturing the overall trend of propensity to research.

$PAT_{i,t}$ is the number of patent application for province i at time t. As suggested by Joutz and Gardner (1996) and Abdih and Joutz (2006), patent application is a good approximation for technological output. We thus use the number of patent applications as a measure of R&D output. Cheung and Lin (2005) discuss the limitations of using this proxy, however, they also argue that patent applications are preferred compared to other suggested proxies since it includes both product and process innovations. To reflect the quality of the knowledge output, we proxy knowledge creation at a point of time by the number of patent applications and the number of patent granted.

All explanatory variables used in equation (7) are lagged for one year for two reasons. Firstly, the output of an innovation production in a given year is realized one year later (Fu 2008). Secondly, using one year lag for the independent variables removes the possible endogeneity of those variables.

As this study focuses on the effects of FDI, we further consider the potential endogeneity problem of using FDI as a regressor, and hence introduce instrumental variables to address this issue. To identify the effects of FDI on research output, we need instruments that are correlated with FDI volumes, but not with patent. In literature, many studies suggest real exchange rates and lagged values of FDI as instruments(Blonigen 1997, Klein and Rosengren 1994, and Wheeler and Mody 1992). As our study focuses on the provinces in one country, the exchange rate is the same for all provinces, which may not truly reflect the change of FDI across regions. Instead, we introduce the variable "FDIIN" which measures the intensity of FDI in one region over time. It is calculated as the ratio between the FDI inflow and GDP at the provincial level.[6]

With the two variables FDI intensity and lagged FDI flow as instruments,[7] we then use the Generalized Method of Moment (GMM) estimator for our econometric analysis (Mullahy 1997; Cameron and Trivedi 2013; Wooldridge 2010). The equation to be estimated is formulated as follows:

$$\begin{aligned} PAT_{i,t} &= \exp(\beta_l \ln L_{i,t-1} + \beta_k \ln K_{i,t-1} + \beta_b SB_{i,t-1} \\ &+\beta_d SD_{i,t-1} + \beta_y PY_{i,t-1} + \beta_f \ln FDI_{i,t-1} + \beta_{Dt} D_t) + u_{i,t} \end{aligned} \tag{8}$$

3.2 Data

This study is based on a balanced China panel data set for a sample of 30 provinces observed over the period 2004 to 2012 (t = 2004-2012). Our study focuses on provinces, autonomous regions, and municipalities in mainland China. Due to incomplete information in statistics, Tibet is excluded from this study. For simplicity, all the units of observations are labeled as provinces thereafter. The data set is based on the information taken from China Statistical Yearbook (2005-2013) and China Statistical Yearbook on Science and Technology (2005-2013).

R&D activity is a process of knowledge accumulation and technological development as a result of R&D investment. The corresponding assests—the stock of knowledge—are intangible assests which are unobservable and difficult to measure in terms of values. The main practical measurement option is to approximate the value of knowledge by capitalized R&D expenditures, in which the expenditures are formed into R&D capital stocks via the perpetual inventory method, $K_{t+1} = (1-\delta)K_t + I_t$. Following Griliches (1980), the initial R&D stock level is computed as $K_0 = \bar{R}/(g+\delta_0)$ where g is the growth rate of R&D expenditures, and $\bar{R}$ is the R&D expenditure in period 0. The depreciation of R&D capital δ is assumed to be 15% (Kuo and Yang 2008). The FDI stock is constructed in a similar way. As it is difficult to obtain the deflators for R&D expenditures and FDI flows, we use the provincial GDP deflators to transform the nominal values from statistics into real values.

The descriptive statistics of all variables used in this study are listed in Table 1.

According to China's statistics, all provinces are classified into three regions: the east region including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian,

[6] FDI inflow values are converted to real values in Chinese Yuan. GDP refers to the real GDP values in Chinese Yuan.

[7] In order to verify the validity of the instruments, we estimate a classic fixed effects model. To test for weak instruments, we compute the Cragg-Donald Wald F test statistic. The value of this statistic (140) is larger than the critical value at 10% level of significance (19.93) suggested by Stock-Yogo (2003). Therefore, we reject the hypothesis that instruments are weak. The Hansen J statistic for testing the overidentification of all instruments does not reject the null hypothesis of valid instruments (Chi-sq(1)=0.11, P-Value=0.74). All these results show that we are able to find reasonable instruments.

Table 1: Descriptive statistics of variables. Source: China Statistical Yearbook and China Statistical Yearbook on Science and Technology, various years.

Variable	Mean	Std. Dev.	Min	Max
Number of patent (1000 units)	28.22	51.73	0.12	472.66
Number of invention (1000 units)	7.42	12.78	0.05	110.09
Number of utility model (1000 units)	10.19	15.96	0.04	108.60
Number of design (1000 units)	10.61	25.84	0.03	255.47
Research personnel (1000 persons)	69.21	75.49	1.21	492.33
Total research expenses (billion in 2004 Yuan)	14.10	18.38	0.10	99.63
R&D stock (billion in 2004 Yuan)	43.77	59.73	0.36	319.58
Share of expenses in basic research	0.07	0.05	0.01	0.43
Share of expenses in applied research	0.14	0.08	0.03	0.42
Share of expenses in experimental development	0.79	0.12	0.21	0.96
Per capita income (2004 Yuan/person)	22427.10	14253.40	4297.64	74661.41
FDI flow (billion in 2004 Yuan)	17.01	24.70	0.23	105.05
FDI stock (billion in 2004 Yuan)	87.22	129.62	1.55	564.86
FDI intensity (%)	1.67	2.19	0.19	20.21

Shandong, Guangdong, Hainan; the central region including Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan; and the west region including Chongqiong, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, Inner Mongolia.

4 Knowledge spillovers and innovation production

The regression results are shown in Table 2. Model (1) and (2) use the provincial patent application and patent granted as the dependent variable, respectively. The results are in line with each other. As the Poisson model is in the form of log-link, so the estimated coefficient can be interpreted as elasticity if the explanatory variables are expressed by the log form in the econometric model.

The results show that both the number of personnels and the quantity of R&D stock positively contribute to the realization of new patent, and are statistically significant in both cases. However, the magnitude of the coefficients varies between two models. In the model with patent application as the dependent variable, R&D stock has a stronger impact to the innovation output; while in the model with patent granted as the dependent variable, the research labor is more important to produce innovation. We know that patent applications are varied in terms of quality. By comparing the results using two different dependent variables, we find that it is easy to fulfill the requirement of filing a patent application by investing in R&D activities. However, the researchers will have to double their efforts to guarantee the patent application to be granted successfully.

When we look at the investment structure, the coefficients of share of basic expenses "SB" and share of experimental expenses "SE" are positive and statistically significant. This suggests that these two types of investment are more important in terms of knowledge production, taking the applied research expenses as the benchmark. The spillover effects

Table 2: Regression results using different proxies for dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5
	Patent				
VARIABLES	application	granted	invention	utilitymodel	design
$\log(\mathrm{FDI})_{-1}$,	0.287***	0.291***	0.222***	0.195***	0.467***
	(0.043)	(0.047)	(0.030)	(0.053)	(0.070)
$\log(\mathrm{L})_{-1}$,	0.244*	0.513***	0.164	0.389***	0.036
	(0.132)	(0.149)	(0.104)	(0.140)	(0.228)
$\log(\mathrm{K})_{-1}$,	0.626***	0.366***	0.727***	0.506***	0.771***
	(0.121)	(0.137)	(0.096)	(0.124)	(0.213)
SA_{-1},	1.767**	1.870*	3.461***	0.619	1.306
	(0.884)	(0.999)	(0.822)	(0.932)	(1.373)
SD_{-1},	1.297***	1.484***	0.542	0.989**	2.469***
	(0.389)	(0.441)	(0.385)	(0.423)	(0.637)
$\log(\mathrm{PY})_{-1}$,	-0.230**	-0.193*	-0.089	-0.227**	-0.534***
	(0.098)	(0.108)	(0.080)	(0.108)	(0.172)
Constant	-13.785***	-11.966***	-16.001***	-10.956***	-18.379***
	(1.103)	(1.234)	(0.879)	(1.177)	(1.911)
Time dummy	Yes	Yes	Yes	Yes	Yes
Number of Obs.	240	240	240	240	240

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Variable "SA" is the share of expenses in basic research; variable "SD" is the share of expenses in experimental development; variable "PY" is the per capita income. The subscript "-1" indicates 1-year lag. Source: author's estimation based on Poisson model.

are estimated through the variables FDI. It shows that 1% increase in FDI, we can expect approximately 0.3% increase in patent application.

As the types of patent applications can also matter, we distinguish the three patent types by using each of the individual type of patent application as the dependent variable. We re-estimate the model by using each of the three patents as the dependent variable. The results are presented in the last three columns of Table 2 (Model 3-5).

There exists a large difference between patent types. Specifically, the effect of personnel is weaker in the creation of invention patent. The increase in total R&D stock will significantly increase the possibility of innovation outcomes: a 1% increase in total investment will lead to 0.7% increase in invention patent application, 0.5% increase in utility model application, and 0.8% increase in design patent application. From the estimated coefficients of two share variables "SB" and "SE" we find each type of patents has its own preference toward a particular type of investment. For invention patent, investment used for basic research is the crucial factor for success. Among the three patent outputs, the return of experimental expenses is the highest on design patent since the estimated coefficient of "SE" is the largest compared to other two types of patent outputs. This suggests that if a firm is marketed for new designs, resources should be directed toward experiment; or more financial budget needs to be allocated to basic research if the firm is oriented for invention patent.

The effect of FDI is the strongest on design patent, followed by invention and utility model. Such ranking in the degree of FDI effects is reasonable because FDI introduces the channels for exchanging ideas with international market, bringing together both domestic and foreign designers. This will significantly smooth the way of transferring knowledge and hence contribute to the productivity increase of producing innovation output. Similarly, invention patent requires the most sophisticated techniques in general, inflow FDI from developed regions is always associated with advanced technologies, management practice, and rich experiences, which can substantially improve the productivity of domestic research performance. Patent for utlity model is less dependent on the FDI because it is usually less technically complicated and its requirement of novelty is low compared to invention.

5 Regional innovations in China

In this section, we highlight the regional heterogeneity of China's research activities. We first show using the official statistics the differences in terms of R&D investment and R&D output. By taking into account the regional heterogeneity and policy preferences, we re-estimate our model with additional specifications and discuss how the spillover effects of FDI differ across regions.

5.1 R&D investment

The growth of R&D expenditure in China is substantial, from 159 billion RMB in 2004 to 1030 billion RMB in 2012. In general, total expenditure can be further disaggregated into three groups based on the usage: basic research, applied research and experimental development. Table 3 provides detailed information on the composition of the total expenditures over time. Overall, basic research takes less than 7% of the total research investment, while more than 70% of the research funds are used in experimental development.

Table 3: The distribution of R&D investment by research type and by region. Source: China Statistical Yearbook for Science and Technology, various years

Year	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Total expenditure in billion RMB	159	201	249	371	462	580	706	869	1030
By research type									
Share of basic research in %	6.28	5.72	6.41	4.35	4.50	4.66	4.59	4.74	4.84
Share of applied research in %	16.88	15.02	13.27	10.48	10.40	12.60	12.66	11.84	11.28
Share of experimental development in %	76.84	79.25	80.22	85.17	85.10	82.75	82.75	83.42	83.87
By region									
East region expenditure in %	70.60	70.45	70.02	72.67	72.09	69.84	70.61	71.17	70.80
Central region expenditure in %	15.17	15.39	16.79	15.44	16.19	17.67	17.01	16.85	17.15
West region expenditure in %	14.23	14.16	13.18	11.90	11.72	12.49	12.38	11.98	12.04

We can also observe that over two thirds of national R&D expenditures flow into the east region, followed by the central region with a share between 15% and 18%. The research expenditure in the west region takes up less than 15% of the national total. This regional distribution also reflects the relative level of economic development. With the highly developed economies in the east region, the available financial sources from the local government and enterprises are abundant compared to the less developed regions. The top five destinations of R&D investment (Jiangsu, Guangdong, Beijing, Shanghai and Shandong) receive roughly 50% of the total research money in the country, suggesting a high degree of spacial agglomeration of innovation activities in China. Furthermore, it is worth noting that even with the increasing value of national R&D expenditures, the share of research expenses in the west region declines over time from 14% in 2004 to 12% in 2012. This implies that the growth rate of research activities in the west region is lagged behind the other two regions or the value of the projects conducted in the west region is relatively low.

5.2 R&D output

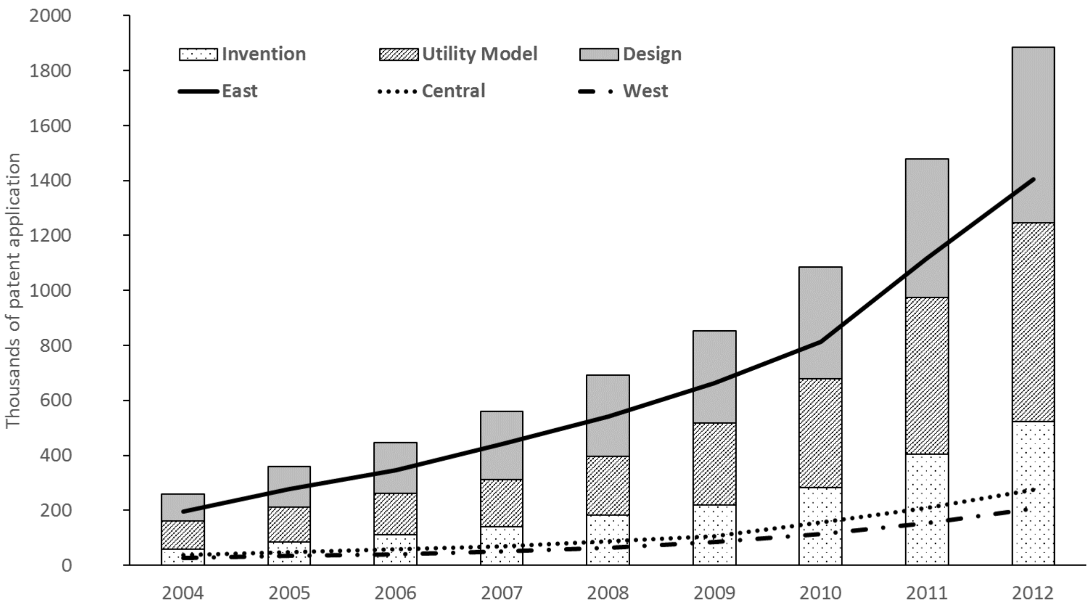
According to the patent law of China, all patent applications can be divided into three categories: invention, utility model and external design. Invention patents are regarded as the major innovation with the requirement of "novelty, inventiveness, and practical applicability" (Cheung and Lin, 2004). The patents for utility model and design have less stringent requirements for application. The share of invention in total domestic patent application is relatively low, remains at the level of about 25-27% for the last decade, though the total patent applications rise substantially.

As we can see from Figure 1, all of the three types of patent applications increase significantly between 2004 and 2012. However, the share of invention remains between 2004 and 2012. A large share of the patent application are still utility model and external design patents. Moreover, around 80% of the domestic patent applications are originated from the east region. The central and west regions are far behind the level of the east region. According to the statistics, the top five provinces in terms of invention are Jiangsu, Guangdong, Beijing, Shanghai, Shandong, all of which are in the east region, account for more than 50% of total patent application in 2012.

5.3 Regional heterogeneity and policy preferences

There are substantial regional differences among China's east, central and west regions in terms of the quantity of FDI inflow, R&D capability, and the level of economic and technology development. We can see the regional heterogeneity in terms of research investment in Table 3. Figure 2 illustrates the regional distribution of foreign invstment over time. The east region obtains more than 80% of the total investment. Therefore, it is expected that the spillover effects of FDI on productivity may also exhibit regional differences.

Figure 1: Domestic patent applications in China by types and by regions. Data source: National Bureau of Statistics China



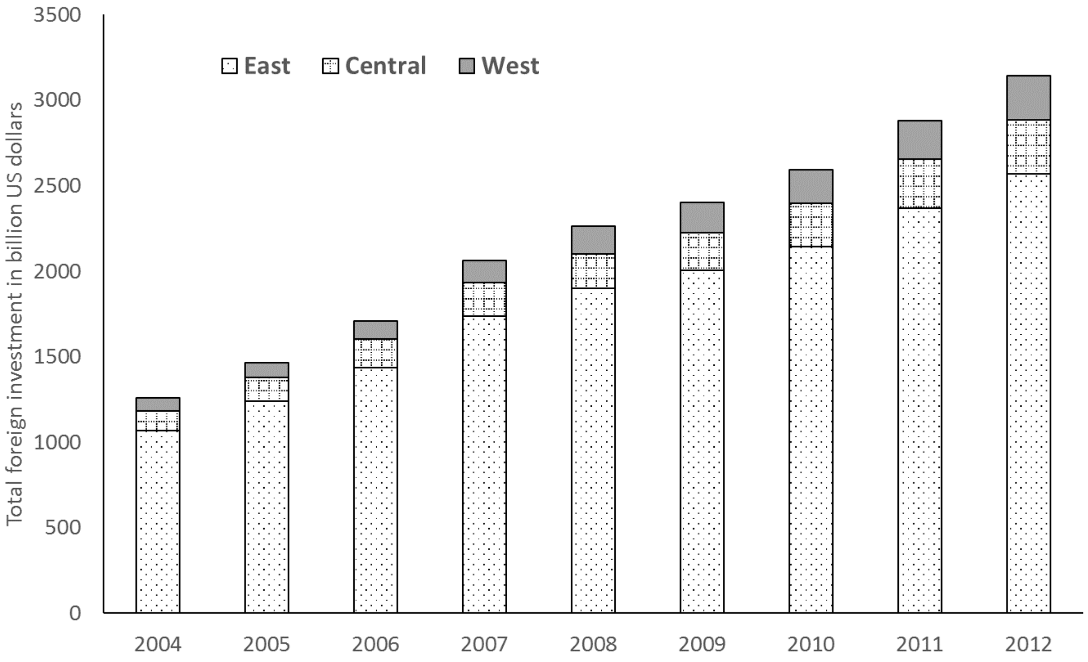
Note: According to China's statistics, all provinces are classified into three regions: the east region including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; the central region including Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan; and the west region including Chongqiong, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, Inner Mongolia.

We first introduce regional dummies into equation 8. This is because we believe there exists persistent effects common to provinces within the same region while vary across regions. For example, some preferential tax policies apply to the coastal provinces, and the "China's Western Development Program" can benefit the provinces in the west region. Over time, the three regions are possibly to form certain regional fixed effects which could affect the innovation production, but not be fully captured through provincial-specific factors. The results in Table 4 show a clear evidence of regional difference in research productivity. The estimated coefficient of regional dummy "WEST" is statistically significant. Choosing the central region as reference, the positive sign of "WEST" indicates that the west region has higher output with equal inputs as other regions. The east region does not differ statistically from the central region. By comparing the coefficients of FDI in Table 4 with those in Table 2, we find the spillover effects of FDI are stronger when taking into account the regional effects.

In addition, to study the spillover effects of FDI at the regional level, we re-estimate the equation 8 for each of the three regions using the poisson model. All the results are shown in Table 5.

We find that the spillover effect of FDI on patent applications is positive and statistically

Figure 2: Inflow of total foreign investment in China by region. Data source: National Bureau of Statistics China, various years



Note: According to China's statistics, all provinces are classified into three regions: the east region including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; the central region including Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan; and the west region including Chongqiong, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, Inner Mongolia.

significant in the east region. With the estimated coefficient of 0.42, the spillover effects of FDI influence the number of patent applications in the east region strongly. The estimated coefficients of FDI in the central and west regions are not statistically significant. Among the three regions, the relatively high and significant value of the FDI coefficient in the east region suggests that the east region benefits the largest productivity boom from spillovers. In the west and central region, the spillover effects of FDI are much smaller.

Moreover, there are substantial differences for the spillover effects on the three types of patent in terms of the magnitude of the effects across regions. In the east region, invention and design exhibit the strong and positive FDI spillover effect, while the spillover effect of FDI on utility model patent is insignificant. The coefficients of FDI for patent and design in the west region are positive and significant, however, the size of the effects is much smaller compared to the east region.

The structure of the investment composition does matter in terms of productivity. The coefficients of basic research investment are always positively and statistically significant in the east region, insignificant in the central region, and negatively, significant in the west region, compared to the reference of applied research investment. This may due to the fact

Table 4: Effects of regional heterogeneity on domestic research activities

	Model 6	Model 7	Model 8	Model 9	Model 10
	Patent				
VARIABLES	application	granted	invention	utilitymodel	design
$\log(FDI)_{-1}$,	0.315***	0.302***	0.267***	0.170**	0.578***
	(0.058)	(0.060)	(0.044)	(0.068)	(0.096)
$\log(L)_{-1}$,	0.328**	0.658***	0.175	0.459***	0.145
	(0.148)	(0.160)	(0.109)	(0.161)	(0.249)
$\log(K)_{-1}$,	0.564***	0.270*	0.710***	0.464***	0.662***
	(0.130)	(0.142)	(0.097)	(0.134)	(0.232)
SA_{-1},	2.088**	2.136**	3.909***	0.463	2.578*
	(0.910)	(0.959)	(0.877)	(0.945)	(1.370)
SD_{-1},	1.291***	1.381***	0.656*	0.877**	2.716***
	(0.405)	(0.428)	(0.394)	(0.439)	(0.632)
$\log(PY)_{-1}$,	-0.223**	-0.229**	-0.023	-0.275***	-0.428**
	(0.102)	(0.103)	(0.093)	(0.100)	(0.188)
East	0.053	0.193*	-0.101	0.140	-0.105
	(0.120)	(0.109)	(0.104)	(0.111)	(0.213)
West	0.194**	0.276***	0.126**	0.041	0.400***
	(0.078)	(0.078)	(0.062)	(0.079)	(0.129)
Constant	-14.070***	-11.303***	-17.555***	-9.630***	-21.088***
	(1.819)	(1.789)	(1.490)	(2.014)	(2.666)
Time dummy	Yes	Yes	Yes	Yes	Yes
Number of Obs.	240	240	240	240	240

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Variable "SA" is the share of expenses in basic research; variable "SD" is the share of expenses in experimental development; variable "PY" is the per capita income. The subscript "-1" indicates 1-year lag. "East" refers to the east region including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; "West" refers to the west region including Chongqiong, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, Inner Mongolia. Source: author's estimation based on Poisson model.

that the three regions are at different stage of innovation development, reflected by the total number of patent applications. The east region conducts the innovation at the advanced level where new patents are mainly dependent on the basic research. The central region is less advanced in innovation development where all the three types of research investments are indifference for innovation output. The west region is at the lowest stage of the innovation process, and most of the patent applications are the results of applied research rather than basic research investment.

The coefficients of research personnel are positive and statistically significant in the east and central region, and insignificant in the west region. Instead, the coefficients of R&D stock are positive and statistically significant in the east and west region, and insignificant in the central region. All of these suggest regions have to identify their innovation priorities and modify the innovation inputs accordingly to maximize the innovation output.

The per capita income shows positive impacts in the east region, but only significant

Table 5: Effects of FDI on different types of domestic patent applications across regions

	East region				*Central region*				*West region*			
VARIABLES	patent	invention	utilitymodel	design	patent	invention	utilitymodel	design	patent	invention	utilitymodel	design
$\log(FDI)_{-1}$,	0.429***	0.392***	0.064	0.879***	0.123	-0.031	0.114	0.379**	0.163	0.216**	0.098	0.329**
	(0.059)	(0.051)	(0.050)	(0.120)	(0.118)	(0.106)	(0.115)	(0.186)	(0.113)	(0.093)	(0.136)	(0.153)
$\log(L)_{-1}$,	0.580***	0.260**	0.250	1.394***	1.324***	1.409***	1.250***	1.354***	0.046	0.064	0.446	-0.682
	(0.180)	(0.107)	(0.170)	(0.351)	(0.243)	(0.251)	(0.237)	(0.389)	(0.320)	(0.267)	(0.445)	(0.423)
$\log(K)_{-1}$,	0.213	0.526***	0.547***	-0.705**	0.374	-0.022	0.388	0.714*	0.852***	0.833***	0.542	1.273***
	(0.171)	(0.106)	(0.161)	(0.333)	(0.268)	(0.248)	(0.261)	(0.430)	(0.244)	(0.205)	(0.330)	(0.324)
SA_{-1},	5.049***	4.209***	3.839***	7.601***	0.757	1.263*	1.117	-0.359	-5.802***	-0.142	-5.497**	-14.049***
	(0.961)	(0.888)	(0.961)	(1.920)	(0.634)	(0.718)	(0.698)	(1.141)	(1.934)	(1.746)	(2.294)	(3.127)
SD_{-1},	2.846***	0.439	3.694***	4.963***	-0.718	-1.101**	-0.087	-1.358	-0.966	0.543	-0.633	-3.320**
	(0.531)	(0.457)	(0.537)	(1.027)	(0.467)	(0.531)	(0.426)	(0.903)	(0.774)	(0.725)	(0.991)	(1.354)
$\log(PY)_{-1}$,	0.073	0.326***	-0.060	0.186	-1.046***	-0.705***	-0.806***	-1.838***	-0.643***	-0.739***	-0.466**	-0.877***
	(0.111)	(0.110)	(0.106)	(0.203)	(0.254)	(0.233)	(0.232)	(0.412)	(0.163)	(0.132)	(0.191)	(0.273)
Constant	-15.710***	-20.707***	-11.041***	-18.203***	-6.421	1.186	-9.212*	-14.123*	-7.938*	-11.032***	-6.183	-10.713
	(1.681)	(1.296)	(1.602)	(3.338)	(4.940)	(4.808)	(5.097)	(7.845)	(4.710)	(3.836)	(5.837)	(6.706)
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	88	88	88	88	64	64	64	64	88	88	88	88

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Variable "SA" is the share of expenses in basic research; variable "SD" is the share of expenses in experimental development; variable "PY" is the per capita income. The subscript "-1" indicates 1-year lag. "East" refers to the east region including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; "West" refers to the west region including Chongqiong, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, Inner Mongolia. Source: author's estimation based on Poisson model.

for invention. The coefficients of the per capita income are negative in the central and west region. This confirms our conjecture that the east region is at the advanced stage of innovation development, representing a high level of absorptive capacity contributing positively to the productivity on the one hand, and showing a high level of difficulty for new innovation contributing negatively to the productivity on the other hand. In the central and west region, the positive effects of absorptive capacity are much smaller due to the small size of own knowledge stock, and hence the negative effects dominate.

6 Knowledge spillovers and innovation efficiency

In this section, we are particularly interested in the effects of spillovers on the innovation efficiency in the presence of FDI. We estimate and compare the innovation efficiency in the case with and without spillover effects of FDI.

6.1 Non-parametric estimation of innovation efficiency

In the literature of efficiency analysis, both parametric (mostly known as Stochastic frontier analysis or SFA) and non-parametric (widely known as Data envelopment analysis or DEA) approaches are commonly used to evaluate the efficiency of a number of producers. In this section, we employ DEA method to estimate the innovation efficiency across Chinese provinces. There are several reasons for the modeling choice. DEA is able to handle multiple input and multiple output models, hence we can include three types of innovation outputs separately in one model. It does not require any assumption of a functional form between inputs and outputs, and both inputs and outputs can have different units. This is particularly an advantage in the case with limited data on inputs and output price and other cost. Finally, there is no Poisson specification available for SFA estimations, and it is difficult to deal with the endogeneity in SFA.

In the DEA framework, for any given time t, let $X_{i,t}$ be the vector of inputs into a producer, usually referred to as a decision making unit or DMU i, i.e. province i in this study. Let Y_i be the corresponding vector of outputs. If $X_{0,t}$ and $Y_{0,t}$ are the inputs and outputs of a DMU for which we want to determine its efficiency, the measure of efficiency for $DMU_{0,t}$ at time t is given by the following linear program:

$$\begin{aligned} &\min_{\theta_t,\lambda_{i,t}} \theta_t \\ &s.t.: \\ &\qquad \sum \lambda_{i,t} Y_{i,t} \geq Y_{0,t}, \\ &\qquad \sum \lambda_{i,t} X_{i,t} \leq \theta X_{0,t}, \\ &\qquad \lambda_{i,t} \geq 0 \end{aligned} \tag{9}$$

where $\lambda_{i,t}$ is the weight given to DMU i in its efforts to determine $DMU_{0,t}$ and θ_t is the efficiency of DMU_0 at time t.

In this paper, the output vector includes the three types of patent applications, namely invention patent $INT_{i,t}$, utility model $UTI_{i,t}$ and design patent $DES_{i,t}$. In terms of innovation input, the basic inputs include the number of personnels working in the research sector $L_{i,t}$, the R&D stock $K_{i,t}$, the share of basic research expenses $SB_{i,t}$ and the share of experimental research expenses $SE_{i,t}$. Again, all the basic inputs are lagged by one year. These are the inputs used to estimate the reference efficiency levels which we assume to be $EF^{ref}_{i,t}$.

To study the effects of FDI on efficiency, we consider two modeling options. In the reference model the four basic inputs are used. In the model variation, we add the lagged FDI stock $FDI_{i,t}$ as the additional input, and re-estimate the efficiency using the above mentioned modeling approach. Assuming the newly estimated efficiency to be $EF^{fdi}_{i,t}$, we are able to calculate the effect of FDI on efficiency by comparing the two efficiency scores:

$$\text{Contribution}_{i,t} = \left(\frac{EF^{fdi}_{i,t}}{EF^{ref}_{i,t}} - 1\right) \times 100\%. \tag{10}$$

6.2 Innovation efficiency and the effects of spillovers

Table 6 shows the estimated efficiency levels using the reference model and one variation where FDI is included as one of the production inputs. The original efficiency level is estimated without spillover variables (i.e. FDI). It indicates that the efficiency level of one province is associated with the level of economic development. The most efficient provinces are developed regions in terms of per capita GDP. For instance, Zhejiang, Jiangsu and Shanghai are the regions with the highest economic development. In the contrary, less developed regions in terms of per capita GDP represent the less efficient provinces to produce new patents, including provinces such as Inner Mongolia, Qinghai and Gansu.

Table 6 also shows the estimated efficiency level with FDI as a proxy variable for spillover. When comparing the efficiency levels with the original ones, it is interesting to see that there exists regional clusters in terms of the efficiency effects of FDI. Most provinces in the central and west regions show a large increase in innovation efficiency; while in the east region, the impacts of FDI on innovation efficiency are small, or even negative. In general, most of the less efficient provinces catch up by exploiting the positive effects of FDI induced spillovers, while the efficient provinces are less likely to benefit from efficiency improvement and may even experience a decline in their respective efficiency levels. One explanation for this may be that the impacts of spillover on efficiency depends on the level of research activities in individual province. Put differently, if a province is at the beginner stage of research activities, spillovers will bring in new ideas which form a complementary element for creating new knowledge. However, when a province is at the advanced stage of conducting research, each unit of spillovers actually has smaller marginal returns compared to the unit

Table 6: Comparison of the estimated provincial average efficiency levels in the period 2007-2012 between with and without spillover effects

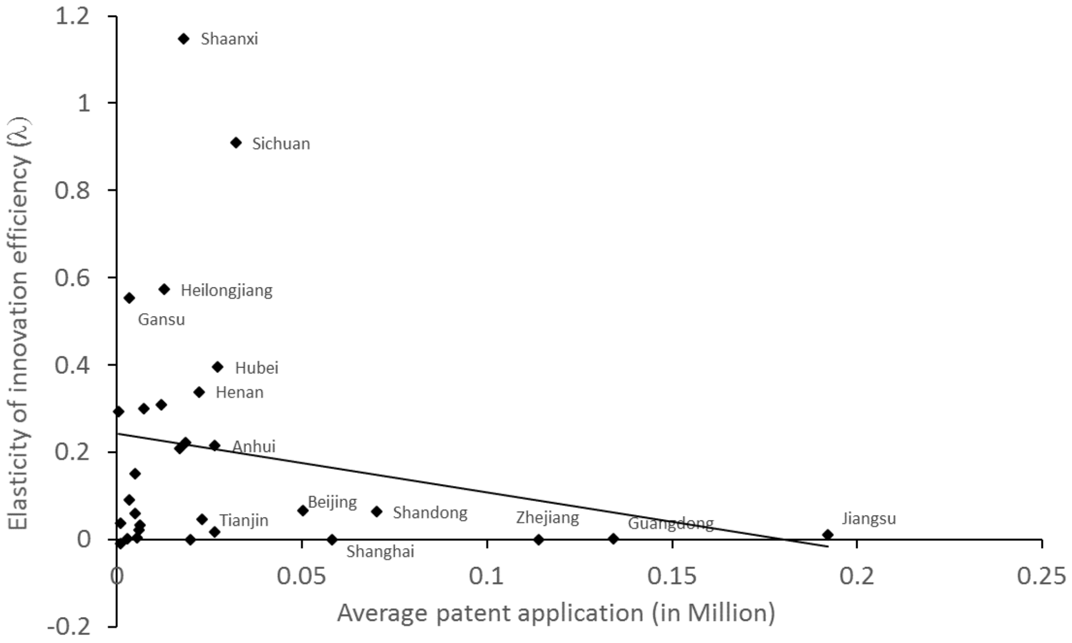
Region	Province	Efficiency score		Contribution
		w/o FDI	w/ FDI	of FDI (%)
East	Beijing	0.95	1.00	5.72
	Tianjin	0.86	0.89	4.07
	Hebei	0.51	0.60	17.46
	Liaoning	0.69	0.71	1.70
	Shanghai	0.96	0.96	0.00
	Jiangsu	0.92	0.93	0.74
	Zhejiang	1.00	1.00	0.00
	Fujian	0.63	0.63	0.00
	Shandong	0.95	1.00	5.81
	Guangdong	0.97	0.97	0.00
	Hainan	1.00	1.00	0.00
Central	Shanxi	0.48	0.62	27.63
	Jilin	0.50	0.51	3.12
	Heilongjiang	0.55	0.85	56.53
	Anhui	0.68	0.78	15.08
	Jiangxi	0.40	0.41	2.06
	Henan	0.76	1.00	32.15
	Hubei	0.66	0.91	38.14
	Hunan	0.78	0.93	18.99
West	Inner Mongolia	0.46	0.46	0.10
	Guangxi	0.73	0.74	0.38
	Chongqing	0.84	0.98	16.79
	Sichuan	0.56	0.99	75.54
	Guizhou	0.88	1.00	13.70
	Yunnan	0.66	0.70	5.73
	Shaanxi	0.47	0.87	85.90
	Gansu	0.46	0.70	53.39
	Qinghai	0.31	0.40	28.77
	Ningxia	0.51	0.52	2.43
	Xinjiang	0.87	0.93	7.22

* Note: Contribution is calculated to reflect the change in efficiency level relative to the original efficiency level. The efficiency levels reported in the table are the average values between 2005 and 2012. Source: author's estimation based on DEA method.

of spillovers at the beginner stage, which lowers efficiency effects of FDI. For example, with fast economic development, Shanghai attracts research labors and takes a leading role in building its technology level, catching up with its peers in other countries. The inflow of FDI from other countries brings in the international competition which has double-edged effects on indigenous firms (Zeng et al. 2009). On the one hand, with intense demonstration and competition from foreign invested enterprises, indigenous firms tend to make further technology progress in order to survive in the market. On the other hand, the mass entrance of foreign invested enterprises into the local market leads to extrusion effects on indigenous firms. Apparently, the results shown in Table 6 imply that for developed provinces such as Shanghai and Fujian, the extrusion effects and the competition effects are canceled out. For some provinces (for example, Shaanxi, Gansu and Qinghai) which are less developed in terms of technology and FDI, the inflow of FDI stimulates innovation and results in an improved efficient use of normal inputs including research labor and investment.

Figure 3 is a scatter plot taking the elasticity of innovation efficiency as the y-axis and taking the average patent applications as the x-axis. This plot confirms the robustness of the

Figure 3: Regions with high level of innovation development tend to have lower efficiency elasticity



Source: average patent application is based on the China Statistical Yearbook (various years); elasticity of innovation efficiency is based on author's own calculation.

theoretical prediction 2 that regions with high (low) level of innovation development are less (more) possibly to be beneficial from FDI spillovers and signaled with lower (high) efficiency elasticity.

7 Concluding remarks

This study fills the gap between the strong government policy direction for innovation growth and the rarely available studies on the heterogeneous effects of productivity and efficiency of research activities across regions in China. By presenting an empirical study on China's research sector, this paper quantitatively shows the regional differences of provincial innovation productivity and efficiency in the presence of FDI-induced spillovers.

With Chinese provincial data for the period of 2004-2012, we find that spillovers induced from FDI have positive and statistically significant effects on the productivity of China's innovation activities. We also find with quality controlled granted patent application as dependent variable, the estimated coefficients for research personnel double. This implies that having a patent application to be granted successfully the researchers have to double their marginal productivity.

Specifically, our results show that each type of innovation outputs has significantly varied demand for research personnel and investment. The structure of the investment profile also plays a significant role in determining the innovation output. Our study confirms the well-known regional heterogeneity existing in China as well. This regional heterogeneity has a strong impact on the spillover effects of FDI, hence on the productivity and efficiency of regional innovation inputs. The productivity effects of FDI spillovers are strongest in the east regions. In terms of the types of innovation, FDI spillovers affect patent application of invention and design more than that of utility model.

Our non-parametric analysis of the innovation efficiency suggests that on average the efficiency level of one province is associated with the economic development of that province. The spillover effects from FDI exhibit double-edged effects on the efficiency level. For provinces with less developed technology levels, the spillovers bring in positive externality by enforcing the indigenous firms to do more innovation and finally boost the innovation output in that province. This also reflects these provinces try to catch up with their peers with the help of external knowhow. However, the negative extrusion effects will start to cancel out the positive effects of FDI if a province belongs to the regions with advanced level of technology. This is because foreign innovation can be treated as competitive products to domestic market. Increased foreign investment in these regions will intensify the market competition and foreign innovation is thus a substitute for local innovation. This substitution effect will finally crowd out local innovations as it is risky or costly to conduct research when foreign knowledge spillovers are of high standard and competitive.

There are several policy implications from above results. First of all, local firms or regional governments are required to carefully evaluate their investment strategy in terms of funding for three types of research activities, depending on which innovation direction (output) the province or firm is moving on. Secondly, though the number of patent applications is a good indicator for the achievement of top management, a thoughtful management needs to motivate and provide incentive for the productivity increase of research labors since a granted patent requires more efforts from researchers than a simple patent application. Finally, the underlying spillover effects of FDI are dependent on the level of innovation development of one region. The skewed distribution of FDI inflow in China has lead to the inefficient use of resources and reduces the positive impacts on innovation efficiency in regions where FDI is over flooded into. Policies in the regional level for resolving the unequal distribution of FDI can benefit both FDI poor and rich regions.

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