# Regional Innovation and Spillover Effects of Foreign Direct Investment in China: A Threshold Approach

by

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**Abstract:**

Using a data set on 29 Chinese provinces for the period 1985-2008, this paper establishes a threshold model to analyse the relationship between spillover effects of foreign direct investment (FDI) and regional innovation in China. There is clear evidence of double-threshold effects of regional innovation on productivity spillovers from FDI. Specifically, only when the level of regional innovation reaches the minimum innovation threshold will FDI in the region begin to produce positive productivity spillovers. Furthermore, positive productivity spillovers from FDI will be substantial only when the level of regional innovation attains a higher threshold. The double threshold divides Chinese provinces into three super-regions in terms of innovation, with most provinces positioned within the middle-level innovation super-region. Policy implications are discussed.

Key Words: Foreign direct investment; Productivity spillovers; Regional innovation; Threshold model; China

JEL Codes: R11; F21, F23, O31

Title, Abstract and Key Words in Chinese

中国区域创新能力与外商直接投资的技术溢出效应: 基于门槛模型的研究

**摘要：**论文利用中国 1985-2008 年省际数据，构建门槛模型实证分析外商直接投资技术溢出及其区域创新能力的“门槛效应”。外商直接投资技术溢出在中国存在显著的创新能力“双门槛效应”。在创新能力达到第一（较低）门槛值的区域，外商直接投资才能产生正的技术溢出效应。只有在创新能力达到第二（较高）门槛值的区域，这种技术溢出方能得到较为充分地吸收。双门槛把中国分成三个不同创新能力的区域，其中大部分省份处于中等创新能力阶段。论文最后讨论了本研究的政策含义。

**关键词：**外商直接投资；技术溢出；区域创新能力；门槛模型；中国

## 1. Introduction

Endogenous growth theory suggests that technological progress is the ultimate source of economic growth (Romer, 1986). In an open economic system, technological progress is made via self-innovation and technological knowledge transfer and spillover through international trade and foreign direct investment (FDI) (Wei and Liu, 2006). However, knowledge transfer and spillovers are never unconditional. In the case of FDI, it is now widely recognised that technology or productivity spillovers are not automatic consequences of the entry or presence of multinational enterprises (Blomström and Kokko 2003; Kokko and Kravtsova, 2006). Rather, they depend on factors such as the technology gap between foreign and local firms and the absorptive capabilities of local firms (Castellani and Zanfei, 2003 and 2006; Sawada, 2010). If the technology gap is given, local firms must develop their technical capabilities or absorptive abilities in order to benefit from FDI (Kedia and Bhagat, 1988; Girma, 2005; Ford et al, 2008).

While local absorptive capacity and FDI as two explanatory variables are often included in a typical empirical growth model (see, e.g. Olofsdotter, 1998; Bengoa and Sanchez-Robles, 2003; Durham, 2004; Wang, et al., 2004: Li and Liu, 2005; Marcin, 2008), relatively few studies examine whether there exists a minimum threshold of technological or absorptive capabilities for local firms to benefit from FDI. Among several exceptions Girma (2005) applies Hansen's (2000) threshold regression techniques to firm-level data from UK manufacturing industry, assessing where the impact of FDI depends on some critical value of absorptive capacity which is defined as the distance of the firm from the

productivity frontier in its industry. Ford et al. (2008) find that FDI has a greater impact on per capita output growth than domestic investment for US states that meet a minimum human capital threshold.

Since 1978 when it started to reform its economy and open to the outside world, China has experienced a dramatic increase in FDI inflows and rapid economic growth. So far China is already the largest recipient of inward FDI in the developing world, and it has enjoyed an average of around 9 percent GDP growth rate in the past three decades. Against this background, a number of studies have been published on the role of FDI in business development, economic growth or technological innovation in China (Wu, 1999; Wei and Liu, 2001; Huang, 2003; Wei and Liu, 2006; Liu and Buck, 2007; Chang and Xu, 2008; Guo, 2008; Wei et al. 2008; Liu et al. 2009). However, it remains unclear whether there is a minimum threshold of absorptive capacity in China for inward FDI to produce positive spillovers.

Unlike the existing studies, this paper examines whether there exist regional (provincial) innovation thresholds which may affect the spillover effects of FDI in China. We choose the region as the unit of analysis for several reasons. Firstly, there is great regional diversity in China in terms of level of international trade, inward FDI, and economic, social and technological development (Wei and Liu, 2001), and this enables us to make a regional comparison of various economic relations. Secondly, China's economic reform enables the regional governments to gain great autonomy in formulating their economic and social development policies (Gu and Lundvall, 2006; Liu and White, 2001; Li, 2009).

Thirdly, innovation activities are not evenly distributed geographically and production of new scientific and technological knowledge tends to cluster spatially (Acs et al. 2002). Spatial proximity facilitates knowledge flows among the actors of a system of innovations, and this justifies the extension of the innovation system framework to the regional dimension (Padmore and Gibson, 1998; Padmore et al., 1998; Acs, 2000; Acs, 2002). Fourthly, the high level of "coherence" and "inward orientation" at the provincial level has made Chinese regions relatively independent innovation systems (Edquist, 2005). Finally, multinational enterprises closely interact with local firms and research institutions, and R&D by FDI becomes integrated into China's innovation system (Liang, 2004). This regional economic and social development setting in the world's largest emerging economy offers an ideal context for studying the relationship between FDI spillover effects and innovation at the regional level.

Using a data set on 29 Chinese provinces for the period 1985-2008, we have found clear evidence of double-threshold effects of regional innovation on productivity spillovers from FDI in China. Specifically, when the level of regional innovation meets a minimum threshold, FDI in the region begins to have positive productivity spillovers. Such spillovers will become substantial only after the level of regional innovation reaches a higher threshold.

The remainder of the paper is organised as follows. The next section reviews the literature. Section 3 establishes our threshold model and discusses the data set and

estimation methods. Empirical results are discussed in section 4. Finally, section 5 concludes by summarising the results and discussing policy implications.

## 2. Literature Review

FDI is widely regarded as a package of capital, technology and managerial skills, and is an important source of both direct capital inputs and productivity and knowledge spillovers. As Balasubramanyam et al. (1996) point out, developing countries can benefit significantly from FDI because it not only transfers production know-how and managerial skills but also produces externalities, or spillover effects. However, as mentioned earlier, technology spillovers are context-dependent, conditional on factors such as the technology gap between foreign and local firms, and the absorptive capabilities of local firms.

In this regard, Castellani and Zanfei (2003; 2006) summarise the relevant literature and label two major hypotheses as follows. The catching up hypothesis suggests that the rate at which new technology is diffused is an increasing function of the technology gap, as a larger gap allows greater potential for "catch-up" (Findlay, 1978; Wang and Blomström, 1992). The findings of Blomstrom and Wolff (1994) and Driffiled and Love (2001) tend to support this hypothesis. However, Lapan and Bardhan (1973) suggest that spillovers are negatively associated with the technology gap between the relatively "backward" host country and the "advanced" home country, because the superior technology may not be appropriate for the backward country. The technological accumulation hypothesis argues that a small technology gap implies a higher adsorptive capability of local firms, and

hence higher benefits can be expected from FDI technology transfer (Cantwell, 1989). Kokko and Kravtsova (2006) also argue that, to benefit from spillovers, sufficient innovative capability is required by local firms to adopt the technologies introduced through FDI (Kokko, 1994; Kinoshita, 2001; Girma 2003). In commenting on the relationship between the two hypotheses, Castellani and Zanfei (2006) argue that technology gap and absorptive capability are two different concepts in the context of heterogeneous firms. While the technology gap indicates the average distance between foreign and domestic firms in a given sector, absorptive capacity may differ between firms in the same sector.

Empirical studies have so far produced mixed results (see, e.g. Liu et al., 2000; Li et al., 2001, Wang et al., 2005; Jabbour and Mucchielli, 2007). Particularly, while there is clear evidence of positive effects of FDI in developed countries, many studies "cast doubt on the existence of spillovers from FDI in developing countries" (Javorcik, 2004). As Aitken and Harrison (1999) point out, FDI can have a negative impact on local productivity. For instance, MNEs may draw demand from local markets and force local firms to cut production and reduce their efficiency. Local firms in developing countries have relatively large technology gaps with MNEs. In addition, they have relatively lower absorptive capacity compared with developed economy firms. If we agree that technology gap and absorptive capability of local firms are two different concepts, then other things being equal, the relatively low absorptive capability of local firms in developing countries will limit the benefits from FDI spillovers. In this sense, the

differences in technological absorptive ability may explain the variation in growth effects of FDI across countries (Borensztein et al., 1998).

While local technical absorptive capacity and FDI are often included as two explanatory variables in a typical empirical growth model, few studies investigate how the former moderates the effects of the latter. In the analytical framework of Borensztein et al. (1998), the level of human capital determines the ability to adopt foreign productivity. Thus, larger endowments of human capital are assumed to induce higher growth rates given the amount of FDI. Furthermore, Borensztein et al. (1998) suggest that countries may need a minimum threshold stock of human capital in order to experience positive effects of FDI.

Two popular approaches have been developed to address how technological absorptive capacity affects the role of FDI in economic growth. First, a whole sample is divided into sub-samples based on a proxy of absorption capacity, and then a comparison is made of the FDI spillover effects from the sub-samples. For example, Girma and Wakelin (2001) divide British electronics enterprises into sub-samples according to size and share of skilled employees. The results indicate that enterprises with a small size and low ratio of skilled labour lack sufficient absorptive capacity to benefit from FDI productivity spillovers. An enterprise needs to attain the scale or human capital threshold in order to benefit from FDI. Haskel et al. (2007) split the sample plants into three groups (0-25th, 25-75th, and above-75th percentiles) based on three alternative performance measures:

their industry-year employment, TFP, or skill intensity, but find no differences in absorptive capacity of the plants.

The other common approach is to add a linear or non-linear cross-term of FDI and a proxy of absorptive capacity in an empirical growth model. Xu (2000) adds a linear cross-term of the human capital stock and FDI in the empirical model and finds that the level of human capital is an important factor influencing technical spillovers from MNEs. To benefit from productivity spillovers from American MNEs human capital in a host country needs to rise beyond the threshold level by 1.9 years (male secondary schooling). In Li and Liu (2005), the linear interaction term of FDI with human capital exerts a strong positive effect on economic growth in developing countries. Based on a data set covering 22 countries for the period 1970-2003, Huang et al. (2007) estimate the impact of FDI on growth by adding a non-linear cross-term of the technical level and FDI in their empirical model. They have identified a technical threshold effect, i.e., a host country's absorption of FDI spillover effects is associated with its level of technology. When the technology level is over the threshold, spillover effects begin diminishing.

The above studies have confirmed the existence of threshold effects with respect to FDI productivity spillovers. However, the existing literature tends to concentrate on the threshold effects of human capital and the level of economic development or economic openness. Little research has been conducted on threshold effects of regional innovative capabilities. Furthermore, the sub-sample and cross-term approaches cannot be applied to estimate endogenous threshold effects and their specific values. This paper attempts to

apply the threshold techniques developed by Hansen (1999) to establish a threshold model and investigate the relationship between the regional innovative level and FDI spillovers, based on China's provincial data for the period 1985-2008.

## 3. Threshold model and estimation methods

### 3.1. Model:

In empirical analysis of FDI spillover effects, a common practice is to establish a production function with FDI as one explanatory variable to assess these effects via examining the contribution of FDI towards total factor productivity. The current study follows this practice.

In the Cobb-Douglas production function, $Y_{it} = A_{it}(K_{it})^{\alpha}(L_{it})^{\beta}$, where $Y_{it}$ is output, and $K_{it}$ and $L_{it}$ are capital and labour input respectively. $\alpha$ and $\beta$ represent output elasticities of capital and labour respectively, and $A_{it}$ is endogenous technological progress. Under constant returns to scale, $\alpha + \beta = 1$. Dividing both sides of the production function by $L_{it}$, and taking natural logarithm, we obtain:

$$\ln(Y_{it}/L_{it}) = \ln(A_{it}) + \alpha \ln(K_{it}/L_{it}) \qquad (1)$$

where $A_{it}$ is TFP of region $i$ in year $t$, and is assumed to be determined by the following four factors: (1) spillover effects from this region's foreign trade; (2) spillover

effects from this region's inward FDI; (3) this region's level of innovation; and (4) this region's level of human capital.

We further assume that

$$\begin{aligned} A_{it} &= F(EXP_{it}, IMP_{it}, FDI_{it}, INO_{it}, HUM_{it}) \\ &= (EXP_{it})^{\gamma_1}(IMP_{it})^{\gamma_2}(INO_{it})^{\gamma_3}(HUM_{it})^{\gamma_4}(FDI_{it})^{\theta} e^{\mu_i+\varepsilon_{it}} \end{aligned} \tag{2}$$

Taking natural logarithm of both sides of (2), and substituting it into (1), we have

$$\begin{aligned} &\ln(Y_{it}/L_{it}) = \mu_i + \gamma_1 \ln(EXP_{it}) + \gamma_2 \ln(IMP_{it}) + \gamma_3 \ln(INO_{it}) \\ &+ \gamma_4 \ln(HUM_{it}) + \alpha \ln(K_{it}/L_{it}) + \theta \ln(FDI_{it}) + \varepsilon_{it} \end{aligned} \tag{3}$$

where $EXP_{it}$ is total exports ; $IMP_{it}$ is total imports, $INO_{it}$ is the regional innovative level, and $HUM_{it}$ is the human capital level. $\mu_i$ is an individual time-invariant effect, representing differences in resource endowments which affect the progress in regional innovation. $\varepsilon_{it}$ is the random disturbance, and assumed to follow the normal distribution with zero mean and finite variance.

In equation (3), $\theta$, the coefficient on $\ln(FDI_{it})$, is the regional FDI spillover effect. If it is positive (negative), then inward FDI has a positive (negative) impact on this region's technical progress. Equation (3) is a zero-threshold model. However, the level of regional innovation as an important determinant of the level of regional productivity is likely to non-linearly moderate FDI spillovers, i.e. there can be threshold effects of

regional innovation on FDI externalities. In order to avoid any bias from an artificially set threshold, we follow Hansen (1999) and determine the endogenous threshold effect based on the characteristics of the data themselves. The following is a single endogenous threshold model for China, based on the level of regional innovation. A multiple endogenous threshold model can be extended accordingly.

Our single threshold model is:

$$\begin{aligned}\ln(Y_{it}/L_{it}) &= \mu_i + \gamma_1 \ln(EXP_{it}) + \gamma_2 \ln(IMP_{it}) + \gamma_3 \ln(INO_{it}) + \gamma_4 \ln(HUM_{it}) \\ &+ \alpha \ln(K_{it}/L_{it}) + \theta_1 \ln(FDI_{it}) I(INO_{it} \le \eta) + \theta_2 \ln(FDI_{it}) I(INO_{it} > \eta) + \varepsilon_{it}\end{aligned} \tag{4}$$

where the regional innovative level $INO_{it}$ is the threshold variable, and $\eta$ is the threshold value to be estimated. $I(\cdot)$ is an indicator function.

We define：

$$\gamma = \begin{bmatrix} \gamma_1 \\ \vdots \\ \gamma_4 \\ \alpha \\ \theta_1 \\ \theta_2 \end{bmatrix}, \quad X_{it}(\eta) = \begin{bmatrix} x_{1it} \\ \vdots \\ x_{4it} \\ x_{5it} \\ x_{6it} \\ x_{7it} \end{bmatrix}$$

where $x_{1it} = \ln(EXP_{it})$ , $x_{2it} = \ln(IMP_{it})$ , $x_{3it} = \ln(INO_{it})$ , $x_{4it} = \ln(HUM_{it})$ , $x_{5it} = \ln(K_{it}/L_{it})$ , $x_{6it} = \ln(FDI_{it})I(INO_{it} \le \eta)$ , and $x_{7it} = \ln(FDI_{it})I(INO_{it} > \eta)$ . Then the matrix form of our single threshold model is:

$$\ln(Y_{it}/L_{it}) = \mu_i + \gamma' X_{it}(\eta) + \varepsilon_{it} \tag{5}$$

**3.2. Model estimation methods:**

Two issues need to be sorted out when a threshold analysis is conducted: one is simultaneously estimating threshold value $\eta$ and slope $\gamma$ ; and the other is testing the threshold effect. In order to estimate the parameters in equation (5), the individual effects $\mu_i$ need to be removed. A common method is to deduct the group average from every observation to obtain the following transformed equation:

$$\ln(Y_{it}/L_{it})^* = \gamma' X_{it}^*(\eta) + \varepsilon_{it}^* \tag{6}$$

where $\ln(Y_{it}/L_{it})^* = \ln(Y_{it}/L_{it}) - T^{-1}\sum_{t=1}^{T}\ln(Y_{it}/L_{it})$ , $X_{it}^* = X_{it}(\eta) - T^{-1}\sum_{t=1}^{T} X_{it}(\eta)$ , and $\varepsilon_{it}^* = \varepsilon_{it} - T^{-1}\sum_{t=1}^{T}\varepsilon_{it}$ .

We express equation (6) in the following matrix form:

$$\ln(Y/L)^* = X^*(\eta)\gamma + \varepsilon^* \tag{7}$$

Given threshold value $\eta$ , OLS can be used to estimate slope $\gamma$ :

$$\hat{\gamma}(\eta) = (X^*(\eta)'X^*(\eta))^{-1} X^*(\eta)' \ln(Y/L)^* \tag{8}$$

After slope $\gamma$ is estimated , we can obtain the corresponding sum of squared residuals, $S_1(\eta)$. The threshold value $\eta$ can then be estimated via minimising $S_1(\eta)$, i.e. $\hat{\eta} = \arg\min_{\eta} S_1(\eta)$. This paper uses Hansen's (2000) grid search method to deal with issues of squared residuals and their minimisation. Once the threshold value is determined, slope $\gamma(\hat{\eta})$ can be obtained.

Two threshold analysis tests are required after the parameters of the threshold model are obtained: the level of significance of the threshold effects; and whether the estimates of the threshold values are equal to the actual values. The null hypothesis of the first test is

$H_0 : \eta_1 = \eta_2$ , and the test statistic is

$$F_1 = (S_0 - S_1(\hat{\eta})) / (\hat{\sigma}^2(\hat{\eta})) \tag{9}$$

where $S_0$ is the sum of the squared residuals after the parameter estimation under the null hypothesis. $\hat{\sigma}^2(\hat{\eta})$ is the variance of the residuals obtained after the parameter estimation under the alternative hypothesis. Under the null hypothesis the threshold value $\eta$ is uncertain, and hence the statistic $F_1$ follows a non-standard distribution. Hansen (1996) suggests the use of a bootstrap technique to simulate its gradual distribution in order to establish the corresponding P values.

The second null hypothesis is

$H_0 : \hat{\eta} = \eta_0$ , and its corresponding statistic is the likelihood ratio test statistic:

$$LR_1(\eta) = (S_1 - S_1(\hat{\eta})) \big/ (\hat{\sigma}^2(\hat{\eta})) \tag{10}$$

The distribution of the statistic $LR_1$ is also non-standard. However, Hansen (1999) provides a simple equation for calculating the area of rejection, i.e. when $LR_1(\eta) > -2\ln(1-\sqrt{1-\alpha})$ , we reject the null hypothesis, where $\alpha$ is the level of significance.

All the above description of the parameter estimation and hypothesis test methods is for the existence of one threshold only. In reality, there may be more than one threshold. We briefly explain how to estimate parameters for a double-threshold model, and a multi-

threshold model can be extended accordingly. A double-threshold model can be established as follows:

$$\begin{aligned}\ln(Y_{it}/L_{it}) &= \mu_i + \gamma_1 \ln(EXP_{it}) + \gamma_2 \ln(IMP_{it}) + \gamma_3 \ln(INO_{it}) + \gamma_4 \ln(HUM_{it}) \\ &+ \alpha \ln(K_{it}/L_{it}) + \theta_1 \ln(FDI_{it}) I(INO_{it} \le \eta_1) + \theta_2 \ln(FDI_{it}) I(\eta_1 < INO_{it} \le \eta_2) \\ &+ \theta_3 \ln(FDI_{it}) I(INO_{it} > \eta_2) + \varepsilon_{it}\end{aligned} \tag{11}$$

Following the rationale for the sequential estimation strategy provided by Hansen (1999), we first use the method for a single-threshold model to estimate $\hat{\eta}_1$ , and then apply the grid search method to find out the threshold value $\eta_2$ in order to minimise $S_2(\eta_2)$. Then $\hat{\eta}_2$ will be the second threshold value. The hypothesis tests for a multi-threshold model are similar to those for a single-threshold model, and are not described here[1].

### 3.3. Sample and variable selection

This study uses data from 29 provinces in China in the period 1985-2008. Tibet is not included in the sample as there is a lack of sufficient statistics. There are separate statistics for Chongqing City only after it became a municipality directly under the jurisdiction of the central government in 1997, and hence its data are combined into Sichuan Province. To remove the influences of price levels, all relevant variables are measured by the 1990 prices. The basic statistics of the sample are provided in table 1.

*Y* is the level of output, measured by real GDP (the 1990 prices) of Chinese provinces for the period 1985-2008. *L* is labour input, measured by the number of employees at the end of year for the period 1985-2008. *EXP* is total annual exports , measured by the value of exports of firms located in the province. *IMP* is total annual imports, measured by the value of imports of firms located in the province. The data for the four variables for the period 1985-1990 are from the *Compilation of Statistical Materials for new China for 50 Years*, and for the period 1991-2008 are from various issues of *China Statistical Yearbook*.

*INO* is the level of regional innovation. In the literature, innovation is measured by either research inputs such as R&D expenditure or intermediate outputs such as the number of patents (Cuddington and Moss , 2001). One problem with R&D expenditure is that it measures only the budgeted resources allocated towards trying to produce innovative activity (Acs et al., 2002). Since the 1970s, the use of patents as a measure of innovative capability has become popular (Griliches , 1990; Arundel , 2001). It is sometimes argued that the use of patents has its limitations as the nature of patents differs across industries, regions and time periods (Furman et al , 2002; Griliches , 1990). Not all new innovations are patented (Griliches, 1979) because secrecy can be used as an alternative way to prevent competitors from imitation (Arundel and Kabla, 1998). Patents also differ greatly in their economic impact (Griliches, 1979; Pakes and Griliches, 1980, p. 378). Despite these difficulties, patents statistics remain a unique resource for the

analysis of the process of technical change as they are readily available, related to inventiveness, and based on an objective and only slowly changing standard (Griliches, 1990). Furthermore, evidence suggests that patents provide a fairly reliable measure of innovative activity at the American regional (state) level (Acs et al., 1991) and the sub-state level (Acs et al., 2002). As discussed in the Introduction, Chinese regions have already become relatively independent innovation systems, and hence a region's patent applications may well represent its innovative capability and potential economic benefits. Similar to Jaffe (1989), Acs et al. (2002) and Fu (2008), in this paper, we use the number of successful patent applications per 10,000 employees as the proxy for the level of regional innovation[2]. The data are from various issues of *China Science and Technology Statistical Yearbook*.

*FDI* is the stock of FDI. We use the stock as we feel that, like any other capital, the remaining value of previous FDI also contributes, and hence this variable is more appropriate than flows. As statistics of inward FDI stock are unavailable, we use the perpetual inventory method to estimate the stock in China:

$$FDI_{it} = FDI_{i,t-1}(1-\delta_{it}) + f_{it} \qquad (12)$$

where $FDI_{it}$ is the FDI stock in province $i$ for year $t$ ; $f_{it}$ is the FDI flows in province $i$ for year $t$ ; $\delta_{it}$ is the depreciation rate in province $i$ for year $t$, and takes the value of 9.6%, the same as in Zhang et al. (2004). The FDI stock in the base period is estimated

using the steady-state method (King and Levine，1994): assuming that the FDI stock and output have the same growth rate, $\lambda_i = dFDI_i / FDI_i = dYF_i / YF_i$ , where $\lambda_i$ is the base-period growth rate of output in the foreign sector in province $i$ , $FDI_i$ is the base-period FDI stock in province $i$, and $YF_i$ is the base-period output in the foreign sector in province $i$. As $dFDI_i = f_i - \delta FDI_i$, $FDI_i = f_i /(\delta + \lambda_i)$, where the depreciation rate $\delta$ is still 9.6%. Because output statistics of the foreign sector are unavailable in China, and because inward FDI is concentrated in the manufacturing sector, we use the base-period output growth rate of China's manufacturing sector as a proxy for the output growth rate of the foreign sector. The data on realised FDI for the period 1985-1990 are from the *Compilation of Statistical Materials for new China for 50 Years*, and for the period 1991-2008 are from various issues of *China Statistical Yearbook*.

*K* is the physical capital stock, and like the FDI stock, is estimated using the perpetual inventory method (Zhang et al，2004), where yearly physical capital flows are proxied by total fixed capital formation, and the depreciation rate $\delta$ is still 9.6%. The base-period total capital stock is also estimated using the steady-state method (King and Levine，1994). The data on fixed capital formation for the period 1985-1990 are from the *Compilation of Statistical Materials for new China for 50 Years*, and for the period 1991-2008 are from various issues of *China Statistical Yearbook*.

*HUM* is the level of human capital, and is measured by the average educational level of residents in the region. *China Statistical Yearbook* and *China Population Statistical Yearbook* have provided the sampled data for the periods 1996-1999 and 2002-2008. The Fourth and Fifth Censuses have provided the data for 1990 and 2000. The data for 2001 is the arithmetic mean of the 1997-2008 data. The data for the periods 1985-1989 and 1991-1995 are estimated using the trend extrapolation and interpolation methods.

< Table 1 about here>

## 4. Empirical Results and Analysis

### 4.1 Empirical Results：

According to the empirical model and test methods introduced earlier, we adopt Hansen's (1999) calculating method to write a Gauss programme and use the Gauss8.0 software package for our empirical analysis. To determine the number of thresholds, we have analysed the threshold effects under the hypotheses of single, double and triple thresholds. Table 2 reports the F statistics and P values following the bootstrap simulations for single, double and triple thresholds. It is clear that the threshold effects are statistically significant at the 5% level for single and double thresholds, but not for triple thresholds. Therefore, our focus will be on the double threshold model (equation 11).

<Table 2 about here>

After the threshold effect tests, we examine the two values of the double threshold model (equation 11). According to Hansen's (1999) calculating method for the critical value of the likelihood ratio , at the 5% level of significance , the likelihood ratio test statistic $LR_1(\hat{\eta})$ is 7.35. Using Gauss8.0 we produce the diagrams for the relationship between the likelihood ratio and threshold parameter in Figs 1 and 2. The dotted lines are the critical values of the likelihood ratio statistic. From Figs 1 and 2, when the estimated value of threshold 1 is 36.012 and that of threshold 2 is 601.195, the likelihood ratio is 0. When the estimated value of threshold 1 lies in the range [12.808 , 40.767], and that of threshold 2 in the range [0.126 , 949.204], the likelihood ratio is less than the critical value at the 5% significance level. This means that the ratio lies in the acceptance interval of the null hypothesis, i.e. the two threshold values are both equal to the actual threshold values. Table 3 reports the estimation results of the double threshold model and the 95% and 99% confidence intervals. After the thresholds $\eta_1$ and $\eta_2$ are estimated, we can estimate the parameters of the double threshold model (equation 7), and the results are presented in table 4.

<Fig. 1 about here>

<Fig. 2 about here>

<Table 3 about here>

<Table 4 about here>

### 4.2. Analysis:

From the double-threshold model estimation results in table 4, it is clear that the coefficients of the capital intensity, exports, imports, regional innovation and human capital variables are all positive and significant, indicating that they have a significant impact on regional technological progress. This shows that our choice of control variables is appropriate.

Also from table 4, the threshold effect tests show that there is a statistically significant non-linear relationship between FDI as an important channel for productivity spillovers and the level of regional innovation in China. In other words, there is a double-threshold effect. When the level of regional innovation is below threshold $\eta_1$, the productivity spillover effect from FDI is not significant in this region. When the level of regional innovation is between thresholds $\eta_1$ and $\eta_2$, the productivity spillover effect from FDI in this region is 0.079. After the level of regional innovation exceeds threshold $\eta_2$, the productivity spillover effect from FDI in the region will reach 0.094.

This result may not be surprising. The externality nature of knowledge makes productivity spillovers possible. However, spillover effects are not unconditional. If the level of regional innovation is very low, the spillover effect from FDI in this region can be insignificant as it does not have sufficient innovative capabilities to learn from multinational enterprises and conduct its own innovative activities, even if there are opportunities for learning and imitation. After the level of regional innovation exceeds

the minimum threshold $\eta_1$, local firms in this region have capabilities to partially absorb and imitate foreign technologies and hence partially benefit from FDI spillover effects. Furthermore, after the level of regional innovation reaches threshold $\eta_2$, local firms have sufficient absorptive capabilities to substantially benefit from productivity spillovers from FDI.

Thresholds $\eta_1$ and $\eta_2$ have divided China's 29 provinces into three super-regions in terms of innovation, namely: low level of regional innovation ($INO \leq 36.012$), middle level of regional innovation ($36.012 < INO \leq 601.195$), and high level of regional innovation ($INO > 601.195$). Table 5 presents the number of provinces in each super-region from the base year 1985 onwards. Figure 3 provides an intuitive illustration of changes in the level of regional innovation and spillover effects from FDI in China in the period 1985-2008. As indicated in the figure, there was a gradual improvement in regional innovative capabilities in China between 1985 and 1997, as the number of regions in the low-level innovation super-region (with no significant productivity spillover effects from FDI) reduced gradually from 29 to 12, while that in the middle-level innovation super-region (with significant productivity spillover effects from FDI being 0.079) increased from zero to 17. In this 12-year period, Beijing was the only region which entered the high-level innovation super-region with significant productivity spillover effects from FDI being 0.094, but only for one single year (1993). In other words, up to 1997, FDI brought about significant although moderate effects in a gradually increasing number of provinces, and only one province (Beijing) benefited from FDI externalities at a higher level for one year only.

There was a big improvement in 1998: the number of regions in the low-level innovation super-region reduced dramatically from 12 to 5, while that in the middle-level innovation super-region increased from 17 to 23. In this year, Beijing re-entered the high-level innovation super-region. Since then, there was a further improvement in regional innovative capabilities in China. Specifically, up to 2007 and 2008, no single province stayed in the low-level innovation super-region. Instead, 23 regions were in the middle-level innovation super-region, and 6 (Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong) in the high-level innovation super-region. It is clear that the majority of Chinese regions have developed a certain level of innovative capabilities so that they could gain some benefits from FDI productivity spillovers, while only 6 regions could benefit more from these FDI externalities due to their higher innovative capabilities than other regions.

The findings tend to support the absorptive capability hypothesis as discussed in the literature review: there is a positive relationship between a region's absorptive capability and technology spillovers from FDI. Given the research design and data set, this paper is not involved in a direct test of the technology gap hypothesis, if technology gap and absorptive capability are seen to be two different concepts as in the case of Castellani and Zanfei (2003). China as an emerging economy relied heavily on technology imported from abroad, but since the end of the last decade China has made significant progress towards developing its innovative capabilities (OECD 2007, p. 9). As a result, from the end of the 1990s, regional innovative capabilities have been relatively quickly enhanced,

and Chinese regions have been able to benefit more from FDI spillovers. However, China's R&D capability is still below OECD countries (Watkins-Mathys and Foster, 2006), and the efficiency of local R&D staff is still relatively low compared with the advanced economies (OECD, 2007, pp. 28-29). While technology gaps provide Chinese regions with good opportunities of technology learning and imitation, to actually benefit more from FDI spillovers, a region's technological absorptive capability needs to be further enhanced.

For comparison we list provinces within the low-level and high-level innovation super-regions in the sample period in Table 6. It is clear that FDI spillover effects were insignificant mainly in western China represented by Guizhou, Gansu and Qinghai. These three provinces (especially Qinghai) remained in the low-level innovation super-region until very recently. The main reason is that while the Chinese government encourages FDI to western China, the levels of innovation in these provinces were so low that they were unable to absorb spillover effects of the FDI. Furthermore, the low innovation levels of these provinces were closely associated with their low levels of economic development, human capital and infrastructure. By comparison, the relatively high innovation levels of eastern coastal areas such as Beijing, Tianjin, Shanghai, Guangdong, Zhejiang and Jiangsu were associated with their high levels of economic development, human capital and infrastructure. This indicates that there may be other thresholds in addition to innovation capability for significant FDI spillover effects.

<Table 5 about here>

<Fig. 3 about here>

<Table 6 about here>

## 5. Conclusions

Based on a data set on 29 provinces in China for the period 1985-2008, this paper has estimated a threshold model to examine the relationship between productivity spillovers from FDI and the level of regional innovation. The following findings are obtained. There is clear evidence of a double threshold effect of the level of regional innovation on productivity spillovers from FDI in China. The externality nature of knowledge makes possible productivity spillover from FDI. However, spillovers are not unconditional, but depend on the level of regional innovation. Only when the level of regional innovation reaches a minimum threshold ($\eta_1$, in this paper) will FDI have significant productivity spillover effects in that region. After reaching this threshold, a region's absorptive ability of foreign technologies still depends on its own level of innovation. Only when the level of regional innovation exceeds a higher threshold ($\eta_2$, in this paper) can that region (such as Beijing, Tianjin, Shanghai, Guangdong, Zhejiang and Jiangsu) substantially benefit from productivity spillovers from FDI. From 2007, all Chinese provinces passed the minimum threshold. As a result, all Chinese provinces are able to benefit from FDI spillovers. Nevertheless, as most Chinese regions have not yet reached threshold $\eta_2$, they have benefited from FDI productivity spillovers only at a relatively low level.

The findings have important policy implications. In 1978 China started its science and technology policy reform, and one important objective was to establish a national innovation system. Since the end of the 1990s, China has made significant progress

towards developing its innovative capabilities. The most recent development was the 2006 National Science and Innovation Conference and the adoption of the Medium- to Long- Term Strategic Plan for the Development of Science and Technology, aiming to shift to a growth path that is less dependent on low-skill, resource-intensive manufacturing (OECD, 2007). Related to this, Chinese officials call for continued openness to foreign technology investments to help improve China's indigenous scientific and technological capabilities (Walsh, 2007). In the case of the central and western regions, the Chinese government encourages the use of foreign capital, advanced technology and equipment and modern management methods in some priority areas such as comprehensive development and utilisation of key resources and ecological environment protection for sustainable economic development (NDRC and MC, 2008). A shift of obsolete technologies and equipment and high-pollution and low-energy/resource efficiency industries or projects to the central and western regions is not allowed (*ibid*). However, the majority of FDI R&D programmes are frequently located in China's major cities along the eastern coast rather than western provinces that remain largely poor and underdeveloped (Walsh, 2007) and lack the absorptive capability necessary to benefit from high-tech FDI. While it is important to use high-tech FDI to develop the above priority areas, low- and medium-tech FDI may also be useful for these regions given the current stage of economic development and absorptive capabilities.

Related to the above discussion, while economic reform and opening to the outside world have provided local Chinese firms with opportunities of technology learning and imitation, all provinces, especially those which have not reached the high threshold, need

to increase their R&D activities and enhance their absorptive capabilities in order to learn more from multinational enterprises, enhance their own innovations and improve productivity. One possible policy programme is government R&D subsidy, as Feldman and Kelley (2006) find that projects awarded R&D subsidies are more likely to be involved in new research joint ventures and connections to universities and other firms, and that receipt of a government R&D subsidy increases funding from other sources compared to firms not awarded funding.

Finally, given that insignificant (significant) FDI spillover effects are closely related to not only the low- (high-) level of regional innovation, but also the low- (high-) levels of economic development, human capital and infrastructure in a region, in future research it will be very fruitful to investigate possible threshold effects of these factors. Given this relationship, government support to the development of infrastructure, education and economic activities in such a region may help local firms to benefit more from FDI. Particularly, government support to the enhancement of regional innovation systems in western China represented by Guizhou, Gansu, Qinghai will help these provinces catch up.

There are several limitations of this study. Given that the unit of analysis is the region, one important limitation of this study is that we are unable to take into consideration some important determinants of the relationship between FDI spillovers and absorptive capacity, such as ownership structure, industry characteristics, firm heterogeneity and technology gap. In a future study, a firm level approach can be adopted to address these

issues. Related to this, a second important limitation is that, like Girma (2005) and Ford et al. (2008), we only use one variable to define our threshold. Other variables such as technology gap may also be important in assessing FDI spillover effects, and hence may also be adopted to measure the threshold.

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Endnotes:

[1] For the technical details of the sequential estimation strategy, please see Section 5.1 of Hansen (1999).
[2] Instead of the number of patents granted to applicants per 10,000 persons we use the number of patents granted to applicants per 10,000 employees as we believe that employees are more representative of the innovative capability than the general population.

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Table **Error! Main Document Only.** Descriptive Statistics of the sample

(Period = 1985-2008 , No. of regions =29; Total observations =696)

| Variable Name | Variable Meaning | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| *Y* | Real GDP (billion yuan) | 1794.916 | 2206.199 | 44.289 | 16176.650 |
| *K* | Physical capital stock (billion yuan) | 3233.948 | 3621.398 | 222.713 | 24788.160 |
| *FDI* | FDI stock(billion yuan) | 256.595 | 560.502 | 0.015 | 4124.821 |
| *L* | Year-end employment (ten thousand) | 2100.697 | 1467.489 | 177.390 | 6711.600 |
| *EXP* | Total exports (billion yuan) | 494.313 | 1501.744 | 1.094 | 15824.890 |
| *IMP* | Total imports(billion yuan) | 411.611 | 1243.500 | 0.106 | 11349.460 |
| *INO* | Successful patent applications per ten thousand employees (number) | 144.980 | 285.839 | 0.000 | 2792.722 |
| *HUM* | Average education (Years) | 7.109 | 1.330 | 4.047 | 11.446 |

Sources : *Compilation of Statistical Materials for new China for 50 Years*, and for the period 1991-2008 are from various issues of *China Statistical Yearbook*. and *China Population Statistical Yearbook*

Table **Error! Main Document Only.** Threshold Effect Tests

| | | | Critical Value | | |
|---|---|---|---|---|---|
| | F Value | P Value | 10% | 5% | 1% |
| Single Threshold Test | 81.605** | 0.018 | 49.420 | 57.139 | 84.680 |
| Double Threshold Test | 58.085** | 0.041 | 40.623 | 51.190 | 69.830 |
| Triple Threshold Test | 25.331 | 0.183 | 28.274 | 33.059 | 44.860 |

Notes;1.P and critical values are the results of the bootstrap simulation for 500 times；

2.*,**and*** represent the 10%, 5% and 1% level of significance.

Table 3 Estimated Threshold Values and their Confidence Intervals

| | Estimated Value | 95% Interval | 99% Interval |
|---|---|---|---|
| Threshold $\eta_1$ | 36.012 | [12.808，40.767] | [11.285，41.705] |
| Threshold $\eta_2$ | 601.195 | [0.126，949.204] | [0.045，1349.632] |

Table 4 Estimated Parameters for Double Thresholds

| Variable | Estimated Parameter | OLS SE | White SE |
|---|---|---|---|
| $K_{it}/L_{it}$ | $0.532^{***}$ | 0.018 | 0.020 |
| $EXP_{it}$ | $0.045^{***}$ | 0.012 | 0.011 |
| $IMP_{it}$ | $0.055^{***}$ | 0.009 | 0.008 |
| $INO_{it}$ | $0.021^{***}$ | 0.004 | 0.005 |
| $HUM_{it}$ | $0.586^{***}$ | 0.081 | 0.101 |
| $FDI_{it}I(INO_{it}\leq 36.012)$ | 0.057 | 0.070 | 0.070 |
| $FDI_{it}I(36.012<INO_{it}\leq 601.195)$ | $0.079^{***}$ | 0.006 | 0.006 |
| $FDI_{it}I(INO_{it}>601.195)$ | $0.094^{***}$ | 0.006 | 0.006 |

Nortes:1. All values in the table are natural logarithms ;

2. OLS SE are OLS standard errors; White SE are White corrected errors.

Table 5 Number of provinces in each super-region in terms of innovation level

| Level of Innovation | $INO\leq 36.012$ | $36.012<INO\leq 601.195$ | $INO>601.195$ |
|---|---|---|---|
| FDI spillover Effects | 0.057 | $0.079^{***}$ | $0.094^{***}$ |
| 1985 | 29 | 0 | 0 |
| 1986 | 28 | 1 | 0 |
| 1987 | 26 | 3 | 0 |
| 1988 | 25 | 4 | 0 |
| 1989 | 23 | 6 | 0 |
| 1990 | 20 | 9 | 0 |
| 1991 | 18 | 11 | 0 |
| 1992 | 15 | 14 | 0 |
| 1993 | 13 | 15 | 1 |
| 1994 | 11 | 18 | 0 |
| 1995 | 10 | 19 | 0 |
| 1996 | 13 | 16 | 0 |

| | | | |
|---|---|---|---|
| 1997 | 12 | 17 | 0 |
| 1998 | 5 | 23 | 1 |
| 1999 | 1 | 27 | 1 |
| 2000 | 1 | 26 | 2 |
| 2001 | 1 | 26 | 2 |
| 2002 | 3 | 24 | 2 |
| 2003 | 2 | 24 | 3 |
| 2004 | 2 | 23 | 4 |
| 2005 | 1 | 24 | 4 |
| 2006 | 1 | 23 | 5 |
| 2007 | 0 | 23 | 6 |
| 2008 | 0 | 23 | 6 |

Table 6 Provinces in Low- and High Innovation Super-Regions

| Year | Low-Innovation Super-Region (Insignificant FDI Spillovers) | High-Innovation Super-Region (FDI Spillover Effects = 0.107) |
|---|---|---|
| 1993 | Shanxi, Neimenggu, Anhui, Jiangxi, Henan, Hunan, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Gansu, Qinghai | Beijing |
| 1994 | Neimenggu, Anhui, Jiangxi, Henan, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Gansu, Qinghai | / |
| 1995 | Anhui, Jiangxi, Henan, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Gansu, Qinghai | / |
| 1996 | Shanxi, Neimenggu, Anhui, Jiangxi, Henan, Hunan, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Gansu, Qinghai | / |
| 1997 | Shanxi, Neimenggu, Anhui, Jiangxi, Henan, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Gansu, Qinghai | / |

| | | |
|---|---|---|
| 1998 | Anhui, Guangxi, Guizhou, Gansu, Qinghai | Beijing |
| 1999 | Guizhou | Beijing |
| 2000 | Guizhou | Beijing, Shanghai |
| 2001 | Guizhou | Beijing, Shanghai |
| 2002 | Guizhou, Gansu, Qinghai | Beijing, Shanghai |
| 2003 | Guizhou, Qinghai | Beijing, Tianjin, Shanghai |
| 2004 | Guizhou, Gansu, Qinghai | Beijing, Tianjin, Shanghai, Guangdong |
| 2005 | Qinghai | Beijing, Tianjin, Shanghai, Guangdong |
| 2006 | Qinghai | Beijing, Tianjin, Shanghai, Zhejiang, Guangdong |
| 2007 | / | Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong |
| 2008 | / | Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong |

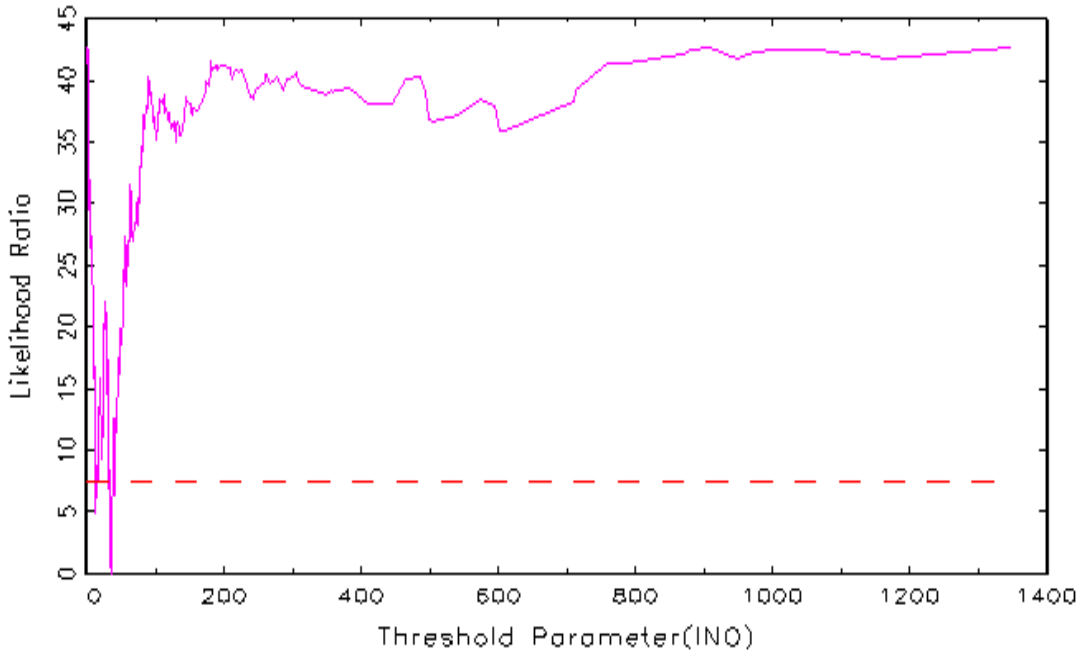


Fig. 1 95% confidence interval construction of the first threshold

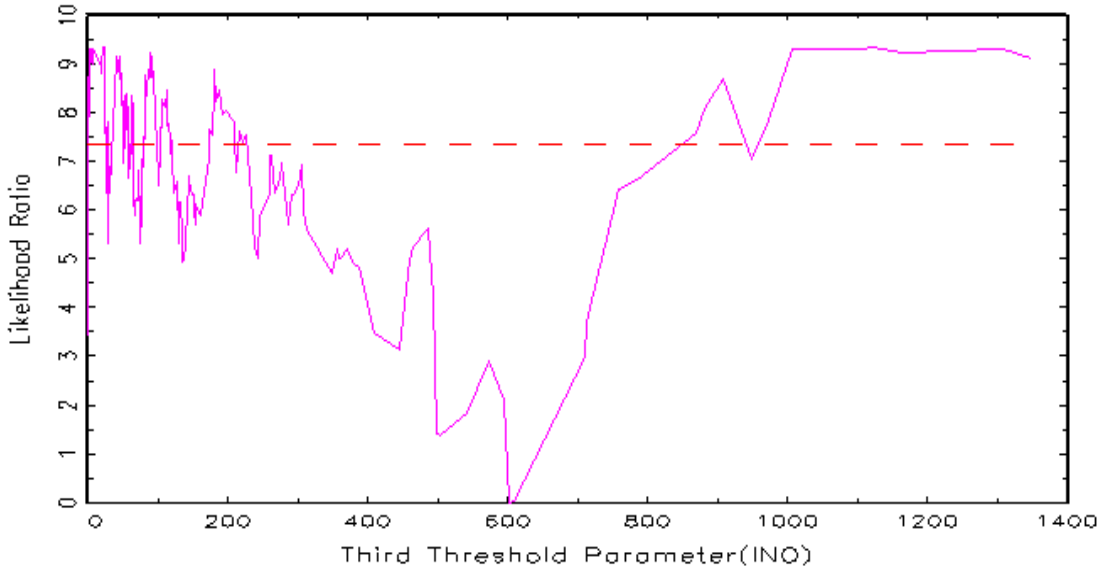


Fig. 2 95% confidence interval construction of the second threshold

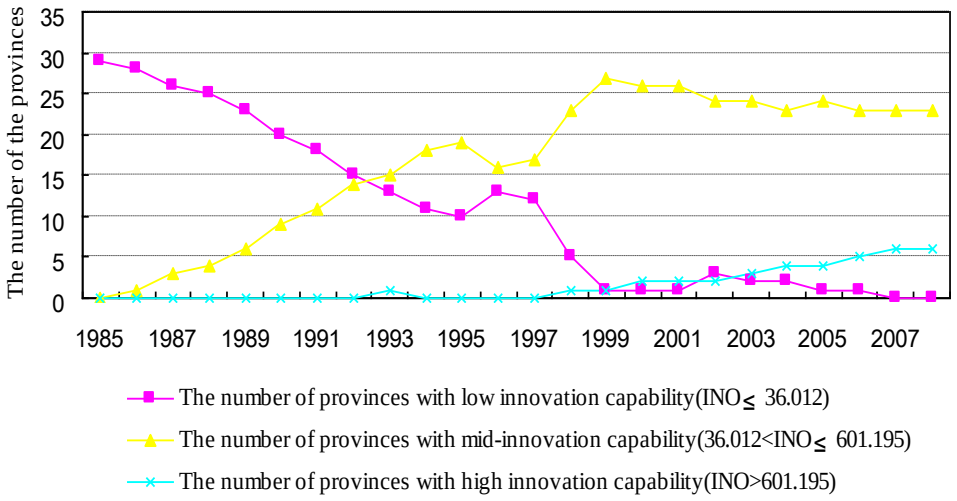


Figure 3 Changes in the Level of Regional Innovation and FDI Spillover Effects