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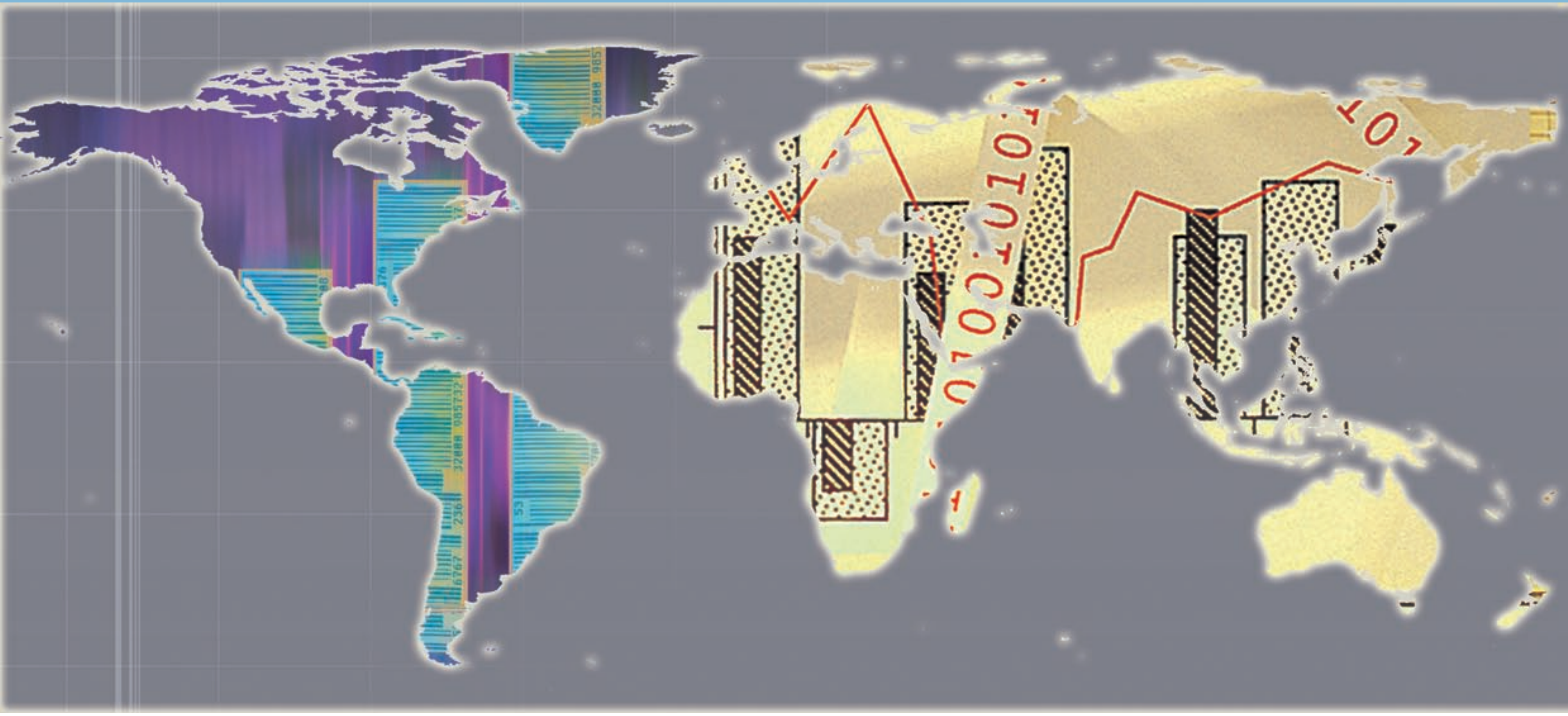

Human capital as a determinant of FDI technology spillovers and its threshold effects in China:
An analysis based on multiple productivity estimates

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Human capital as a determinant of FDI technology spillovers and its threshold effects in China: An analysis based on multiple productivity estimates

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Abstract

This paper analyzes the absorptive capacity of human capital for FDI technology spillovers using threshold regression. The estimated human capital thresholds are 4.92 per cent, 10.99 per cent and 30.49 per cent, in terms of percentage of the labour force that received higher education. When the quality of human capital exceeds 4.92 per cent, the negative effects of FDI mitigate significantly. Subsequently, when it exceeds the sign-change threshold of 10.99 per cent, the negative effects of FDI transform into positive spillover effects. An additional threshold of 30.49 per cent further strengthens the positive effects. The sign-change threshold corresponds with 3.42, in terms of average years of secondary school attainment by the work force. The comparison between realistic human capital and the estimated thresholds shows that while most developed countries exceed the threshold of 10.99 per cent, some developing countries, including China, are below this threshold.

In a big country like China, some regions meet the sign-change threshold; others do not. This partially explains why productivity growth lags behind economic growth and why inequalities in productivity exist among regions. Fortunately, the percentage of Chinese provinces above the sign-change threshold has been increasing in recent years. Moreover, significant interregional technology transfers are found, which means backward regions are able to adopt foreign technologies already assimilated by advanced regions. Besides those external causes of technological progress, internal factors, such as public infrastructure and Research and Development (R&D) capital stock, also have positive effects on knowledge. Different productivity calculations including growth accounting and long-memory data-envelopment analysis (LMDEA) have been used in the regression, to obtain proximate estimates of thresholds. The analyses also reveal that Chinese economic growth in the past was capital-driven, but is currently becoming more technology-driven, with a productivity growth rate of some 4 per cent.

Keywords: Technology spillovers; human capital; developing countries; threshold regression; DEA

1. Introduction

Since China embarked on reforms and adopted the opening-up policy in the late 1970s, inflows of foreign direct investment (FDI) to China have been dramatic. According to *China Statistical Yearbooks*, the realized value of inward FDI to China, which stood at a mere \$1.96 billion in 1985, had soared to \$69.47 billion in 2006. China has thus become the largest host country for FDI among developing countries, is the second largest host country in the world (UNCTAD, 1995), and could become the most attractive location for FDI over the next three years (UNCTAD, 2008). Foreign investment has played an increasingly important role in Chinese economic growth. During the period 1978 to 2006, China's average annual GDP growth rate stood at 9.8 per cent, in constant prices.

Some authors point out that China's remarkable performance is mainly attributed to factor accumulation of capital and labour (Sachs and Woo, 1997; Zheng, 2005; Ozyurt, 2007); productivity growth, represented by total factor productivity (TFP), is low. Young (2003) finds that TFP growth in China's non-agricultural economy is 1.4 per cent per year. Zheng's (2005) estimation, based on the UNIDO productivity database, shows that the average annual rate of change in TFP during the period 1962 to 2000 was 0.5 per cent, with its contribution to economic growth only 7.9 per cent. An important question arises from these findings. Is productivity progress in host countries, promoted by FDI, commensurate with the scale of inward foreign investments? Empirical tests by Hale and Long (2006b) reveal positive FDI technology spillovers for technologically advanced native firms, but find no, or negative, spillovers for backward ones. Focusing on countries other than China, some works find positive technology spillover effects from FDI for developed countries (Caves, 1974; Globerman, 1979; Liu et al., 2000), while others find insignificant or negative results for less developed countries (Haddad and Harrison, 1993; Singh, 1992; Aitken and Harrison, 1999). These results imply that negative or positive effects of FDI technology spillovers depend largely on the absorptive capacity of host countries.

This paper attempts to determine a threshold which can serve as a benchmark for reviewing the positive or negative effects of FDI technology spillovers. The threshold, represented by human capital for the latter, is regarded as a good measurement for absorptive capacity (Nelson and Phelps, 1966; Keller, 1996; Borensztein et al., 1998). It also endeavours to answer the following questions: First, why does productivity progress, brought about by FDI, conflict with FDI-induced economic growth in some developing countries? Second, how can one explain why some regions or countries derive positive FDI technology spillovers, while others do not? Third, when human capital of a country is below a specified threshold, can FDI technology spillovers continue to be utilized? Fourth, can skilled labour-scarce countries depend on intra-national technology spillovers to complement deficient international technology spillovers? Finally, taking into account human capital thresholds and FDI technology spillovers, will domestic Research and Development (R&D), infrastructure construction and institutional changes influence productivity progress?

This paper adopts a new approach with threshold regression, as suggested by Hansen (1999), based on Chinese provincial panel data. This approach generates thresholds endogenously, and tests them with an asymptotic distribution simulated on the basis of a bootstrap procedure. It differs from other methods adopted in existing literature on human capital thresholds for FDI spillovers (Borensztein et al., 1998; Xu, 2000). The estimated human capital thresholds represented here are in terms of the proportion of the labour force that received higher education. To avoid problems caused by flow variables, the labour force that received higher education is gauged by the cumulative stock of annual tertiary school graduates, with depreciation. This proxy of human capital highlights the absorptive capacity of higher education and the active workforce.

Since TFP is sensitive to estimation approaches, both growth accounting and the long-memory data-envelopment analysis (LMDEA), suggested by Forstner and Isaksson (2002), are used to estimate TFP. Variable returns to scale (VRS), constant returns to scale (CRS) and other facets of the two approaches are also considered in these estimations. As a totally different measurement of technology, in addition to TFP, patents are also used to calculate the correlation coefficients between TFP estimates and patents in order to select better estimators. Three selected TFP estimates are used simultaneously in analysis or regression. A comparison between those results precludes any risk of being biased by using a single TFP estimator.

Section II reviews existing literature, while section III presents human capital threshold models related to knowledge production and technology spillovers. R&D stock, R&D human capital, public infrastructure, degree of marketization, interregional technology spillovers and FDI technology spillovers absorbed by human capital are regarded as explanatory variables in the model. Section IV estimates provincial TFP series using the different approaches mentioned above, compares different TFP estimates, and discusses Chinese economic growth. Section V then provides the empirical findings with regard to FDI technology spillovers with human capital thresholds, interregional technology spillovers, the impact of domestic R&D, public infrastructure and institutional changes caused by market reform. Having determined three thresholds, facts about who satisfies these thresholds are presented. Finally, section VI concludes with a discussion on policy implications.

2. Literature review

Openness is a well-known factor that facilitates economic development. Investments from developed to least developed countries are a major channel for realizing this procedure. In addition to direct investment effects, FDI also has indirect effects, such as technology spillovers, on indigenous firms (MacDougall, 1960). Evidence of FDI technology spillovers is found in empirical studies by Kokko et al. (1996), Blomstrom and Kokko (1997) as well as in case studies by Larrain, Lopez-Calva and Rodriguez-Clare (2000); Moran (1998, 2001).

The technology gap and absorptive capacity determined by human capital are also addressed in existing literature. Findlay (1978) postulates that the rate of technological progress in a backward country is an increasing function of the technology gap between its own level and that of a foreign advanced country, which means that keeping other factors constant, less advanced countries with big gap gain more from technology diffusion than relatively advanced countries. Nelson and Phelps (1966) consider the technology gap and human capital integrally. They argue that education accelerates technology diffusion, therefore technical progress increases with the increase of education attainment and is proportional to the technological gap between theoretical and practical levels. Alternatively, Keller (1996) does not agree with the idea that technological gaps bring about convergence, and suggests that even if the distribution of technological information is freely available, those technologies cannot be utilized unless the labour force possesses the corresponding skills. Eaton and Kortum (1996) also highlight the indispensable role of human capital in the absorption and transfer of intra-national and international ideas.

However, the emphasis on human capital, as a determinant of technology spillovers, does not provide clear direction to policy makers. A feasible guide should specify the quality level of human capital. In this paper, this is represented by the proportion of labour force that received higher education. When host countries attain this level—termed here as the threshold—significant and positive technology spillovers, instead of negative or insignificant ones, take place.

Several authors endeavoured in their search for minimal human capital conditions. Borensztein et al. (1998) find that FDI from Organisation for Economic Co-operation and Development (OECD) countries to developing countries has positive effects on output growth only if host countries have reached a minimum human capital threshold of 0.52-1.13 years (in terms of male secondary school attainment over age 25). They claim that human capital stock of most developing countries exceeds this threshold.

Alternatively, Xu (2000) presents a higher threshold level of 1.4-2.4 years, suggesting that as most developing countries are below this threshold, rich developed, not the poor, countries benefit more from FDI technology spillovers. As foreign advanced technologies are usually absorbed by the segment of human capital that received higher education, a threshold given in terms of secondary school attainment could frustrate the endeavours of developing countries. Moreover, due to the rapid development in China, the educational structure of the older generation is totally different from that of the new generation that currently constitutes the active labour force. Thus the human capital threshold, based on adults over 25 years of age, may underestimate the real educational level of fast developing countries.

In addition, Borensztein et al. (1998) and Xu (2000) regard a developing country as a whole. Problems arise when applying their conclusions to explain the growth of a large developing country, such as China, where regional differentiation is pronounced. Empirical studies show that technology spillovers vary across regions. Chen et al. (2004) argue that spillovers correspond more with higher levels of education and are highly concentrated in the eastern areas of China. Fu (2007) studies the inequalities between coastal and inland areas, and claims that the uneven distribution of FDI and human capital are major reasons for economic inequalities. Fleisher et al. (2007) also argue that the distribution of human capital affects technology growth and hence induces regional inequalities. Therefore, the absorptive capacities of the eastern and mid-western areas of China are diverse, with varying spillover patterns across the country.

The key features of Chinese economic growth are capital- and labour-driven, such as large-scale inward foreign capital and peasant labour, basically from rural areas. Growth accounting analysis reveals that apart from contributions by capital and labour, technological progress has also played an increasingly important role in economic growth over the past few years. Nevertheless, some researchers question the efficiency of Chinese R&D because R&D investment in China is more intensive in the public than in the private sector (Yao and Zhang, 2001).

Though the importance of indigenous R&D cannot be denied, it is true that the bulk of new technologies in the world is created by a handful of the richest countries (Eaton and Kortum, 1996; Keller, 2004). Jones and Ruffin (2008) imply that uncompensated technology imitation accounts for the fast growth of China. Thus, technology spillovers from abroad are crucial for developing countries and explain the technological progress of a developing country where human capital surpasses the threshold. However, the same absorptive mechanism may not apply if a developing country's human capital is below the threshold and where the subsequent effects of FDI are negative, as in the case of China.

To explain technology advance in such countries, regional inequalities and intra-national technology spillovers should be considered as a complement to international spillovers. In fact, Madariaga and Poncet (2006) highlight that FDI spillovers in China are spatially correlated. Chang et al. (2007) also find intensive technology spillover effects from modernized local firms to other local firms, in addition to FDI spillovers. When studying the technical relationship between firms in the United States and Japan, Branstetter (2001) finds deficient international spillovers, suggesting that technology spillovers are primarily intra-national.

Most studies related to Chinese FDI technology spillovers do not consider the threshold effects. Liu and Liu (2006) study the Chinese human capital threshold of FDI technology spillover based on Borensztein et al. (1998). As Liu and Liu already noted, a multi-collinearity problem arises because of insufficient samples, which only cover the period 2000 to 2003. Their estimated threshold is 0.049 per cent, in terms of proportion of annual tertiary graduates to total population. Such a threshold analysis, based on annual graduates, may lead to a conclusion that when a region increases its number of annual tertiary graduates and reaches the required level, it immediately crosses the threshold, even if its well-educated human capital stock is still low. Thus, substituting human capital with a stock variable and including more observations could improve the quality of empirical results.

The research here differs from existing literature in following aspects: First, the threshold is estimated endogenously using the threshold regression provided by Hansen (1999). Borensztein et al. (1998), Xu (2000) and Liu and Liu (2006) obtain their threshold values by splitting samples into groups, based on a series of exogenously chosen thresholds, or by estimations using a group-specific dummy. A threshold is confirmed when there is a significant sign-change of the spillover efficient, or when the *t*-statistic of the dummy variable reaches a maximum value. In this paper, thresholds are achieved by minimizing the total sum of squared errors. Tests are then carried out to determine the significance of these thresholds with a likelihood ratio statistic of which asymptotic distribution is simulated using a bootstrap procedure. This approach rules out the arbitrary choice of thresholds, and inferences are based more on statistical data. Girma (2005) uses threshold regression to analyze FDI technology spillovers. The threshold variable - absorptive capacity - is measured by technological distance, which is defined as local TFP divided by the maximum TFP of technological frontiers. As TFP is sensitive to data sources and estimation approaches, this limits the comparability of TFP thresholds contained in different studies. Hence, human capital, instead of technological distance, is used in the model here.

Second, the human capital thresholds here are set in terms of the proportion of labour force that received higher education, which are different from the thresholds set by Borensztein et al. (1998) and Xu (2000) that are set in terms of secondary school attainment of male adults over 25 years of age. This threshold, which is generated by accumulated and depreciated tertiary graduates, emphasizes the absorptive capacity of higher education and the effective workforce.

Third, in addition to FDI technology spillovers, regional inequalities and intra-national technology transfers are considered. Physical and human capital, public infrastructure and geographic environment vary significantly across regions. Therefore, if regional differences and interregional technology transfers are neglected, some relevant external causes for technological progress in less advanced regions, whose absorptive capacities are below the threshold, will be partially omitted, and could cause regression errors. Chen et al. (2004) and others treat regional differences by separating samples into eastern and western areas, but fail to address interregional technology transfers.

Fourth, by comparison, some regions appear to satisfy this minimum requirement, while others do not. This means that skilled labour-scarce regions below the threshold should not depend on the negative effects of FDI foreign technology spillovers.

Fifth, as public infrastructure plays a key role in Chinese economic development, to the extent that it improves efficiency, allocates resources and decreases production costs, it is included in the model.

3. Empirical specification based on threshold model

With regard to the choice between TFP and patents—two most frequently used technology measurements—preference is for the former. As Griliches (1990) points out, not all inventions are patented. Moreover, as patented inventions differ immensely in quality, they will not affect productivity unless they are applied. Consequently, the number of patents cannot adequately represent active technology and can therefore not be considered good indicators for technology efficiency.

In contrast to patents, TFP includes both technology change and technology efficiency. Such a standpoint is appropriate for this study because productivity and efficiency spillovers constitute a major part of FDI technology spillovers. To formulate the production function of TFP, first the determinants of TFP are sought. Chen and Dahlman (2004) argue that the determinants of TFP include the institutional and economic regime of the economy (*g*), education and training (*e*), domestic innovation capacity or stock of knowledge (*r*), and information and communication infrastructure (*i*). Zheng (2005) and Isaksson (2007) also support these determinants. Chen and Dahlman provide the following equation.

$$TFP = f(g, e, r, i) \tag{1}$$

First, the domestic innovation capacity which is denoted by *r* in equation (1) is discussed. Based on the theories of Romer (1990), R&D human capital and knowledge stock in the R&D sector are the determinants of new knowledge creation.[1] R&D human capital in the R&D sector is indicated here with *H* later. However, the measurement of knowledge stock continues to be a problem for current studies. Even though TFP is a good measure of technology and while some authors place TFP on the right hand side of equations (Cameron et al., 1998; Griffith et al., 2004), TFP is not considered a good indicator for knowledge stock as TFP can recede in certain years, whereas knowledge stock would not regress under peaceful circumstances.

While TFP adequately represents active technology applied in production, this is not the case with basic knowledge adequately, which is necessary for new knowledge production.[2] Accordingly, Zheng (2007) argues that TFP only reflects instant productivity. A good substitute for knowledge stock and a usual explanatory variable for knowledge production is R&D capital stock. Griliches (1979) suggests that past and current R&D expenditure, that is, stock of R&D capital is a good measure for knowledge

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[1] The formula of Romer (1990) is $dA = \delta HA$, where *H* is human capital in R&D sector and *A* denotes knowledge stock. Jones (1995) extended this model to $dA = \delta H^{\lambda} A^{\Phi}$.

[2] For example, the effects of basic investment in research may not be reflected in the TFP in the near future.

stock. R&D capital stock is divided into two parts: R&D capital stock in the host region, represented by *RD;* and the weighted sum of R&D capital stock of other regions, excluding the host region, the variable of which is denoted by *RDO*. The latter corresponds to knowledge externalities, suggested by Romer (1990). Coe and Helpman (1995) also view the weighted sum of R&D capital stock of other countries as representing technology spillovers. Thus, *r* in equation (1) is segmented into *H*, *RD* and *RDO*.

With regard to the institutional and economic regime, represented by *g* in equation (1), the most outstanding changes in China are the introduction of a market mechanism and the opening-up policy (Zheng, 2005). Market reforms in China are characterized by the increasing non-State-owned share of the economy. Hence, the pace of market reform is indexed by a ratio of non-State employees to total employed labour force, following the method of Zhang (2001). This ratio is denoted by *M*.

As a result of the opening-up policy, the influx of foreign capital resulted in significant changes. These impacts are reflected not only in the scale of investment, but also in the improvements in the technology level, management skills, quality of public services, income distribution system and protection of property rights. In other words, it increases productivity as a whole. Thus FDI capital stock is used as a share of total capital stock, which represents the influences of FDI. This variable is referred to as *F,* and ratios for both institutional variables *F* and *M* are used to eliminate scale differences among provinces. As Borensztein et al. (1998) and Xu (2000) state, developing countries need to reach a minimum human capital threshold before they are able to reap the benefits from FDI technology spillovers. Accordingly, education and training are combined with FDI technology spillovers in an interactive way. Hence, in this model, human capital is involved both in independent domestic innovation and in the absorptive capacity for FDI technology spillovers, which are represented by *H* and *E,* respectively. *E* reflects the proportion of labour force that received higher education to total labour, and is the threshold variable for FDI spillovers. In so doing, *g* in equation (1) is divided into *M* and *F* and substitutes *e* with E to extend the equation.

Démurger (2001), Fu et al. (2004) and Fleisher et al. (2007) regard public infrastructure as a determinant of economic growth and technological progress in China. Following these perspectives,

P, which corresponds to i in equation (1), is added and reflects the length of the regional highway network, which represents public infrastructure development. Extending the determinant factors in equation (1) to include the detailed variables above and involve the threshold effects, equation (2) in Cobb-Douglas form is obtained.

$$TFP_{i,t} = \delta_i H_{i,t-1}{}^{\alpha} RD_{i,t-1}{}^{\beta} RDO_{i,t-1}{}^{\gamma} P_{i,t-1}{}^{\eta} M_{i,t-1}^{\rho} e^{\lambda_1 F_{i,t-1} I(E_{i,t-1} \le \theta) + \lambda_2 F_{i,t-1} I(E_{i,t-1} > \theta)}$$
$$\ldots, where \ldots RDO_{i,t-1} = \sum_{j, j \ne i} \zeta_j RD_{j,t-1} \tag{2}$$

In equation (2), the period is denoted by t and the subscript i represents different regions in the country. All variables are at the provincial level and vary across regions and time. α and β stand for the output elasticities of R&D labour force and R&D capital stock, respectively. γ measures the technology spillover effects from other domestic regions. I(.) is an indicator function and θ is the threshold. λ_1 and λ_2 are FDI technology spillover coefficients, below or above the threshold, respectively. ζ_j denotes the weight of region j's R&D capital stock. In line with endogenous growth theory, technologically advanced regions are usually economically advanced and vice versa. Hence, ζ_j is assumed to be equal to the ratio of the GDP in region j to the sum of the GDP in all regions. All explanatory variables lag for one year because knowledge outputs are usually the outcome of previous R&D inputs. Mansfield (1985) finds that 70 per cent of new innovations "leak out" within a year. As duplicated development of the same knowledge is invalid and knowledge can be shared at low cost, the output elasticity of each input factor is not limited. Hence, constant returns to scale are not assumed.

Considering the logarithm on both sides of equation (2) and inserting an error term $\varepsilon_{i,t}$, the econometric equation specified in equation (3) is obtained for the threshold regression. c_i stands for fixed effects. Here c_i is allowed to vary across regions and therefore it also represents the initial technology level of different provinces and spots any effects of omitted time-invariant and cross-section fixed variables.

$$\ln(TFP_{i,t}) = c_i + \alpha \ln(H_{i,t-1}) + \beta \ln(RD_{i,t-1}) + \gamma \ln(RDO_{i,t-1}) + \eta \ln(P_{i,t-1})$$
$$\ldots\ldots + \rho \ln(M_{i,t-1}) + \lambda_1 F_{i,t-1} I(E_{i,t-1} \le \theta) + \lambda_2 F_{i,t-1} I(E_{i,t-1} > \theta) + \varepsilon_{i,t} \tag{3}$$

In contrast with studies by Borensztein et al. (1998) and Xu (2000), the threshold variable θ in the model is compromised by an indicator function, and the estimate of the threshold can be generated endogenously, according to procedures suggested by Hansen (1996, 1999). The first step for estimating equation (3) is to test the existence of the threshold, based on a likelihood ratio test shown in equation (4). Null hypothesis for this test is the non-existence of the threshold, which can be denoted by H_0: $\lambda_1 = \lambda_2$. In equation (4), $\hat{\theta}$ is an estimate of the threshold, S_0 denotes the sum of squared residuals under the null hypothesis, whereas $S(\hat{\theta})$ stands for the sum of squared residuals with threshold $\hat{\theta}$. Further, $\hat{\sigma}^2$ represents the residual variance when a threshold exists, and is equivalent to $S(\hat{\theta})/[N(T-1)]$.

$$LR_1 = \frac{S_0 - S(\hat{\theta})}{\hat{\sigma}^2}, \ldots and \ldots \hat{\theta} = \arg\min_{\theta} S(\theta) \tag{4}$$

If LR_1 significantly rejects the null hypothesis, then the threshold exists and its estimate equals $\hat{\theta}$. Asymptotic distribution of LR_1 can be simulated using the bootstrap procedure recommended by Hansen (1996). The bootstrap procedure generates critical values at different significant levels, and generates p values for the LR_1 statistic.

If a threshold effect is observed, the second step is to obtain the confidence interval for the threshold value. The likelihood ratio test provided by Hansen (1999) for H_0: $\theta = \theta_0$ is shown in equation (5). The asymptotic distribution of $LR(\theta_0)$ follows $p(LR(\theta_0) \leq x) = (1 - exp(-x / 2))^2$. This distribution makes it possible to form valid asymptotic confidence intervals for the estimated thresholds and obtain critical values of significant level α with equation (6).

$$LR(\theta_0) = \frac{S(\theta_0) - S(\hat{\theta})}{\hat{\sigma}^2} \tag{5}$$

$$c(\alpha) = -2\ln(1 - \sqrt{1-\alpha}) \tag{6}$$

Once the threshold value and its confidence interval are attained, the coefficients of the model are estimated. There may be more than one threshold in this application. The model takes the form of equation (7) when there are two thresholds, θ_1 and θ_2. The estimation of the two-threshold model can be divided into two stages. At the first stage, estimate θ_1 as if there is only one threshold. During the second stage, estimate θ_2 as if the first threshold θ_1 is given. The inference also includes two stages. The model with three thresholds and its estimation can be deduced by analogy.

$$\begin{aligned} \ln(TFP_{i,t}) &= c_i + \alpha\ln(H_{i,t-1}) + \beta(RD_{i,t-1}) + \gamma\ln(RDO_{i,t-1}) + \eta\ln(P_{i,t-1}) + \rho\ln(M_{i,t-1}) \\ &\ldots\ldots \lambda_1 F_{i,t-1} I(E_{i,t-1} \le \theta_1) + \lambda_2 F_{i,t-1} I(\theta_1 < E_{i,t-1} \le \theta_2) + \lambda_3 F_{i,t-1} I(E_{i,t-1} > \theta_2) + \varepsilon_{i,t} \end{aligned} \quad (7)$$

Based on existing literature, the following hypotheses are presented below:

Hypothesis 1. The sign and magnitude of FDI spillover coefficient λ_i *(i = 1, 2, 3)* will vary in accordance with the thresholds. Positive effects of FDI will take place only if the host country has a minimum threshold stock of human capital (Borensztein et al., 1998). Thus, a sign-change point for the international spillover coefficient can be expected. Moreover, other thresholds may exist which induce significant changes in the coefficient, in addition to the sign change.

Hypothesis 2. As the gap in human resources among indigenous regions is much smaller than the international gap, interregional technology spillovers are supposed to take place more easily, that is, γ is assumed to be positive, following the views of Branstetter (2001) and Coe and Helpman (1995). Branstetter (2001) suggests that with respect to technological progress, intra-national knowledge spillovers are more important than international spillovers. This hypothesis is in line with externalities of knowledge.

Hypothesis 3. In addition to the external factors, internal factors, such as R&D labour force and R&D capital stock, public infrastructure and the marketization variable, have effects on knowledge production. That is, α and β are positive according to the theories of Romer (1996), which means that both the educated labour force and capital stock in the R&D sector contribute to technological progress. The coefficient of public infrastructure, that is, η, is positive, as argued by Démurger (2001) and Fu et al. (2004). This hypothesis is especially rational in China. The coefficient of marketization, namely, ρ, is positive because this institutional improvement provides the necessary structural condition for productivity increases, according to the perspectives of Zheng (2005).

4. TFP estimation and discussion on economic growth

Before analyzing the threshold model, first, it is necessary to estimate the dependent variable of TFP and study the contributions of the labour force, capital stock and technology to economic growth. For this, original data are taken from *China Statistical Yearbook* 1991-2007, and all pecuniary variables are deflated in 1990 constant prices. Investment is deflated by the price index of investment in fixed assets. Since GDP deflators and real GDP growth rates are not available at the provincial level, a compound index is constructed, based on the price index of investment in fixed assets and the consumer price index. The two component indices are weighted by their shares in GDP.[3] Capital stock is then calculated, based on the perpetual inventory method, and is demonstrated in equation (8).

$$K_{i,t} = I_{i,t} + (1-\delta)K_{i,t-1} \tag{8}$$

K stands for capital stock, I denotes gross capital formation, δ is the depreciation rate and i, t indexes, regions and periods, respectively. According to Zhang et al. (2004), for China, δ takes the value of 9.6 per cent. Capital stock in the initial year is also taken from Zhang et al. (2004). The labour force is represented by the number of persons employed at the end of the year.

[3] *GDP = C + I + G + X*, where *I* includes public investment and *G* represents government consumption. Thus, *compound index = price index of investment * I / GDP + consumer price index * (1 – I / GDP)*. Although this compound index is not the perfect substitute for GDP deflator, it is better than using price index of investment or consumer price index alone. In 2006, in country level, the share of investment is 42.5 per cent, and the share of resident and government consumption is 49.9 per cent.

To calculate TFP and analyze the contribution of the labour force and capital stock, their output elasticities should be obtained. These are denoted by α and β, respectively. There are two ways to estimate α and β. The first is by calculating the income shares of capital and labour, which, when perfect competition in factor markets prevails, they equal the respective marginal products. Unfortunately, factor markets in China are far from perfect due to restrictions on labour flow, immature factor markets and a long history of transitional economy. This partially explains why the elasticities estimated with this approach are totally different from the others.[4]

The second approach is to estimate the parameters in the production function in an econometric way. The estimation function is shown in equation (9). Here t is added to the model, as done by Lau and Park (2003). $Y_{i,t}$, $K_{i,t}$, and $L_{i,t}$ denote GDP, capital stock and labour force of region i in period t, respectively.

$$lnY_{i,t} = A_{i,0} + \lambda t + \alpha \ln K_{i,t} + \beta \ln L_{i,t} + \varepsilon_{i,t} \tag{9}$$

Totally differentiating the production function above, equation (10) is obtained. The first term of λ on the right hand side may be identified as the proportional growth rate of Y, holding inputs of K and L constant; in other words, the growth rate of TFP. Thus, by adding t to the model, it is possible to detect changes in TFP over time.

$$\frac{dlnY_i}{dt} = \lambda + \alpha \frac{d \ln K_i}{dt} + \beta \frac{d \ln L_i}{dt} \tag{10}$$

[4] With the marginal product approach, Ye (2002) finds that the output elasticity of labour equals 0.611, which is contrary to the finding of other studies noted in the rest of this paper.

When the elasticities of labour force and capital stock are given, TFP is calculated by equation (11) based on the definition of TFP.[5] TFP is assumed to vary across periods and regions.

$$TFP_{i,t} = \frac{Y_{i,t}}{K_{i,t}^{\alpha} L_{i,t}^{\beta}} \tag{11}$$

Based on provincial panel data and the fixed effects selected by the Hausman test, regression results of model (9) find that 1 per cent significant estimates of α, β and λ are 0.3563, 0.2717 and 0.0496, respectively[6]. $\lambda = 0.0496$ means that TFP grew at a rate of 4.96 per cent during the period of this study. To estimate TFP, first, constant returns to scale are not assumed. Instead, the estimated elasticities of 0.3563 and 0.2717 are used to calculate TFP, and this result is denoted by *TFPVRS*. However, *TFPVRS* would be much larger than the traditional estimates of TFP as $\alpha + \beta = 0.628$, which is usually assumed to equal 1. In line with the definition on growth accounting and keeping the estimated values of TFP within the traditional interval, the estimated VRS elasticities are normalized: $\alpha' = 0.3563 / (0.2717 + 0.3563) = 0.5673$, $\beta' = 1 - \alpha' = 0.4327$.[7] This normalization procedure corresponds with the method used by Zhang and Shi (2003), the results of which are widely accepted by the Chinese academic circle. TFP estimates based on normalized elasticities are denoted by *TFPNRM*.

The normalized elasticities are similar to estimates by Zhang and Shi (2003). Based on country-level data series from 1952 to 1998, Zhang and Shi (2003) find that $\alpha = 0.609$ and $\beta = 0.391$. Thus, even with different data sources, there is a similarity between the estimated elasticities presented here and

5 Comparing equation (11) with (9), $TFP_{i,t}$ in equation (11) represents not only $A_{i,0}$ but also variable t because we allow the change of TFP with time. Thus, variable t is reflected on the LHS instead of RHS in equation (11).

6 $\alpha + \beta = 0.628$ means decreasing returns if we only consider K and L as inputs. Such result from panel data may be different from the corresponding result estimated from cross section data which do not allow the change of TFP over time. If we take out t from equation (9) and assume the TFP of a region is constant over time, the new regression results shows that $\alpha + \beta = 1.101$, which is consistent with the common understanding. This implies that if we allow TFP changes across time, we should take TFP as an input in addition to K and L.

7 In the calculation of *TFPNRM*, we assume that $\alpha + \beta = 1$. This is according to the definition of TFP, which is calculated by dividing outputs by total factors. As there are two input factors, total factors mean the weighted averages of the two factors. Thus $\alpha + \beta = 1$ is to assure that the denominator of equation (11) is an average operation, like geometric mean, $a^{1/2}b^{1/2}$, where $1/2 + 1/2 = 1$. Otherwise, estimates of TFP may be out of traditional range and this makes different estimates incomparable.

those by Zhang and Shi. Nevertheless, as TFP is very crucial to this study, it needs to be measured through other approaches, and the advantages of various estimation methods should be checked further by comparison. First, TFP is estimated, with elasticities estimated by a non-*t*-term function, that is, $ln\ Y_{i,t} = A_i + \alpha\ Ln\ K_{i,t} + \beta\ Ln\ L_{i,t}$, which shows that $\alpha = 0.7264$ and $\beta = 0.3748$. As the sum of α and β is close to 1 this time, TFP is calculated without normalizing the elasticities and this result is indicated as *TFPNT*.

Further, TFP is also estimated using the LMDEA approach suggested by Forstner and Isaksson (2002), which deals with "receded technology" by appending previous frontiers to the latest calculation of the Malmquist index. Following Färe et al. (1994), Coelli (1996) and Fu (2005), the formula for calculating the output-oriented Malmquist index is shown in equation (12). This non-parametric method has the following advantages: The decision-making unit (DMU) can be technically inefficient, the form of production function may be unknown, and neutral technical changes are not necessary. Productivity changes can be decomposed into efficiency and technical changes, denoted as *effch* and *techch*, respectively, in equation (12). And *effch* equals the ratio outside the brackets.

$$m_o(y_{t+1}, x_{t+1}, y_t, x_t) = \frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)} \times [\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^{t+1}(x_{t+1}, y_{t+1})} \frac{d_o^t(x_t, y_t)}{d_o^{t+1}(x_t, y_t)}]^{1/2} = effch \times techch \qquad (12)$$

For a DMU *i* in period *t*, $d_o^t(x_t, y_t)$ can be estimated using the following linear programming under constant returns to scale:

$$\begin{aligned} &[d_o^t(x_t, y_t)]^{-1} = \max_{\phi,\lambda} \phi, \\ &st.\ldots -\phi y_{i,t,m} + Y_{t,m}{}'\lambda \geq 0, \ldots \forall m = 1,\ldots,M \\ &\ldots\ldots x_{i,t,k} - X_{t,k}{}'\lambda \geq 0, \ldots \forall k = 1,..K \\ &\ldots\dot{}\ \lambda \geq 0, \end{aligned} \qquad (13)$$

where x, y, K and M represent the input variable, the output variable, number of input and output variables, respectively. ϕ is a scalar and λ is a N x 1 vector of constants. N is the number of DMUs. X and Y are N x 1 vector of x and y, respectively. $d_o^t(x_{t+1}, y_{t+1})$ can be estimated by changing the period subscripts of x and y from t to $t + 1$ and maintaining the period subscripts of X and Y to t. The formulas for $d_o^{t+1}(x_{t+1}, y_{t+1})$ and $d_o^{t+1}(x_t, y_t)$ can be obtained by similar adjustments. By adding a restriction of $\sum_{i=1...N} \lambda_i = 1$, the results for variable returns to scale are obtained.

Reflecting on earlier technology, frontiers of past years are appended as artificial DMUs and applied to current estimations, thus, extending N to N^*, where $N^* - N$ equals the number of the retained previous frontiers. As the Malmquist index measures the change in productivity, to obtain the level of productivity, the accumulated product of annual Malmquist indices are calculated and assume $d_o^1(x_1, y_1)$ as the initial technological level. The results of LMDEA under CRS assumption are denoted by *MALMCRS,* and those of LMDEA under VRS assumption are indicated by *MALMVRS*.

As good estimated values should reveal realistic values, one can assume that good TFP estimates from different methods will correlate well with each other because they are based on realistic values. However, to ensure that the unexpected cluster of bad estimates do not conflict with decisions taken here, the varied numbers of patents are added to the result group as it is assumed that regions with high productivity will generate more patents. The correlation matrix of the TFP estimates and patents are shown in table 1.

Table 1. Correlation matrix of different TFP estimates and patents

	TFPNRM	TFPVRS	MALMCRS	MALMVRS	TFPNT	PAT
TFPNRM	1.0000	0.8535	0.9044	0.6802	0.8540	0.2219
TFPVRS	0.8535	1.0000	0.7235	0.7589	0.5425	0.1328
MALMCRS	0.9044	0.7235	1.0000	0.6916	0.7729	0.1630
MALMVRS	0.6802	0.7589	0.6916	1.0000	0.4836	0.0772
TFPNT	0.8540	0.5425	0.7729	0.4836	1.0000	0.1635
PAT	0.2219	0.1328	0.1630	0.0772	0.1635	1.0000

Source: China Statistical Yearbook, 1991 to 2007.

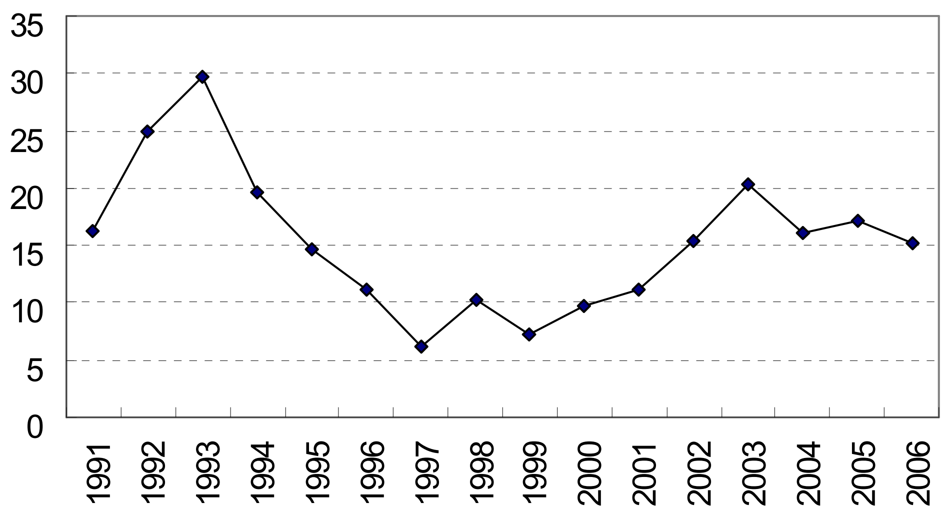
Looking at table 1, one finds that the correlation coefficient of *TFPNRM* and *MALMCRS*, namely, 0.9044, is the biggest. The correlation coefficient of *TFPNRM* and *TFPNT*, 0.854, is next. Second, on average, *TFPNRM* correlates with other measurements more intensively than the others. Third, the correlation coefficients of patents and TFP estimates are low, which implies that patents partially represent technology instead of productivity. This result supports the choice between TFP and patents with regard to productivity. Finally, assuming that patents are the raw indicator of pure technology—technology and productivity are closely related—this paper finds that *TFPNRM* has the highest correlation coefficient with patents, followed by *TFPNT*, *MALMCRS*. Consequently, following the correlation analysis above and the assumptions on the nature of good estimates, *TFPNRM*, *MALMCRS* and *TFPNT* are selected for the further discussion in this paper.

When estimating *TFPNRM* and *TFPNT*, the proportion of the elasticity of *K* to the elasticity of *L* is found to be around 6:4. This is contrary to the general benchmark of 4:6 (Romer, 1994).[8] However, it is important to note that other researchers in China also found similar elasticities. Chow (1993) and Zheng and Hu (2004) used a value of 0.40 for the output elasticity of labour. The labour shares estimated by Hu and Khan (1997) were 0.386 and 0.453 during the pre-reform and reform periods, respectively. Zhang and Shi (2003) obtained 0.391 for the elasticity of L. All these results suggest that capital formation in China plays a key role in economic growth. Calculations based on this output elasticity show that the contribution of capital stock is very high. In 1991, capital formation accounted for some 68.7 per cent growth in China and this percentage stayed above 50 per cent between 1991 and 1999.

[8] Solow (1957) finds that United States' output elasticity of *K* is around 0.35, which indicates that the elasticity of *L* is even larger than 0.6 in industrialized countries.

The capital-driven feature of Chinese economic growth is induced by increasing foreign investments attracted by the booming economy and by the quick capital accumulation of the economy itself. During the period 1991-2006, the average GDP growth rate was 10.24 per cent, while the average growth rate of fixed capital formation was 15.33 per cent. In 1993, the growth rate of the latter reached 29.73 per cent. The comparison of the growth rates of fixed capital formation in different countries is shown in table 2. It is found that among Brazil, Russia, India, and China (BRIC countries) and OECD countries, during the periods shown in the table, China has the highest growth rate. Another interesting fact about Chinese fixed capital formation is that it has a political cycle. Figure 1 demonstrates that the corresponding growth rate peaked in 1993, 1998 and 2003; the years when elections were held. This suggests that the fixed capital formation is extensively Government sponsored.

Figure 1. Fixed capital formation growth rate in China



Source: China Statistical Yearbook, 1991 to 2007.

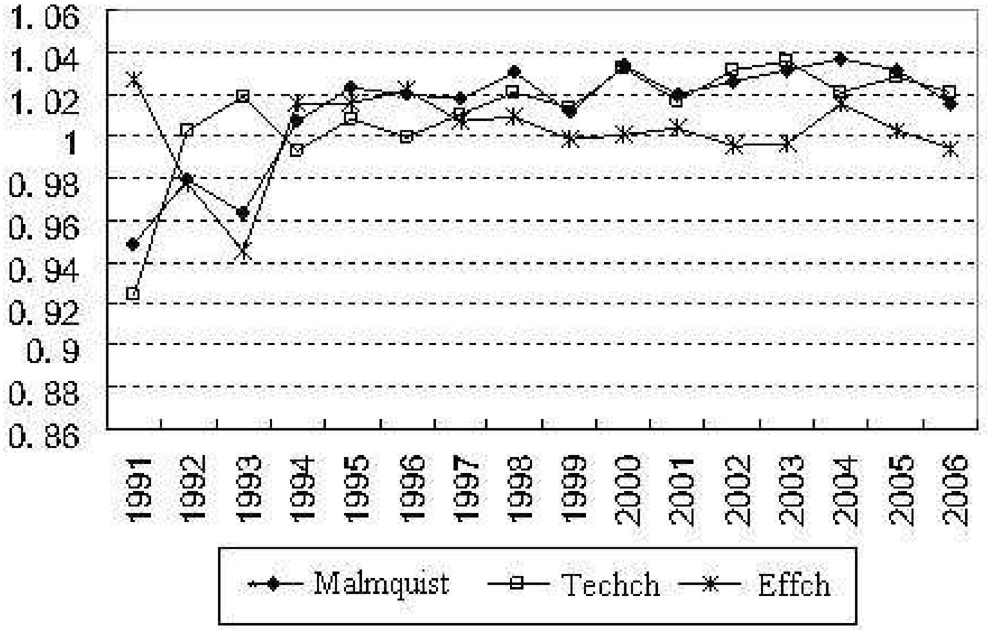
Table 2. Comparison of the average growth rate of fixed capital formation

Regional grouping, country	Rate (percentage)	Period	Country	Rate (percentage)	Period
China	15.33	1991-2006	Ireland	7.29	1998-2006
India	10.49	2001-2006	Italy	1.69	1989-2006
Russia	3.08	1996-2006	Japan	-0.18	1995-2006
Brazil	2.75	1992-2006	Republic of Korea	6.08	1989-2007
South Africa	4.11	1989-2006	Luxembourg	5.69	1996-2006
OECD	3.41	1996-2006	Mexico	5.75	1989-2006
OECD Europe	3.31	1996-2006	Netherlands	2.85	1989-2006
Australia	4.83	1989-2006	New Zealand	4.62	1989-2006
Austria	2.21	1989-2006	Norway	2.92	1989-2006
Belgium	3.32	1996-2006	Poland	7.03	1996-2006
Canada	3.67	1989-2006	Portugal	2.43	1996-2006
Czech Republic	1.91	1997-2006	Slovak Republic	6.27	1996-2006
Denmark	4.24	1991-2006	Spain	6.26	1996-2006
Finland	1.36	1989-2006	Sweden	5.03	1994-2006
France	2.43	1989-2006	Switzerland	1.49	1989-2006
Germany	0.90	1992-2006	Turkey	6.57	1989-2006
Greece	9.10	2001-2007	United Kingdom	3.13	1989-2006
Hungary	4.61	2001-2006	United States	3.77	1989-2007
Iceland	13.00	1998-2006			

Source: OECD Main Economic Indicators; All variables are deflated to constant prices.

Economic growth, which depends heavily on physical capital investment, could cause the economy to overheat, and Government-motivated investments could probably crowd out private investments. To embark on a new, efficient and sustainable development path, the Government highlighted technological and innovative industries in recent years. This is reflected in the TFP growth rate estimated by model (10), which reaches 4.96 per cent. The change of Malmquist productivity index estimated by LMDEA, presented in figure 2, also demonstrates such a trend.

Figure 2. Estimation results of LMDEA: Country level



Source: *China Statistical Yearbook*, 1991 to 2007.

Following the speeches made by Deng Xiaoping while on his trip in 1992 to the south, China began improving basic elements to develop its market economy. Figure 2 shows that the technical-change component in the Malmquist index exceeded 1 in 1992, and the efficiency-change component of Malmquist index stayed around 1 since 1994. The change in the Malmquist productivity index, which comprises the technical-change and efficiency-change components, is approximately 4 per cent as of 2000, and this value is equivalent to 4.96 per cent; the estimate of growth accounting. Productivity growth is achieved more through technical progress than through efficiency improvement. This is similar to the conclusions by Zheng and Hu (2004).

Technical progress can be further divided into duplicated technological progress and innovative technological progress (Hoekman et al., 2005). Duplicated technological progress focuses on mature technologies that are the public domain or are available cheaply (Kim, 2002). Innovative technological progress requires more creative activities, such as independent R&D, to grasp new technologies. During the initial stages of technological progress in developing countries, duplicated approaches may prevail, with technologies mainly diffused from abroad. As these countries develop, independent technological innovations will become the mainstream. To facilitate this process, it is important to find out the crucial factors that can be attributed to the increase in knowledge, penetrate the black box of interregional and international technology spillovers and study the threshold effects empirically.

5. Empirical findings

Provincial R&D data are taken from *China Statistical Yearbook on Science and Technology,* 1991-2007 and other data are from *China Statistical Yearbook,* 1991-2007. TFP is calculated in accordance with the methods mentioned above. The labour force in the R&D sector in this paper is represented by the number of persons engaged in scientific and technological activities. Intramural expenditure for science research and technical development is viewed as the annual R&D investment, and R&D capital stock is measured using the perpetual inventory method. Accordingly, the depreciation rate of R&D capital stock is set at 10 per cent, based on studies by Griliches (1990) and Coe and Helpman (1995). Coe and Helpman (1995) deploy depreciation rates of 5 per cent and 10 per cent separately, and derive similar results. Griliches (1990) finds that it takes 10 years to find significant decreases in the proportion of renewed patents, which suggests that knowledge depreciates at an annual rate of some 10 per cent. FDI capital stock is calculated on the basis of the perpetual inventory method with a depreciation rate of 9.6 per cent, which is consistent with the depreciation rate of K in the previous section. Annual investments in R&D and FDI are deflated by the price index of investment in fixed assets.[9]

The labour force that received higher education is considered as an accumulated variable of students enrolled in higher education institutions with a two-year lag; it takes an average of two years for in-school students to graduate. To assure that the human capital thresholds in this paper are estimated based on the active workforce, instead of the population including the older generation, human capital stock is depreciated annually. There is some econometric evidence for the depreciation rate in human

9 Specific deflators for R&D and FDI are not available in China, hence the deflator for general investment is used.

capital. Heckman (1976) finds that human capital depreciation rate ranges from 4 per cent to 9 per cent per year, while Haley's (1976) estimates range from less than 1 per cent to over 4 per cent. Echevarría's (2003) estimate of 2.5 per cent, which considers life expectancy, retirement and endogenous growth and is somewhere between the Haley's and Heckman's estimates, is used here.[10] The age group of the well-educated labour force in China usually ranges between 20 and 60 years, which is similar to that of Echevarría (2003). The summary statistics of the variables are shown in table 3.

Table 3. Summary statistics of variables

Variable	Mean	Median	Maximum	Minimum	Std. Dev.
Ln(TFPNRM)	-0.6266	-0.6570	0.1149	-1.1658	0.2638
Ln(MALMCRS)	-0.2915	-0.3323	0.9711	-0.7991	0.2971
Ln(TFPNT)	-1.4167	-1.4286	-0.9411	-1.8035	0.1821
Ln(H)	1.8894	1.9626	3.6448	-2.2867	0.9939
Ln(RD)	4.2900	4.2664	7.2161	0.2262	1.2200
Ln(RDO)	5.0682	4.9552	6.4407	3.9405	0.6884
Ln(P)	10.5563	10.6965	12.4874	8.0229	0.8243
Ln(M)	-0.5249	-0.4337	-0.0775	-1.8546	0.3326
F	0.0593	0.0317	0.3074	0.0000	0.0714
E	8.1076	5.4096	45.7737	1.3910	7.9535

Source: *China Statistical Yearbook on Science and Technology*, 1991 to 2007, and *China Statistical Yearbook*, 1991 to 2007.
Notes: Data are from 1990 to 2006.

[10] The model was also estimated with the maximum human capital depreciation rate of 9 per cent provided by Heckman instead of 2.5 per cent for comparison purposes. With the depreciation rate of 9 per cent, the percentage of high quality human capital in workforce will decrease significantly, and the spillovers will still occur as other variables are not changed. As a result, when regressing with TFPNRM, three thresholds of 2.77, 6.74 and 16.82 are obtained, and the significant sign-change threshold is 6.74. Three estimated thresholds are 2.76, 5.49 and 17.38 when regressing with MALMCRS, and the significant sign-change threshold is 5.49. All these values are relatively lower than those results estimated with the depreciation rate of 2.5 per cent. The reason for which we chose 2.5 per cent is that the maximum deprecation rate of 9 per cent is close to the deprecation rate of physical capital in China and human capital usually depreciates slower than physical capital, because humans can accumulate experience and knowledge when they grow old. It is hard to say that people at the age of t + n are not as good as those at the age of t. Thus, we regard human capital as a generic concept. Their quality does not change during working period of their lives, and suddenly depreciates to 0 when they retire, which means that we just annually remove the retired people from the human capital stock with higher education. The working age for well-educated people usually ranges between 20 and 60 in China, so every year 2.5 per cent (1 / 40) is removed from the stock.

5.1. Human capital thresholds for the absorption of FDI technology

Here, an attempt is made to find out the potential human capital thresholds, and study their impact on FDI technology spillovers. First of all, it is necessary to test the existence of human capital thresholds; otherwise normal OLS or panel regression should be used directly instead of threshold regression. The likelihood ratio tests for the existence of thresholds are shown in tables 4 and 5. For all regions in China, when the dependent variables are *MALMCRS* and *TFPNRM*, bootstrapped *p* values demonstrate that single, double and triple thresholds are significant either at the 1 per cent or 5 per cent level. When the dependent variable is *TFPNT*, then single and double thresholds are significant at the 1 per cent level, whereas triple threshold is not significant. Hence, there is evidence that at least two thresholds exist in this case. Additionally, as regional disparities are salient in China, the threshold effects for the mid-western areas are tested independently when the dependent variable is *TFPNRM*. Results show that the single threshold becomes significant at the 5 per cent level. The double and triple thresholds are however insignificant for the mid-western areas. As far as the threshold effects for the eastern areas are concerned, these could not be tested due to insufficient observations.

Table 4. Likelihood ratio test for threshold effects: TFPNT and MALMCRS

	TFPNT: All regions		**MALMCRS: All regions**	
	Likelihood ratio	**P value**	**Likelihood ratio**	**P value**
Single threshold	87.9296	0.0000	76.5050	0.0033
Double threshold	36.4400	0.0333	49.1775	0.0100
Triple threshold	19.7204	0.2033	30.4190	0.0500

Source: *China Statistical Yearbook on Science and Technology*, 1991-2007, and *China Statistical Yearbook*, 1991-2007.

Table 5. Likelihood ratio test for threshold effects: TFPNRM

	All regions		Mid-west area	
	Likelihood ratio	P value	Likelihood ratio	P value
Single threshold	78.8777	0.0000	35.1974	0.0267
Double threshold	33.1647	0.0400	11.7224	0.5500
Triple threshold	25.03045	0.0600	7.3120	0.6167

Source: *China Statistical Yearbook on Science and Technology, 1991 to 2007, and ChinaStatistical Yearbook, 1991 to 2007.*

Notes: The observations of the eastern regions are not sufficient for the threshold test.

Next, the values of thresholds and their 95 per cent confidence intervals are estimated. The results are presented in tables 6 and 7. The number of thresholds estimated corresponds with the results shown in tables 4 and 5. In the case of all regions, for *TFPNRM*, the three estimates of the thresholds are 4.92 per cent, 10.99 per cent and 30.49 per cent. For *MALMCRS*, the three thresholds are 4.91 per cent, 9.16 per cent and 30.04 per cent, and for *TFPNT*, the two thresholds are 4.91 per cent and 10.99 per cent. Comparing these values, it is found that the estimated thresholds are quite stable, despite the change of dependent variables. For the mid-western areas, a single threshold of 4.91 per cent is found, and this value is equivalent to the first threshold of all regions.

Table 6. Threshold estimates and their 95 per cent confidence intervals: TFPNT and MALMCRS

	TFPNT: All regions		MALMCRS: All regions	
Threshold	Estimate (percentage)	95 per cent confidence interval	Estimate (percentage)	95 per cent confidence interval
First	4.9066	[4.3049, 5.1821]	4.9065	[4.2504, 5.1821]
Second	10.9945	[10.7145,12.0706]	9.1645	[4.6699, 11.1688]
Third			30.0384	[24.14888,31.2604]

Source: *China Statistical Yearbook on Science and Technology*, 1991 to 2007, and *China Statistical Yearbook*, 1991 to 2007.

Table 7. Threshold estimates and their 9.5 per cent confidence intervals: TFPNRM

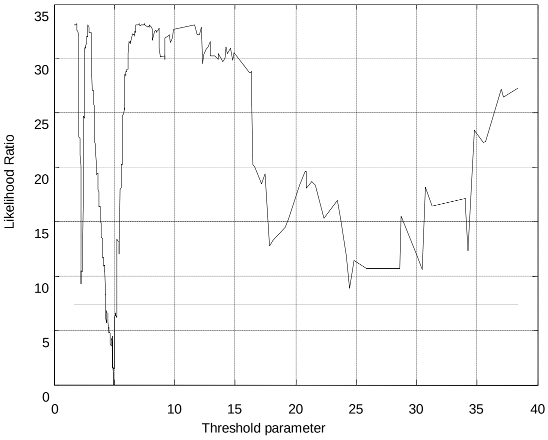
Threshold	All regions		Mid-west area	
	Estimate (percentage)	**95 per cent confidence interval**	**Estimate (percentage)**	**95 per cent confidence interval**
First	4.9207	[4.2798, 5.1821]	4.9066	[3.7612, 5.0363]
Second	10.9944	[10.7144, 12.0706]		
Third	30.4921	[2.2872, 34.2334]		

Source: *China Statistical Yearbook on Science and Technology*, 1991 to 2007, and *China Statistical Yearbook, 1991 to 2007.*

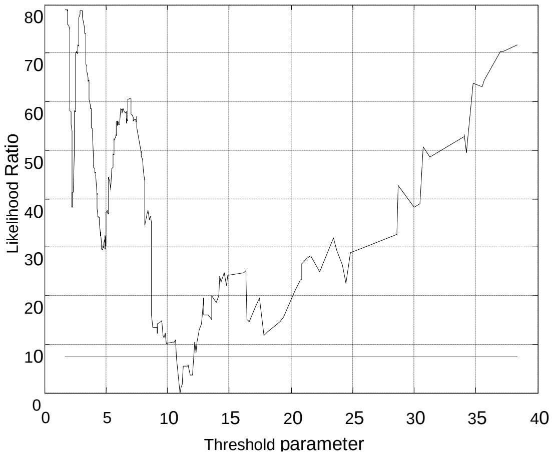
The likelihood ratio diagrams of the thresholds for all regions and *TFPNRM* are presented in figures 3.a, 3.b and 3.c, and that for the mid-western areas is illustrated in figure 3.d. The flat lines drawn in the figures correspond to equation (6). When the likelihood ratios are above these lines, they significantly deny the hypothesis of $\theta = \theta_0$ at the 5 per cent level. Thus, the confidence interval for $\theta = \theta_0$ is below the flat line and between the two intersecting points of the flat line and likelihood ratio curve. Appendix figures A and B, present the likelihood ratio diagrams for *MALMCRS* and *TFPNT,* respectively.

Figure 3. The likelihood ratio diagram and confidence interval: TFPNRM

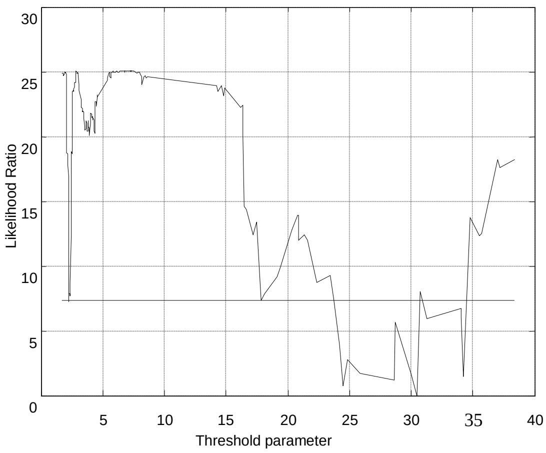
3.a For threshold 4.92 per cent and all regions



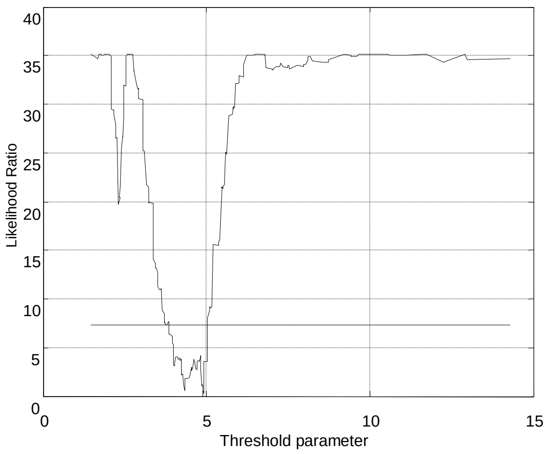
3. b. For threshold 10.99 per cent and all regions



3.c. For threshold 30.49 per cent and all regions



3. d. For threshold 4.91 per cent and mid-west



Sources: China Statistical Yearbook, 1991 to 2007, and *China Statistical Yearbook on Science and Technology*, 1991 to 2007.

After identifying the threshold values, the model is regressed, the results of which are shown in tables 8 and 9. By comparing normal standard errors and White-corrected standard errors of estimated coefficients, the two standard errors are found to be approximate. This means that no significant heteroskedasticity exists in this case. Thus, the significant levels of the estimated coefficients can be decided by normal standard errors.

Table 8. Threshold regression results from knowledge production model: TFPNT and MALMCRS

	TFPNT: All regions			**MALMCRS: All regions**		
	Coefficient	**S.E.**	**Wht S.E.**	**Coefficient**	**S.E.**	**Wht S.E.**
Ln(H)	0.0062	0.0165	0.0130	0.0016	0.0156	0.0119
Ln(RD)	-0.0006	0.0208	0.0196	0.0820***	0.0195	0.0214
Ln(RDO)	0.0050	0.0222	0.0210	0.0226	0.0209	0.0214
Ln(P)	0.0621**	0.0268	0.0272	0.0571**	0.0255	0.0258
Ln(M)	0.0220	0.0411	0.0387	0.0209	0.0389	0.0403
$F \cdot I(E \leq \theta_1)$	-1.3249***	0.1688	0.1482	-0.4046***	0.1585	0.1341
$F \cdot I(\theta_1 < E \leq \theta_2)$	-0.6757***	0.1717	0.1638	0.1520	0.1615	0.1220
$F \cdot I(\theta_2 < E \leq \theta_3)$	0.8657***#	0.1787	0.1850	1.1574***	0.1652	0.1443
$F \cdot I(E > \theta_3)$				2.5238***	0.2191	0.2335
θ_1	4.9066			4.9065		
θ_2	10.9945			9.1645		
θ_3				30.0384		

Source: *China Statistical Yearbook on Science and Technology*, 1991 to 2007, and *China Statistical Yearbook*, 1991 to 2007.

Notes: (i) * Significant at 10%; ** significant at 5%; *** significant at 1%.
(ii) # Coefficient of $F \cdot I(E > \theta_2)$.

Table 9. Threshold regression results from knowledge production model: TFPNRM

	All regions			Mid-western areas		
	Coefficient	**S.E.**	**Wht S.E.**	**Coefficient**	**S.E.**	**Wht S.E.**
Ln(H)	0.0055	0.0145	0.0111	-0.0086	0.0157	0.0097
Ln(RD)	0.0225	0.0181	0.0168	0.0162	0.0192	0.0166
Ln(RDO)	0.1297***	0.0194	0.0194	0.1442***	0.0210	0.0216
Ln(P)	0.0497**	0.0234	0.0233	0.0438*	0.0302	0.0300
Ln(M)	-0.0069*	0.0359	0.0356	-0.0778**	0.0415	0.0430
$F\cdot I(E\leq\theta_1)$	-0.7962***	0.1485	0.1355	-0.7247***	0.1608	0.1482
$F\cdot I(\theta_1<E\leq\theta_2)$	-0.2123*	0.1497	0.1331	-0.1528#	0.1736	0.1566
$F\cdot I(\theta_2<E\leq\theta_3)$	0.9132***	0.1580	0.1693			
$F\cdot I(E>\theta_3)$	1.7022***	0.2070	0.2214			
θ_1	4.9207			4.9066		
θ_2	10.9944					
θ_3	30.4921					

Source: *China Statistical Yearbook on Science and Technology*, 1991 to 2007, and *China Statistical Yearbook*, 1991 to 2007.
Notes: (i) * Significant at 10%; ** significant at 5%; *** significant at 1%.
(ii) # Coefficient of $F\cdot I(E>\theta_1)$.
(iii) The observations of the eastern areas are insufficient for threshold regression.

The first explanatory factor discussed here is the interaction term of FDI and the indicated human capital threshold. For all regions and regressions with various dependent variables, if human capital, represented by the percentage of labour force that received higher education, is below the first threshold of 4.9 per cent, the effects of FDI on technological progress are significantly negative and the FDI spillover coefficient is between -1.325 and -0.405. This indicates the strong negative effects of FDI when human capital is low. There are several reasons for this phenomenon.

- New substituted goods produced by foreign affiliates draw demand away from their local counterparts, and host firms are unable to imitate the relatively advanced foreign products because of the poor quality of human capital. Aitken and Harrison (1999) refer to this effect as "market-stealing". In the case of China, Buckley et al. (2006) recognize that the capabilities of some local firms are insufficient to enable them to absorb the externally-generated knowledge from FDI, thus restricting spillover effects. Theories of Nelson and Phelps (1966) also suggest that human capital stock in host developing countries limits their absorptive capability.

- As wages of foreign firms are usually higher than those of domestic ones, brain-drain occurs, worsening knowledge creation in domestic firms. Hale and Long (2006a) state that the presence of FDI is associated with larger differences in wages and the quality of skilled workers, and the presence of FDI is negatively associated with the performance of State-owned enterprises because they do not have flexible wage and personnel policies to attract talent. R&D laboratories of transnational corporations (TNCs) can also exert a negative impact by drawing talent away from indigenous ones (Zhou, 2005).

- Foreign firms in host developing countries do not pay much attention to R&D. They are more concerned with markets and human and natural resources. UNCTAD (2007) argues that TNCs are more interested in extractive industries, as they wish to gain direct control over the mineral resources required as inputs for their manufacturing and infrastructure-related industries. Ali and Guo (2005) point out that China's large potential market size and cheap labour are the two important factors that influence the decisions of TNCs to invest in China. In turn, R&D foreign affiliates are uncommon in developing countries. According to UNCTAD data (2005), only 1.02 per cent R&D foreign affiliates are located in developing countries. Even in technology-intensive foreign affiliates, most domestic intellectuals hired by foreign investors are usually engaged in marketing or technical services, instead of research.

- Foreign firms prevent their core technologies from leaking out to host countries. Such efforts could become more effective when the host absorptive capacities for advanced technology are low. Zhou (2005) reports that TNCs do not focus on patents to avoid disclosure of technology know-how. Besides, most of their R&D laboratories in China are wholly foreign owned in order to better protect their intellectual property rights. A survey undertaken by the Chinese Academy of Social Sciences shows that 77 per cent of the foreign enterprises never formally cooperated with Chinese R&D laboratories, and 79 per cent do not have any intention to do so in this regard.

Subsequently, if the quality of human capital is between 4.9 per cent and 10.99 per cent, the negative coefficients of FDI interaction, in the regressions of *TFPNT* and *TFPNRM*, will be halved or quartered, respectively, in absolute terms. For *MALMCRS*, when it ranges from 4.9 per cent to 9.16 per cent, neither negative nor positive effects are significantly caused by the presence of FDI. Therefore, negative effects of FDI are alleviated when the quality of human capital increases.

Finally, if human capital surpasses 10.99 per cent, in terms of the percentage of workforce that received higher education - in the regressions of *TFPNRM* and *TFPNT* - or is above 9.16 per cent - in the regression of *MALMCRS*, the spillover effects of FDI on technological progress become significantly positive. (Henceforth this threshold is referred to as the sign-change threshold).

The sign change of the coefficients shows very strong evidence of the existence of human capital thresholds with regard to the absorption of FDI technology spillovers. Borensztein et al. (1998) and Xu (2000) also find sign-change thresholds in their studies. The ideas presented by Grilliches (1979) could help to understand this change. Grilliches insists that the purchase of foreign high-technology goods cannot be considered as real knowledge spillovers. He claims that true spillovers are ideas borrowed by research teams. Thus, the change in the coefficient sign is similar to the change from goods purchased, to product imitations, or independent innovations. As the quality of human capital increases and exceeds the sign-change threshold, domestic firms can learn from these foreign goods by employing reverse engineering, and benefit from the imitation and thus improve their ability to resist "market -stealing" and brain drain.

Another way the sign-change can be explained is through spillover channels. When qualified human capital is scarce, limited positive technology spillovers may occur via demonstration or contagion effects yielded by foreign entrants, but not through competitive effects (Buckley et al., 2006). To overcome the negative effects of FDI, a developing country should not only depend on demonstration or contagion effects, but also on positive competitive effects which can transfer more advanced technology. Foreign capital intensifies market competition in host countries and forces indigenous firms to become more efficient (Kokko, 1994). Competitive pressures thus have a twofold effect on their domestic counterparts. However, the outcome here suggests that the quality of human capital is one of the crucial factors that turns competitive effects from negative to positive.

The third threshold of 30 per cent is significant when the dependent variables are *TFPNRM* or *MALMCRS*. In this case, the positive spillover coefficients of FDI almost doubled when this threshold was reached, demonstrating a pronounced increase in imitation or innovation capacities when the quality of human capital increases.

For the mid-western areas and in the regression of *TFPNRM*, when human capital is below the single threshold of 4.9 per cent, negative effects are significant, which is similar for all regions. However, when human capital exceeds 4.9 per cent, the negative effects decrease, albeit insignificantly, and no significant sign-change threshold appears in mid-western areas. These differences suggest that the technological progress trajectory of these areas should be distinguished from that of the eastern areas of China. As the threshold estimates in the regression of *TFPNRM* are close to those of *TFPNT*, and because *TFPNRM* has the best characteristics, as shown in table 1, the following is based on estimates of *TFPNRM*.

5.2. The realities about who satisfies these thresholds

Turning now to another feature of threshold studies, namely, finding facts about who satisfies the estimated thresholds, table 10 presents the human capital statistics for the whole country. They comprise promotion rates and rates of educated workforce related to various education levels. Looking at table 10, it is possible to figure out the approximate average years of schooling for that segment of Chinese workforce educated between 1978 and 2006. The average years of schooling equals 2.79 per cent×0 + 29.53 per cent×5 + 37.01 per cent×9 + 24.03 per cent×12 + 6.64 per cent×15.72 = 8.73. The proportion of the workforce without any education is 2.79 per cent. Here five years, instead of six, are used to measure the duration of the primary education because of unreported drop-outs in rural areas. The duration of normal undergraduate education and specialized higher education are four and three years, respectively, an additional three years for a Masters degree and a further three years for a doctoral degree are needed. Taking into account the number of students in different types of schools, the weighted average duration of higher education is 3.72, and the corresponding average schooling years for people who received higher education is 15.72.

As reforms in China started in 1978, the population educated as of that year forms the major part of current labour force. Thus, 8.73 is the approximate average number of schooling years of the workforce. This number is usually higher than the average number of schooling years for the entire population because the latter comprises the older generation that was educated prior to 1978, and received little education, on average.[11]

Table 10. Human capital in China: Average promotion rate and rates of educated workforce

Promotion rate	Percentage	Rates of educated workforce	Percentage
Net enrolment rate of school-age children	97.21	Workforce with no education	2.79
Primary school graduates entering junior secondary schools	69.63	Workforce with only primary education	29.53
Junior secondary graduates entering senior secondary schools	45.31	Workforce with junior secondary diploma	37.01
Senior secondary graduates entering institutions of higher learning	21.65	Workforce with senior secondary diploma	24.03
–	–	Workforce with higher educational diploma	6.64

Source: *China Statistical Yearbook*, 1991 to 2007, and *China Compendium of Statistics*, 1949-2004.

Notes: (i) Data sources are *China Statistical Yearbook* and all values averaged from 1978 to 2006.

(ii) Promotion rate is calculated with graduates instead of entrants to eliminate drop-outs.

(iii) Senior secondary education comprises regular senior secondary education, regular specialized secondary education, technical education and vocational senior secondary education because the purpose here focuses on the workforce with different educational level. Thus the rate of senior secondary graduates entering institutions of higher learning is lower than the admission rate provided in *China Statistical Yearbooks*, which only considers regular senior secondary graduates.

[11] For example, entrants to tertiary schools were 79,000 in 1952, and this number amounts to 5,461,000 in 2006. According to World Bank data, the average number of schooling years of Chinese population over age 15, including the older generation, was 6.36 in 2000.

As Borensztein et al. (1998) and Xu (2000) set their thresholds in terms of average years of male secondary school attainment for population over age 25, the sign-change threshold of 10.99 per cent is calculated on these terms - based on table 10, and becomes 3.42 - in terms of average years of secondary school attainment in workforce.[12] This means that, on average, the workforce should comprise at least junior secondary graduates for positive FDI technology spillovers to occur. Thresholds by Borensztein et al. and Xu are set at 0.83 and 1.9, respectively. However, it is not appropriate to state that the thresholds - active labour force - set in this paper are higher than those by Borensztein et al., and Xu - male adults, including the older generation. For technology spillovers, the active labour force, including female labour, is more important than that which includes retirees, because the latter would underestimate the real quality of the labour force, especially in rapidly developing countries, where the educational structure of the older generation differs totally from that of the new.

To compare the practical quality of human capital with the threshold of 3.42, in terms of secondary school attainment, the prior secondary schooling years of 6 is subtracted from 8.73 resulting in 2.73 years. This indicates that human capital in China is below the estimated threshold of 3.42. The comparison in terms of the percentage of the workforce that received higher education also reveals the same result. Table 10 shows that 6.64 per cent of the workforce received higher education; which is below the threshold of 10.99 per cent. If estimates in the model consider FDI directly without interacting with human capital thresholds, the effects of FDI on technological progress are negative, which coincides with the fact that human capital is below the sign-change threshold.

For comparative purposes, the corresponding threshold is given in terms of secondary school attainment - term not considered better than higher education - as a measurement related to the absorptive capacity vis-à-vis FDI technology spillovers. In reality, as China maintains a compulsory nine-year education policy - six years in primary school and three in junior secondary school - it is easy for the average years of secondary education to reach three, which exceeds the threshold, albeit,

[12] Calculated by: 2.79 per cent×0 + 29.53 per cent×5 + 37.01 per cent×9 + 24.03 per cent×12 + 10.99 per cent×15.72 = 9.42, and 9.42 – 6 = 3.42.

as long as the policy is maintained. The segment of the labour force that received tertiary education, excluding those that only received secondary education, plays a more important role in the absorption of FDI technology spillovers. If spillover effects are judged in accordance with secondary education thresholds, or even junior secondary education, results could be plausible. In the past, the majority of the labour force only received primary or secondary education, as a result low-technology manufacturing flourished. Furthermore, the effects caused by the lack of qualified human capital have already undermined the independent innovation capacity of the country. For this reason, the proportion of labour force that received higher education is used as the threshold variable in this paper.

Although China as a whole does not satisfy the sign-change threshold, a few regions meet this minimum level of human capital. Table 11 shows the percentages of provinces in the three regimes segmented by the two thresholds estimated with *TFPNRM*. Prior to 1998, most regions were below the first threshold of 4.92 per cent, and major effects of FDI on technological progress were negative. Since 1999, human capital in most provinces has exceeded the first threshold. More importantly, one can see that the percentage of provinces above the sign-change threshold of 10.99 per cent is increasing with time. In 2006, 41.38 per cent of Chinese provinces exceeded this threshold and benefited from positive technology spillovers from FDI.

Table 11 also partially explains why direct investment effects of FDI prevail in China, while the indirect effects of FDI-induced productivity growth in China are low. Prior to 2002, the percentage of provinces above the sign-change threshold of 10.99 per cent was below 20 per cent. This limits the positive effects of FDI technology spillovers and implies that the positive effects were geographically localized. However, prospects appear to be promising as this percentage has increased dramatically since 2004.

Table 11. Percentage of provinces in the three regimes segmented by thresholds

Year	E ≤4.92 per cent	4.92 per cent <E≤10.99 per cent	10.99 per cent <E	10.99 per cent <E(Mid-west)
1990	75.87	13.79	10.34	0
1991	72.42	17.24	10.34	0
1992	72.42	17.24	10.34	0
1993	65.52	24.14	10.34	0
1994	65.52	24.14	10.34	0
1995	62.07	27.59	10.34	0
1996	58.63	31.03	10.34	0
1997	58.63	31.03	10.34	0
1998	51.73	34.48	13.79	0
1999	44.83	37.93	17.24	5.56
2000	41.38	41.38	17.24	5.56
2001	34.48	48.28	17.24	5.56
2002	20.69	51.72	27.59	22.22
2003	13.79	58.62	27.59	22.22
2004	13.80	51.72	34.48	27.78
2005	3.45	58.62	37.93	33.33
2006	0	58.62	41.38	38.89

Sources: China Statistical Yearbook, 1991-2007, and *China Statistical Yearbook on Science and Technology*, 1991-2007.

Notes: (i) E is the human capital represented by the ratio of labour force that received higher education.

(ii) The last column reflects the mid-western areas; other columns are of all regions.

Regional inequalities in human capital are clearly demonstrated in table 11. In the mid-western areas, the percentage of provinces above the sign-change threshold is relatively lower than that of all regions. Prior to 1999, in the mid-western areas, the percentage was 0 per cent, which completely denies the possibility of positive FDI technology spillovers. During recent years, the human capital quality level has increased. The percentage of provinces above the threshold in the mid-western areas shows a tendency to equal that of all regions. In 2006, 38.89 per cent of mid-western provinces exceeded the sign-change threshold.

Finally, a brief description is provided on the percentages of the workforce that received higher education in other countries. According to World Bank data, in 1997, this figure stood at 25.23 per cent in high-income OECD countries, 30.9 per cent in Japan, 23.2 per cent in Germany, and 23.3 per cent in United Kingdom. It was 13 per cent in Poland, 2001; 12 per cent in Sri Lanka, 2000, 6.9 per cent in Brazil, 1999; 1 per cent in Ethiopia, 1999; and 3 per cent in Guinea, 1998. It is true that while most developed countries are above the threshold of 10.99 per cent, some developing countries are still below this threshold. However, this does not mean that human capital-scarce developing countries cannot benefit from foreign technology spillovers, mainly because regional inequalities have yet to be considered.

5.3. Interregional technology spillovers as the complement of international spillovers

As already known, some regions are below the sign-change threshold. Thus the only unanswered question is whether these regions benefit from foreign technology spillovers or not. The answer is provided by the estimated coefficients of *RDO*, the sum of other regions' R&D capital stock. In table 9, the significant coefficient of *RDO* suggests that the currently studied region adopts technologies transferred from other regions. One finds that all regions as well as the mid-western areas benefit significantly from interregional technology spillovers. In addition, the coefficient of mid-western areas is 0.1442 - much larger than that of all regions, which is 0.1297. It is known that even if interacted with human capital, the coefficient of FDI technology spillovers is negative, or insignificant, for the mid-western areas, which means that it is difficult for the mid-western areas to directly absorb foreign technology spillovers because of the low quality of human capital. In contrast, since domestic technologies are more appropriate for recipient regions than foreign ones and interregional technological distances are smaller than the international ones, interregional spillovers occur, and technologies transferred interregionally comprise FDI technologies that have been absorbed by the advanced regions where human capital has exceeded the sign-change threshold. The higher the interregional spillover coefficient of backward areas, the greater the benefits derived from interregional technology spillovers. By comparing the coefficients of *RDO* and FDI, one finds that if the quality of human capital is low, intra-national knowledge spillovers become a more important source for technological progress than international spillovers. This result is the same as that of Branstetter (2001), and is also in line with the appropriate technology theories proposed by Basu and Weil (1996) and Eicher (1999).

5.4. Other explanations for technological progress

In table 8, the coefficient of the local R&D stock is significantly positive when regressed with *MALMCRS*. However, in other regressions, the same coefficients are not significant. This result indicates that independent R&D is relevant to local technological progress, but has more complicated implications.

- R&D has two sides. In addition to the conventional role of independent innovation, it enhances the absorptive capacity for technology spillovers (Griffith et al., 2004). Thus, effects of R&D partially comprise international and intra-national technology spillovers.

- R&D not only changes TFP directly, it also impacts economic growth, reflected by the effects of input factors, that is, capital and labour. Zheng (1999) argues that TFP, measured as the residual of the production function, only represents technological progress, which it is not reflected by the effects of input factors. R&D improves the quality of labour and capital stock, which is already reflected in the inputs, but not reflected in TFP. Therefore, regressions depending on TFP will probably underestimate the contribution of R&D. This downward bias may be more serious for China as physical inputs play a key role in economic progress.

- The coefficient of R&D labour is insignificant in all regressions, indicating that the R&D labour force does not affect technological progress significantly. This result contradicts hypothesis 1. One reason for this is that the R&D labour force is already partially represented by R&D capital stock. Given that applied technology development usually needs sufficient R&D capital investment, without support of the latter, the R&D labour force can only engage in paper-based research, which cannot increase productivity in a short time. TFP does not reflect the technologies in pure theoretical fields, but represents the technologies in applications. Another explanation is the broken link between research institutes and industrial production. As most R&D activities in China belong to the public sector (Yao and Zhang, 2001), this makes it even worse.

Estimated TFP, here, comprises many factors: innovation-based technological progress, imitation-led technological progress, institutional change, efficiency change and omitted variables. Infrastructure provides goods or services that are crucial for the efficiency, competitiveness and growth of production (UNCTAD, 2008). For instance, better transport conditions can save costs and time, connect more enterprises along the production chain, and intensify geographic competition more extensively. Thus, infrastructure is important for TFP growth, with respect to efficiency change, resource allocation and competitive pressure.

There is significant evidence for this conclusion. The coefficients of infrastructure are relatively large and significant in all regressions, which are better than the coefficients of R&D capital stock and R&D labour force. This result reveals a crucial feature of Chinese development. As China is a big country and transportation costs are the key factor considered by most investors, most local governments pay attention to the construction of public infrastructure to attract investments. In addition to attracting investment, public infrastructure can also solve problems caused by unequal distribution of natural and human resources. Therefore, empirical results support the policy of infrastructure construction. The studies of Fu et al. (2004) and Démurger (2001) also highlight the role of public infrastructure for China. It is true that most Chinese local governments invest more in infrastructure than in R&D. Therefore, as public infrastructure develops further over time, the policy should be adjusted to ensure greater innovative technological progress.

Comparing the regression of all regions with that of the mid-western areas in table 9, the infrastructure coefficient is larger in all regions than that in the mid-western areas. Metcalfe's (1995) law may explain this phenomenon. Metcalfe states that the value of a communication network is proportional to the size of the network, squared. Thus infrastructure will be more valuable in developed regions than in less developed regions. This means that mid-western areas should invest more in infrastructure in order to receive increasing returns. Other distinguished characteristics of mid-western areas, such as insignificant sign-change threshold, the negative coefficient of FDI technology spillovers and the large coefficient of interregional technology spillovers, imply that mid-western areas should focus on interregional technology spillovers as well as on increasing investment in infrastructure investment to enhance technological progress.

The coefficients of market reforms - another institutional variable - are insignificant in table 8, and significantly negative in table 9. This result does not coincide with hypothesis 3. To understand this, one needs to focus on the relationship between market reforms the productivity growth. The former affects the latter through the introduction of various types of ownership, market competition, market mechanism of resource allocation and decentralization of economy (Zheng, 2005). According to this perspective, marketization mainly concentrates on efficiency improvement instead of pure technical progress. However, figure 2, which illustrates that productivity growth is dependent more on technical progress than efficiency. Thus, efficiency improved by marketization is not a major part of productivity growth. Hence, the link is broken.

Furthermore, with regard to pure technological progress, as imitation of foreign advanced technology is the key source for such progress (Jones and Ruffin, 2008), the effects of pure technological progress are mainly captured by openness instead of marketization. This is the reason for the positive and large coefficients of FDI interaction term when human capital is high, in contrast to the insignificant or negative ones of marketization. Zhang (2001) also points out that market reforms do not play a direct and significant role in provincial growth.

6. Conclusions

Different perspectives relate to technology spillover effects of FDI. Some authors argue that these effects are positive, while others insist that they are insignificant or even negative. The human capital threshold analysis of the absorptive capacity vis-à-vis FDI technology spillovers probably provides solutions for assimilating these discrepancies. Unlike existing studies on thresholds, in this paper, the proportion of the labour force that received higher education is used to represent human capital, and the thresholds are generated endogenously using the threshold regression, as suggested by Hansen (1996, 1999). The major empirical findings of this paper are as follows:

First, three thresholds are found for human capital, namely, 4.92 per cent, 10.99 per cent and 30.5 per cent. When the percentage of the labour force that received higher education is below the first threshold, the external effects of FDI on technological progress are significantly negative, indicating that the major effects of FDI are negative. When the quality of human capital in a region exceeds the first threshold, although the sign of negative coefficients does not change, the absolute magnitude decreases significantly, suggesting an alleviation of negative effects. The most important threshold, however, is the sign-change threshold of 10.99 per cent. When this threshold is crossed, the region enjoys positive FDI technology spillover effects. However, even more positive effects will occur if the third threshold of 30.5 per cent is reached.

By comparing the human capital level with the sign-change threshold, one finds that the disproportionate growth rate of productivity, in contrast with the fast economic growth of China, is partially caused by the low absorptive capacity of human capital. The inequality in TFP growth rates between the eastern and mid-western areas are also induced by the uneven geographic distribution of human capital. An international comparison shows that most developed countries exceed the threshold of 10.99 per cent, while some developing countries are still below this threshold.

The policy implications of this threshold are emphasized. It highlights the importance of human capital for the absorption of FDI technology spillovers and proposes the achievement of clear human capital targets for developing countries. It also provides a primary threshold to mitigate the negative effects of FDI, a sign-change threshold to overcome the negative effects and an additional threshold to further increase the positive effects.

Based on the threshold effects of human capital, this paper explains the regional inequalities in growth rates, sheds light on the interregional or international variety in FDI technology spillovers, and reconciles several findings of single country studies, for example, the positive technology spillover effects in advanced countries (Caves, 1974; Globerman, 1979), and the insignificant or negative effects in less developed countries (Haddad and Harrison, 1993; Aitken and Harrison, 1999). Since human capital is geographically unevenly distributed in China, the eastern areas with abundant human capital should focus on advanced foreign technologies and facilitate the process of FDI technology transfer, while the mid-western areas should pay more attention to intra-national technology transfer and increase human capital in order to attract FDI on a larger scale.

Second, the sign-change threshold of 10.99 per cent, as a percentage of labour force that received higher education, corresponds to 3.42, in terms of average years of secondary school attainment by the workforce. This somewhat compares with the estimated thresholds of Borensztein et al. (1998) and Xu (2000), which are 0.83 and 1.9, respectively, in terms of secondary school attainment of male adult in population over age 25. The thresholds here, in terms of proportion of labour force that received higher education, are more practical and are easier to explain than those based on average years of secondary school attainment, simply because advanced foreign technologies are usually absorbed by highly-qualified human capital. Moreover, focusing on this aspect of human capital, reduces the risk of policy being misled. Further, the new index comprises only effective labour force and not adults over 25, and retirees who received little education. Thus, the downward bias induced by the latter can be avoided. Besides, the new index only considers tertiary education, making such calculations easy.

Third, the higher threshold does not deny the possibility of FDI technology spillovers in countries where the quality of human capital is below the sign-change threshold. As China is a developing country with significant regional disparities, some regions exceed the sign-change threshold and benefit from positive spillovers of FDI, whereas other relatively backward regions are below this threshold. In backward areas, the coefficient of FDI interaction term is negative, but the coefficient of the sum of R&D capital stock of other regions is positive and higher than that of advanced areas. This suggests that in backward areas, interregional spillovers substitute for international spillovers with regard to external causes of technological progress.

In line with the above concepts, advanced foreign technology should first be absorbed by advanced areas and then transferred to less advanced areas. The findings on both positive FDI technology spillovers in advanced regions and significant interregional technology transfers encourage efforts of those countries where thresholds are below the sign-change as a whole and where regional disparities exist. In addition, the percentage of regions in China above the sign-change threshold has been increasing in recent years.

Finally, while economic growth in China in the past was capital-driven, it is currently changing to becoming more technology-driven, which is more important for sustainable development of China. FDI technology and interregional spillovers play a key role at this stage. Besides these external factors, internal causes, such as R&D capital stock and public infrastructure, also have significantly positive effects on technological progress. Infrastructure construction appears to have the Metcalfe effect, which suggests increasing returns, thus making infrastructure construction in developed areas more effective. As regards transportation costs, and natural and human resource disparities in China, infrastructure construction is an important way to decrease such costs and disparities. On the other hand, once public infrastructure becomes saturated, interest in public construction should be transferred to indigenous R&D investment to ensure innovative technology-driven progress.

As industry-specific provincial FDI data, industry-specific capital stock and balanced provincial FDI data with source countries are not available currently, FDI technology spillovers and their human capital threshold effects related to specific industries and source countries are not considered in this paper. These fields are, nevertheless, important for future study.

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Appendix A. The likelihood ratio diagram and confidence interval: MALMCRS

Figure A.1 For threshold 4.91 per cent and all regions

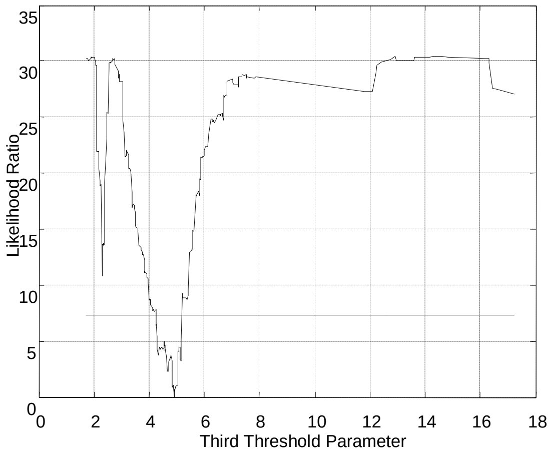


Figure A.2 For threshold 9.16 per cent and all regions

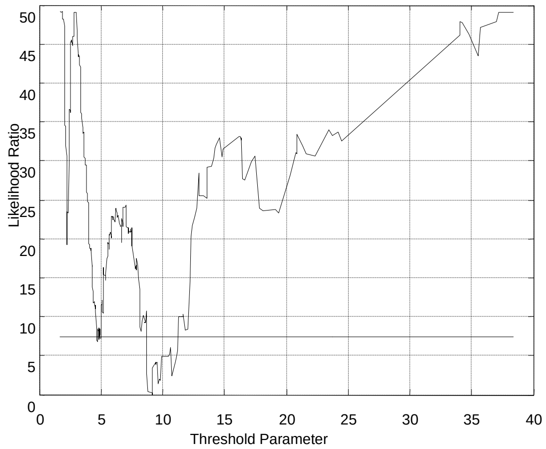
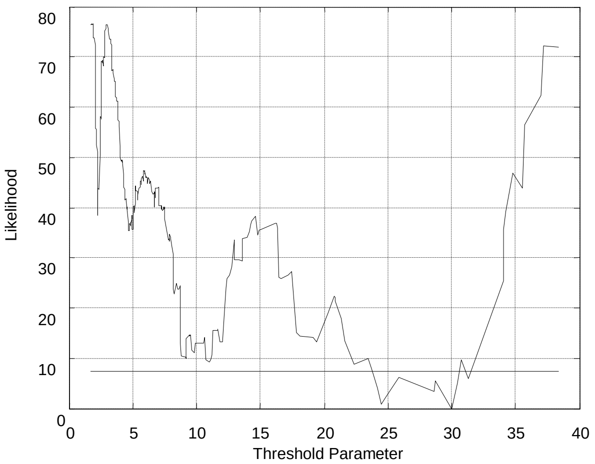


Figure A.3 For threshold 30.04 per cent and all regions



Sources: China Statistical Yearbooks 1991-2007 and China Statistical Yearbooks on Science and Technology 1991-2007.

Appendix B. The likelihood ratio diagram and confidence interval: TFPNT

Figure B.1 For threshold 4.91 per cent and all regions

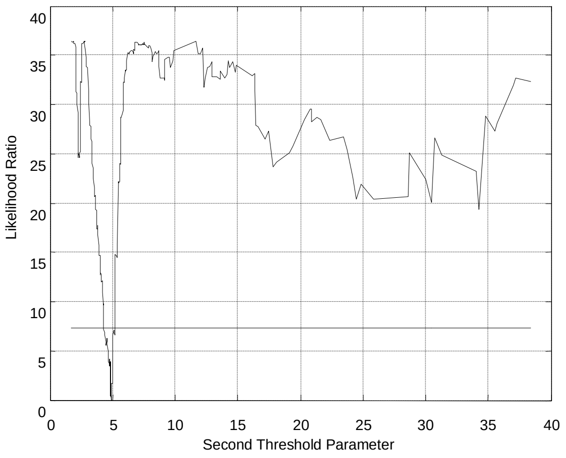
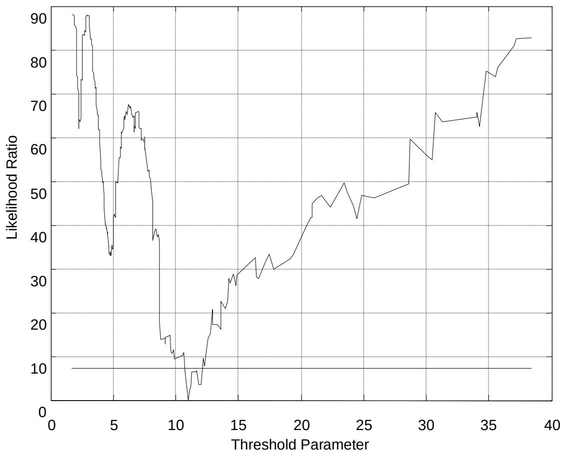


Figure B.2 For threshold 10.99 per cent and all regions



Sources: China Statistical Yearbooks 1991-2007 and China Statistical Yearbooks on Science and Technology 1991-2007.

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