Three Essays on Economic Growth and Technology Development: Considering the Spillover Effects

Shaojuan Liao

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Kwok Ping Tsang, Chair
Richard Ashley
Christopher Parmeter
Djavad Salehi-Isfahani
Wen You

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(Abstract)

This dissertation consists of three essays on the empirical analysis of economic growth and technology development. In particular, I consider spillover effects in different frameworks. The first chapter outlines the three topics involved and briefly discusses the motivations, methods as well as some conclusions in each of the following chapters.

The second chapter considers the spillovers in economic growth and convergence. Spillovers are prevalent in nowadays' economy. I formally model the spillover effects as the interdependence of total factor productivity (TFP), and develop a model in which spillover effects of R&D through the channel of international trade make the TFPs correlated among countries. In this sense, I apply the thoughts of international trade to the economic growth framework. Empirically, I develop a three-stage generalized method of moment (GMM) to estimate the dynamic panel spatial error autoregressive model. Simulation results show that my estimator is consistent and efficient. Through counterfactual analysis, I find that there are positive spillovers through both geographic connection and trade connection. Such a positive spillover effect, however, slows down the convergence speed. Moreover, there were little spillovers in the early 1960s. Spillover effects become stronger overtime.

The third chapter is about the determinants of technology development in China. What makes my paper different from others is that I take a full consideration of the spillover effects: provincial spillovers in Science and Technology (S&T) capital as well as S&T personnel, and international spillovers through trade and FDI. The most interesting point in my paper is that I consider the indirect effects of institutions on technology development. Marketization, mea-

sured by the share of state-owned enterprises (SOEs) in the economy, affects the production of technology through different channels at different stages. I use a semiparametric varying-coefficient model to account for the effects. In this paper, I find that provincial spillovers are mainly through the externalities of S&T capital stock while international spillovers occur through trade. Marketization affects the technology development through S&T capital, S&T capital spillovers and trade. Although a certain share of SOEs is necessary for technology production, the marketization process will promote the development of technology in China in the long run.

The fourth chapter looks into the provincial technology spillovers from another aspect. Instead of the S&T endowment spillovers from the nearby provinces, I consider the technology transfer from the frontier province to the targeted province as well as the absorptive capacity of the targeted province itself. Two forms of technology transfer are analyzed: the technology distance due to the structural discrepancy in the patent portfolio and the technology gap because of the difference in the patent level. Through the empirical analysis, several factors contributing to patent growth, such as S&T investment, road density, international spillovers from imports and FDI, are identified. Moreover, I find that technology transfer due to the technology distance can stimulate patent growth. However, I fail to find robust evidence of technology transfer due to the technology gap, which implies that the provincial technology convergence does not exist in China.

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Chapter 1

Introduction

When a butterfly flaps its wings in one part of the world, it can eventually cause a hurricane in another. *- Edward Lorenz Chaos Theory*

Similar to the butterfly effect in Chaos Theory, where a small change in one place can lead to unexpected change in other places, spillovers are common in today's economy. Along with the development of transportation equipment, nternational trade has been increasing by around fifty times since 1960, while FDI in 2010 is nearly hundred times as big as it was in 1960[1]. Thanks to the development of information technology, tons of information can be transmitted within a second. In this sense, countries are closely related to each other. The financial crisis of the U.S. in 2008 spread to other countries such as China, Japan and countries in the European Unions, and led to a world-wide recession. Aware of the above phenomena, my dissertation is aiming at examine the effects of spillovers on economic growth and technology development from different points of view.

Growth literature has been interested in spillovers and technology externalities since the renaissance of the endogenous growth theory in the late 1980s. Lucas (1988) proposes a model

[1]Data source: United Nation Conference on Trade and Development (UNCTD) Stat

where income per capita of a country is affected by its own human capital as well as the aggregate human capital level. Aghion and Howitt (1992) assume no contemporaneous spillovers but emphasize the intertemporal spillovers. So an innovation raises the productivity at an economy-wide level forever. Each new innovation destroys the monopoly rents that motivated the previous creation, which results in "creative destruction". Grossman and Helpman (1991) consider the variety of innovations so the spillovers happen in the product scale instead of the economy scale. Eaton and Kortum (1996) treat the inventions from a country adopted in another country as a function of their technology gap. Eaton and Kortum (1999) assume that ideas can be diffused from the technology frontier stochastically with lag, which then increases the non-frontier countries' productivity and leads to the same steady-state economic growth rate. Acemoglu and Zilibotti (2001) assume frictionless contemporaneous technology spillovers. And they think lower productivity in LDCs is due to the mismatch between the requirements of the technologies designed for the OECD economies and the skills of LDC workers. Griffith et al. (2003) incorporate the potential of technology transfer and R&D's role in promoting the "absorptive capacity" into the endogenous innovation model. Ertur and Koch (2007) develop a spatial augmented Solow model in which the level of technology in a country depends on its own physical capital as well as its neighbors' physical capital. Ertur and Koch (2011) treat the research productivity parameter as an increasing function of the technology gap to the frontier to explain the growth processes in Schumpeterian framework. However, these papers have not yet explicitly specified the mechanism of the spillovers. They just arbitrarily impose the spillovers in their models.

On the other hand, literature has successfully identified the channels of spillovers in the framework of international trade both theoretically and empirically. Eaton and Kortum (2006) use a dynamic Richardian model to examine the relation between technology diffusion, trade and the incentive to innovate. Spulber (2008) presents a model of innovation and international trade in which inventors auction their technology in both domestic and foreign markets, which leads to technology diffusion. Keller (2009) considers the technology transfer as the trade off between import and FDI. He proposes that the share of intermediate inputs imported from the parent firm (technology spillovers) is strictly decreasing in transport cost, which may be related to the geographic distance. Empirical analyses test the technology spillovers from different aspects. Wolfgang (2004) makes a good survey of it. Technology, which can be measured by R&D input, patents or total factor productivity (TFP), is distributed through the channels of imports [2], learning-by-exporting [3], FDI and geographic factors. The seminal work of Coe and Helpman (1995) (CH95) measures the technology spillover as the import-share weighted average of foreign R&D. It finds that among OECD members, a country's TFP depends on not only domestic R&D investment but also the weighted R&D of its trade partners. A lot of alternative specifications are generated (Lichtenberg and Pottelsberghe de la Potterie (1998), Potterie and Lichtenberg (2001), Keller (2002) and Branstetter (2001)), and the existence of the spillovers is proven.

This dissertation contributes to the literature by incorporating the mechanism of spillovers in economic growth and testing the regional technology spillovers in developing countries such as China. In this sense, I combine the literature of economic growth and the literature of international trade. The second chapter considers the international technology spillovers in the Solow growth and convergence model based on Islam (1995). It formally specifies the correlations among countries as the interdependence of TFP, and develop a model in which spillover effects of R&D through the channel of international trade make the TFPs correlated among countries. This chapter derives a reduced form as the spatial error autoregressive model in the dynamic panel framework and develops a three-stage GMM to estimate it. Counterfactual analysis shows that there exist positive spillovers in the context of both geographic connection and trade connection. In this sense, developing countries can benefit from the innovations initiated in developed countries. However, instead of promoting the economic convergence,

[2] See Eaton and Kortum (1999)(2001, 2002)

[3] Clerides et al. (1998) find that firms become more efficient after becoming exporter because of self-selection.

however, such a positive spillover slows down the convergence speed.

The third chapter analyzes the effects of provincial S&T spillovers on the technology development in China. Although evidences have been found in international R&D spillovers in OECD countries, regional and local spillovers are seldom talked about[4]. Domestic spillovers may happen more often and easily than international spillovers due to the smaller language barrier and geographic distance. However, the "special characteristics" of China (the socialist system with a big share of state owned enterprises (SOEs)) may change the patterns of the spillovers. The institutions may affect technology development indirectly through different channels such as S&T endowment and S&T spillovers. To take the effects into account, this chapter adopts the semiparametric partial linear varying-coefficient model. Through the empirical analysis, the chapter finds that provincial spillovers are mainly through the externalities of S&T capital stock. The existence of SOEs helps stimulate the technology development through encouraging S&T accumulation and promoting S&T spillovers only if the share of SOEs is small.

The fourth chapter looks at the regional spillovers from a different point of view. Economists specify the potential of technology transfer as the technology gap to the frontier, which implies technology convergence[5], and they find the evidence in the OECD countries (Griffith et al. (2004)). This chapter tries to test whether provincial technology convergence exists in China. The potential of technology transfer is defined in two ways: technology distance due to the structural discrepancy in the patent portfolio and technology gap because of the difference in the patent level. Empirical analysis suggests that technology transfer due to the technology distance can stimulate patent growth. However, it fails to find he robust evidence of the technology transfer due to technology gap, so the provincial technology convergence does not exist in China.

[4]I only find a few related papers, such as Agrawal et al. (2008)

[5]See Eaton and Kortum (1996), Griffith et al. (2003) and Ertur et al. (2006). Klenow and Rodriguez-Clare (2005) has a good summary of the related literatures.

Chapter 2

A New Look at Growth and Convergence:Dynamic Panel with Spillover Effects

(ABSTRACT)

This paper is aimed at examining the effects of spillovers on economic growth and convergence in a dynamic panel framework. Based on the externalities stemming from R & D, we model the spillover effects as the interdependence of total factor productivity (TFP) through the channel of international trade. In this sense, we successfully apply the literature of international trade to the economic growth framework. Empirically, we estimate the spillovers via a spatial error autoregressive model in the dynamic panel framework, and develop a three-stage spatial GMM estimator. Compared with other estimators, our method is computational simpler and requests less assumptions. By counterfactual analysis, we are able to separate the effects of spillovers on growth and convergence from the conventional endowment effects. We find that there exist significant positive spillovers in the context of geographic connection and trade connection, and such effects actually weaken the convergence instead of enhancing it.

2.1 Introduction

A butterfly flapping its wings in South America can affect the weather in Central Park, which is true not only in Chaos Theory, but also in economics. These types of impacts are termed "spillovers". In growth theory, technology can be redistributed all over the world through trade and foreign direct investment due to its non-rival and non-excludable nature. This is especially true in nowadays economy, with high-speed internet transmitting vast amount of information in just seconds and advanced transportation equipment lowering costs of shipping. A country can benefit from both domestic technology development and the innovations of its closely related economic partners. Moreover, a negative shock in one country may hurt other countries' economies. Aware of the importance of the "spillover effects", our paper not only focuses on how endowments affect growth and convergence as previous research, but also pays attention to investigating the interactivity between countries within standard growth models.

Previous empirical analyses have tried to resolve the on-going debates on economic convergence theory and endogenous growth theory without taking into account the impact of spillovers. The seminal work of Barro (1991), Barro and Sala-i Martin (1992) and Barro and Sala-i Martin (1995) argue that countries converge to their steady-state level of per capita income at approximately 2% or 3% per year based on the standard Solow model. Mankiw et al. (1992) propose the augmented Solow model, adding human capital into the production function and solving the problem of too big contribution of savings to income growth. Due to the limitation of econometric tools at that time, they use the cross-sectional regression. The omitted variable problem and the endogenous explanatory variable problem they may encounter would make the estimation inconsistent. To make a better treatment of the inconsistency problem, dynamic panel framework is adopted. Islam (1995) is perhaps the first to put Solow model into a dynamic form empirically. In his model, a country's per capita income not only depends on the traditional steady state determinants, but also depends on previous per capita income levels. His work makes it possible to allow for differences in the unobservable country effects. Caselli et al. (1996) adopt Islam (1995) dynamic panel data framework while use the Arellano and Bond (1991) GMM, correcting the inconsistency problem. They seem to close the debate of convergence. However, they neglect the cross-sectional autocorrelation among countries.

The concept of spillovers in growth literature is first proposed by Lucas (1988). In his model, income per capita of a country is affected by its own human capital as well as the aggregate human capital level. Spillovers can be interpreted in a plenty of forms in economics. The most prominent one is the international technology spillovers in international trade literature. By assuming the free diffusion of technology all over the world with time lag, Eaton and Kortum (1999) decomposes growth into the contributions by itself and other countries. But they haven't specified the channel of diffusion and they treat this process as costless. Keller (2009) thinks of the technology transfer as the trade off between import and FDI, proposing that the share of intermediate inputs imported from the parent firm (technology spillovers) is strictly decreasing in the transport cost, which may related to the geographic distance. Spulber (2008) presents a model of innovation and international trade in technology with inventors auctioning their technology in both domestic and foreign markets, which leads to technology diffusion.

International economists are also trying to empirically test the technology spillovers from different points of view. Wolfgang (2004) makes a good survey of it. Technology, which can be measured by R&D input, patents or TFP, is distributed through the channels of imports [1], learning-by-exporting [2], FDI or geographic effects. About the technology spillover, Coe and Helpman (1995) (CH) measure it as the import-share weighted average of foreign R&D. They find that a country's TFP depends not only on domestic R&D investment but also

[1] See Eaton and Kortum (1999)(2001, 2002)

[2] Clerides et al. (1998) find that firms become more efficient after becoming exporter because of self-selection. They also find some evidence of positive regional externalities.

on the weighted R&D of its trade partners[3]. Following this work, a large literature on R&D spillovers have emerged. Lichtenberg and Pottelsberghe de la Potterie (1998) suggest that CH's functional form is subject to an "aggregation bias" and construct their weights by the ratio of imports to GDP. Potterie and Lichtenberg (2001) go beyond CH's analysis and also consider the inward or outward FDI-share weighted average of foreign R&D as the determinants of TFP. Others consider the geographic distance and use the exponential distance-decaying function of foreign R&D to represent the R&D spillovers (Keller (2002)). Moreover, Branstetter (2001) uses "technology distance" as weights, which reflects the degree of similarity in the foreign firms and the targeted firm's patent portfolios. Griffith et al. (2004) consider technology transfer the process leading to technology convergence, using the gap between a country's TFP and the technology frontier's TFP to measure the potential of technology transfer and the interaction term of technology gap and domestic R&D as the absorptive capacity.

However, all the above papers try to analyze the source of productivity spillovers but are not directly related to economic growth. Growth economists often link the spillovers with space and geography (Abreu et al. (2005)). Focusing on the spillover effects under the framework of growth and convergence, spatial econometricians model the spillovers as the correlation across individuals and establish two forms of specifications: spatial lag model and spatial error autoregressive model. Empirical works on spillovers are mainly focusing on the European Union. Ertur et al. (2006) reestimate the growth regression using spatial error dependence model with distance based binary weighting matrix. They not only identify the spatial autocorrelation, but also consider the spatial heterogeneity of north and south by implementing different weight matrices. Ramajo et al. (2008) examine the β-convergence by utilizing the model with spatial lags of both explanatory variables and the dependent variable which combine spatial heterogeneity, groupwise-heteroscedasticity and spatial dependence. Papers consider the spatial effect on international growth and convergence are relatively sparse. Ertur and Koch (2007)

[3] Coe and Helpman (1995) have another specification which also considers the degree of openness when calculating foreign R&D

consider the worldwide technological interdependence within a neoclassical growth framework. By assuming the externalities of physical capital due to the technology spillovers, they develop an estimable growth convergence function with spatial lag and spatially correlated explanatory variables. Using the maximum likelihood estimation, they get the convergence rate similar to the suggested 2% level. They model the spillover effect as the interdependence of growth determinants while we model it as the interdependence of total factor productivity.

In this paper, we analyze the growth and convergence within the dynamic spatial panel framework. The major contribution of this paper is that we explicitly model the spillover effect as the interdependence of TFP. The externality of R & D through the channel of trade makes the technological productivity autocorrelated among countries. In this way, we successfully link the growth theory and the technology spillovers theory and provide a formal explanation for the spatial error autocorrelation in the growth analysis. After obtaining the intensity of spillovers, we can analyze the self-multiplication effect and the feedback effect of technology spillovers, both locally and globally. By counterfactual analysis, we separate the total contribution to growth (or convergence) into two parts: the contribution of a country's own endowment and the spillover effects. If developing countries have close economic relationships with developed countries, they can growth faster by the positive technology spillovers and pull up the world convergence speed. On the other hand, if developing countries trade a lot more with their developing counterparts while developed countries mainly trade with developed ones, developing countries cannot benefit from the high-tech innovation of developed countries. The poor become poorer and the rich become richer even under the positive spillovers.

The second contribution of this paper lies on the method used to estimate the spatial error dependence in the dynamic panel framework. Here we develop a three-stage GMM estimation procedure. The first stage is the standard dynamic panel Arellano and Bond (1991) GMM estimator. In the second stage, we find three spatial moment conditions similar to Kelejian and Prucha (1999) through the first-differenced errors, and estimate the spatial parameter by minimizing the sum squares of the sample moments' residuals. In this way, we eliminate the individual effect and simplify the estimation. Moreover, we can avoid putting assumptions on the individual effect. In the third stage, we use the spatial parameter from the second stage to filter the spatial effect and obtain more efficient parameter estimates. Compared with Jacobs et al. (2009)[4], our method does not need to specify the fixed effect or random effect. It is computationally easier and provides the variance of the spatial parameter.

Our paper also contributes to the spatial growth literature in finding the trade volume a good proxy for economic distance in the spatial weighting matrix. It is commonly known that trade can reflect the interactivity between countries precisely and dynamically. The reason why trade volume is not widely used is that it would be correlated with the right-hand side variables. The potential endogeneity of it makes the estimation inconsistent[5]. We make some specific treatments of trade volume when constructing the weights so as to mitigate the traditional concerned endogenous problem. Therefore, we provide another candidate for economic distance besides the geographic distance.

The remainder of this paper is organized as follows. Section 2.2 develops a dynamic growth convergence model based on Islam (1995). We model the spillover effects through the total factor productivity, which is spatially correlated because of the spillovers of R & D by the channel of trade. Section 2.3 describes the three-stage GMM estimation for the dynamic panel data model with spatially autocorrelated errors. In section 2.4, we use the method in section 2.3 to estimate the growth convergence model and try to find the effects of spillovers on convergence rate by two different spatial weighting matrices: geographic distance based

[4]Jacobs et al. (2009) considers the spatial lag and spatial error dependent model in the dynamic panel framework. They also use three-stage GMM approach. Their method is more complex since they use errors instead of first-differenced errors so they also need to estimate the individual random effect. Their method does not provide the variance of spatial parameter while our method does.

[5]See Anselin and Bera (1998): It is important to note that the elements of the weights matrix are non-stochastic and exogenous to the model.

weights and trade flow based weights. Section 2.5 provides three robustness checks: spillover effects over the period 1960-1985, the changes in the number of neighbors and the exogeneity of trade. Section 2.6 concludes and makes implication for the future research.

2.2 Theoretical model

We use Islam (1995) dynamic model as the benchmark. Here we include human capital in the production function.

$$Y(t) = K(t)^{\alpha} H(t)^{\beta} (A(t)L(t))^{(1-\alpha-\beta)} \quad \alpha + \beta < 1 \tag{2.1}$$

In the steady state[6],

$$\begin{aligned} \dot{\tilde{k}}(t) &= s^k \tilde{y}(t) - (n+g+\delta)\tilde{k}(t) \\ \dot{\tilde{h}}(t) &= s^h \tilde{y}(t) - (n+g+\delta)\tilde{h}(t) \end{aligned} \tag{2.2}$$

where $\tilde{y} = Y/AL$, $\tilde{k} = K/AL$, $\tilde{h} = H/AL$ are quantities of per effective unit of labor and we use $y = Y/L$, $k = K/L$, $h = H/L$ to represent the quantities of per unit of labor. From Equation 2.2, we can get the steady state level of $\tilde{k^*}$ and $\tilde{h^*}$. Approximating around the steady state, we can get the speed of convergence. Rearranging terms, we have:

$$\begin{aligned} \ln y(t_2) =& (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln s_k(t_1) - (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(n(t_1)+g+\delta) + (1-e^{-\lambda\tau})\frac{\beta}{1-\alpha}\ln h(t_1) \\ &+ e^{-\lambda\tau}\ln y(t_1) + (1-e^{-\lambda\tau})\ln A(t_1) + g(t_2-t_1) \end{aligned} \tag{2.3}$$

where $\lambda = (n+g+\delta)(1-\alpha-\beta)$

[6] For detailed derivation, please refer to Mankiw et al. (1992) and Islam (1995)

Since $A(t)$ represents not just technology but resource endowment, climate, institutions and so on, it may therefore differ across countries (Islam (1995)). In this paper, we treat $A(t)$ as TFP and model the spillovers in economic growth as the interdependence of it. Based on the technology spillovers, a country's TFP depends not only on domestic R & D investment but also on the R & D investment of its trade partners. It suggests the existence of international technology spillovers on economic growth. In this paper, we mainly follow the Coe and Helpman (1995) specification. We treat the human capital as the growth determinant so TFP accounts for the innovations not captured by human capital. Imports reflects the potential of technology imitation while export may stimulate the technology development through learn-by-exporting. To account for both effects, we use the total trade volume instead of imports to measure the economic connections between countries. We also consider the traditional measurement: geographic distance. Therefore, $\ln TFP$ is given as:

$$\ln TFP = \ln Y - \alpha \ln K - \beta \ln H - (1 - \alpha - \beta) \ln L = (1 - \alpha - \beta) \ln A \tag{2.4}$$

Follow Coe and Helpman (1995) specification, we get:

$$\ln TFP_i = a \ln S_i^d + b \sum_f \frac{m_{i,f}}{\sum_f m_{i,f}} \ln S_i^f, \quad \ln TFP_j = a \ln S_j^d + b \sum_f \frac{m_{j,f}}{\sum_f m_{j,f}} \ln S_j^f \tag{2.5}$$

where a is the effect of domestic R & D stock on TFP, while b represents the effect of trade-share-weighted average of foreign R & D stock on TFP.

If country j is country i's trade partner, $\ln S_j^d$ is actually one of $\ln S_i^f s$. we can substitute $\ln S_j^d$ from the second equation of 2.5 into the first equation. Suppose country i has N trade partners, we need to do such a substitution for N times, then we can get:

$$\begin{aligned}
\ln TFP_i = {} & \frac{b}{a}\left(\frac{m_{i,1}}{\sum_f m_{i,f}}\ln TFP_1 + \frac{m_{i,2}}{\sum_f m_{i,f}}\ln TFP_2 + \cdots\right) \\
& + a\left(1 - \frac{b^2}{a^2}\frac{m_{i,1}}{\sum_f m_{i,f}}\frac{m_{1,i}}{\sum_f m_{1,f}} - \frac{b^2}{a^2}\frac{m_{i,2}}{\sum_f m_{i,f}}\frac{m_{2,i}}{\sum_f m_{2,f}} - \cdots\right)\ln S_i^d \\
& - \frac{b^2}{a}\left(\frac{m_{i,1}}{\sum_f m_{i,f}}\sum_f\left(\frac{m_{1,f}}{\sum_f m_{1,f}}\ln S_1^{f\neq i}\right) + \frac{m_{i,2}}{\sum_f m_{i,f}}\sum_f\left(\frac{m_{2,f}}{\sum_f m_{2,f}}\ln S_2^{f\neq i}\right) + \cdots\right)
\end{aligned} \tag{2.6}$$

Therefore, a country's TFP is affected by its trade partners' TFP weighted by its trade share with those partners, its own R&D stock, and the indirect effect from partners' R&D stock of its trade partners'. From the last part of the Equation 2.6, we can see that even country j is not country i's direct trade partner, the R & D stock of country j still possibly affects country i's TFP through their common partners. We call it higher-order spillover effect. For simplicity, we assume that the effect of domestic R & D on TFP is relatively constant over time, so we treat it as the country's specific effect. Since we are only interested in the interdependence among TFP, we put the indirect effect from foreign R&D stock as residuals. Then Equation 2.6 becomes:

$$\ln TFP_i = \frac{b}{a}\left(\frac{m_{i,1}}{\sum_f m_{i,f}}\ln TFP_1 + \frac{m_{i,2}}{\sum_f m_{i,f}}\ln TFP_2 + \cdots\right) + \mu_i^1 + v_{it}^1 \tag{2.7}$$

Stack all the countries' TFP in a matrix form through all time periods, we get:

$$\ln TFP = \frac{b}{a}(I_T \otimes M_N)\ln TFP + \mu^1 + v^1 \tag{2.8}$$

Where $\ln TFP$ is an $NT \times 1$ vector, M_N is an $N \times N$ matrix. The diagonal elements $M_{N,ii}$ are 0, meaning that each country's TFP is not the function of itself. The off-diagonal elements $M_{N,ij}$ is $\frac{m_{i,j}}{\sum_j m_{i,j}}$, measuring the share of the trade flow with country j within the total trade volumes of country i. For every row of M_N, the N elements are summed up to 1. In spatial econometrics, we call M_N standardized spatial weighting matrix. From Equation 2.8, we can see that countries' TFP are correlated with each other through the channel of trade because of R & D spillovers.

Substitute Equation 2.4 into 2.8, we get:

$$\ln A = \frac{b}{a}(I_T \otimes M_N) \ln A + \frac{1}{1-\alpha-\beta}(\mu^1 + v^1) \tag{2.9}$$

In the empirical analysis, we treat $\ln A$ as residuals, therefore, we get:

$$u_i = (1 - e^{-\lambda\tau}) \ln A_i \tag{2.10}$$

Plug Equation 2.10 into 2.9, we get:

$$u = \frac{b}{a} Mu + \epsilon \tag{2.11}$$

where $\epsilon = \mu + v$, $\mu = \frac{(1-e^{-\lambda\tau})\mu^1}{(1-\alpha-\beta)}$, $v = \frac{(1-e^{-\lambda\tau})v^1}{(1-\alpha-\beta)}$ and $M = I_T \otimes M_N$. Mu is called the spatial lag of u.

Country i's error term is correlated with other countries' error terms (in the expression of TFP) conditional on the spatial weighting matrix. We call it spatial error autoregressive model in the spatial econometrics. In the dynamic panel framework, the growth regression becomes:

$$\ln y_{it} = \gamma \ln y_{i,t-1} + \beta_1 \ln s_{k,i,t-1} + \beta_2 \ln h_{i,t-1} + \beta_3 \ln(n_{i,t-1} + 0.05) + u_{it} + \eta_t \tag{2.12}$$

where:

$$\gamma = -e^{\lambda\tau}$$

$$\beta_1 = (1 - e^{\lambda\tau})\tfrac{\alpha}{1-\alpha}$$

$$\beta_2 = (1 - e^{\lambda\tau})\tfrac{\beta}{1-\alpha}$$
$$\beta_3 = -(1 - e^{\lambda\tau})\tfrac{\alpha}{1-\alpha}$$
$$\eta_t = g(t_2 - t_1)$$
$$u = \rho M u + \epsilon,\ \epsilon_i = \mu_i + v_{it}$$

2.3 Estimation method

Jacobs et al. (2009) (JLV) develop a three stage approach to estimate the dynamic panel data model with a spatially lagged dependent variable and the spatially autocorrelated errors. Following their strategy, we also develop a three stage method. The difference is that we use the first-differenced errors to construct the spatial moment conditions. By this method, we do not need to consider the individual effect so that we need less moment conditions and are able to get the variance for the spatial parameter. We also run the Monte-Carlo simulation and prove that our estimator is consistent and efficient(the simulation results are shown in the appendix).

To simplify the model, we can rewrite the estimation function as:

$$\begin{aligned} y_{it} &= \gamma y_{i,t-1} + X_{it}'\beta + u_{it} \\ u_{it} &= \rho M_{N,i}.u_{it} + \mu_i + v_{it} \;\; for \;\; i = 1, ...N, \;\; y_0, \dots, y_T, X_1, \dots, X_T \end{aligned} \tag{2.13}$$

First difference the equation, the matrix form is:

$$\begin{aligned} \Delta y &= \gamma \Delta y_{-1} + \Delta X \beta + \Delta u = ZB + \Delta u \\ \Delta u &= \rho M \Delta u + \Delta v \quad v \sim N(0, \sigma_v^2) \end{aligned} \tag{2.14}$$

Where $Z = [\Delta y_{-1}, \Delta X]$ and $B = [\gamma, \beta']'$. Here, the observations are stacked first by time and then by individuals. Notice that the individual effect is eliminated by the first difference.

2.3.1 The first stage

The first stage is to obtain residuals to proximate the error terms using Arellano-Bond estimator[7]. We ignore the spatial error dependence and temporarily set $\rho = 0$, therefore, $\Delta u = \Delta v$. From Equation 2.14, we can see that the twice and higher lagged dependent variables are uncorrelated with the first difference of the errors, so we can write the moment condition as:

$$E(y'_{t-j}\Delta v_t) = 0,\ \ t = 2, \dots, T,\ \ j = 2, 3, \dots, T \tag{2.15}$$

When the remaining explanatory variables are predetermined, we have additional moment conditions:

$$E(X'_{t-j}\Delta v_t) = 0,\ \ t = 2, \dots, T,\ \ j = 1, 2, \dots, T-1 \tag{2.16}$$

These moment conditions collectively provide the instrument matrix:

$$W_i = \begin{pmatrix} y_{i,0}, X'_{i,1} & 0 & \cdots & 0 \\ 0 & y_{i,0}, y_{i,1}, X'_{i,1}, X'_{i,2} & & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & y_{i,0}, \cdots, y_{i,T-1}, X'_{i,1}, \cdots, X'_{i,T-2} \end{pmatrix} \tag{2.17}$$

The corresponding GMM esitmator is:

$$\begin{pmatrix} \hat{\gamma} \\ \hat{\beta} \end{pmatrix} = ([\Delta y_{-1}, \Delta X]' W A^{-1} W' [\Delta y_{-1}, \Delta X])^{-1} [\Delta y_{-1}, \Delta X]' W A^{-1} W' \Delta y \tag{2.18}$$

[7]The first stage is to get consistent first-differenced errors. We can also use Arellano and Bover estimator, Blundell and Bond system GMM estimator.

Assuming v_{it} is IID, we have:

$$E(\Delta u_i \Delta u_i') = E(\Delta v_i \Delta v_i') = \sigma_v^2 G, \;\; G = G_{T-1} \otimes I_N \tag{2.19}$$

where

$$G_{T-1} = \begin{pmatrix} 2 & -1 & 0 & \dots & 0 & 0 & 0 \\ -1 & 2 & -1 & \dots & 0 & 0 & 0 \\ 0 & -1 & 2 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 2 & -1 & 0 \\ 0 & 0 & 0 & \dots & -1 & 2 & -1 \\ 0 & 0 & 0 & \dots & 0 & -1 & 2 \end{pmatrix}$$

$$A = W'GW \tag{2.20}$$

2.3.2 The second stage

In the second stage, the spatial GMM estimator is adopted to estimate ρ and σ_v^2, using $\Delta\hat{u}$ from the first stage. Since the individual effect is eliminated by the first difference, we don't need to use the six panel moment conditions developed by Kapoor et al. (2007) to estimate both σ_v^2 and σ_1^2. We derive three Pseudo cross-sectional moment conditions similar to Kelejian and Prucha (1999) (KP99)

. To begin we have:

$$\Delta u = \rho(I_{T-1} \otimes M_N)\Delta u + \Delta v \tag{2.21}$$

Here M_N is the spatial weighting matrix which satisfies the following conditions: (1) M_N is an $N \times N$ matrix with diagonal element 0. (2) To ensure $|\rho| < 1$, M is row standardized. Following the notation of KP99, let $\bar{u} = M_{NT}u, \bar{\bar{u}} = M_{NT}M_{NT}\bar{u}$, correspondingly, $\Delta\hat{\bar{v}} =$

$M_{N,T-1}\Delta\hat{v}, \Delta\hat{\bar{\bar{v}}} = M_{N,T-1}M_{N,T-1}\Delta\hat{v}$

The three moment conditions are:

$$E\left[\frac{1}{2N(T-1)}\Delta v'\Delta v\right] = \sigma_v^2 \quad E\left[\frac{1}{2N(T-1)}\Delta\bar{v}'\Delta\bar{v}\right] = \frac{1}{N}\sigma_v^2 Tr(M_N'M_N) \quad E\left[\frac{1}{2N(T-1)}\Delta\bar{v}'\Delta v\right] = 0 \tag{2.22}$$

Considering $\Delta v = \Delta u - \rho\Delta u, \Delta\bar{v} = \Delta\bar{u} - \rho\Delta\bar{u}$, we can transfer the three moment conditions in the forms below:

$$\Gamma_{NT}[\rho, \rho^2, \sigma_v^2]' - \gamma_{NT} = 0 \tag{2.23}$$

Using the $\Delta\hat{u}$ from the first stage, we can use the sample moment condition to rewrite:

$$\hat{\Gamma}_{NT}[\rho, \rho^2, \sigma_v^2]' - \hat{\gamma}_{NT} = s_{NT}(\rho, \sigma_v^2) \tag{2.24}$$

$$\hat{\Gamma}_{NT} = \begin{bmatrix} \frac{1}{N(T-1)}\Delta\hat{u}'\Delta\hat{\bar{u}} & -\frac{1}{2N(T-1)}\Delta\hat{\bar{u}}'\Delta\hat{\bar{u}} & 1 \\ \frac{1}{N(T-1)}\Delta\hat{\bar{\bar{u}}}'\Delta\hat{\bar{u}} & -\frac{1}{2N(T-1)}\Delta\hat{\bar{\bar{u}}}'\Delta\hat{\bar{\bar{u}}} & \frac{1}{N}Tr(M_N'M_N) \\ \frac{1}{2N(T-1)}(\Delta\hat{u}'\Delta\hat{\bar{\bar{u}}} + \Delta\hat{\bar{u}}'\Delta\hat{\bar{u}}) & -\frac{1}{2N(T-1)}\Delta\hat{\bar{u}}'\Delta\hat{\bar{\bar{u}}} & 0 \end{bmatrix} \hat{\gamma}_{NT} = \begin{bmatrix} \frac{1}{2N(T-1)}\Delta\hat{u}'\Delta\hat{u} \\ \frac{1}{2N(T-1)}\Delta\hat{\bar{u}}'\Delta\hat{\bar{u}} \\ \frac{1}{2N(T-1)}\Delta\hat{u}'\Delta\hat{\bar{u}} \end{bmatrix} \tag{2.25}$$

where the 3×3 vector $s_{NT}(\rho, \sigma_v^2)$ can be viewed as a vector of residuals. Minimizing the square of residuals, we can get the spatial parameters ρ and σ_v^2.

$$(\rho, \sigma_v^2) = argmin\{s_{NT}(\rho, \sigma_v^2)'s_{NT}(\rho, \sigma_v^2)\} \tag{2.26}$$

Kelejian and Prucha (2010) derive the asymptotic distribution of ρ from the last two moment conditions in Equation 2.22. We rewrite these two moment conditions as:

$$E\left[\frac{1}{2N(T-1)}\Delta v'A_{1,NT-1}\Delta v\right] = 0, E\left[\frac{1}{2N(T-1)}\Delta v'A_{2,NT-1}\Delta v\right] = 0 \tag{2.27}$$

where $A_1 = M'_N M_N - diag_{i=1}^N(m'_{.i,N} m_{.i,N}), A_2 = M_N,$ correspondingly $A_{1,NT-1} = I_{T-1} \otimes (M'_N M_N - diag_{i=1}^N(m'_{.i,N} m_{.i,N}))$,$A_{2,NT-1} = I_{T-1} \otimes M_N$

Then we have $\hat{G}_{NT}[\rho, \rho^2]' - \hat{g}_{NT} = \nu_{NT}$.

$$\hat{G}_{NT} = \begin{bmatrix} \frac{1}{N(T-1)}\Delta\hat{u}' M'_N A_1 \Delta\hat{u} & -\frac{1}{2N(T-1)}\Delta\hat{u}' M'_N A_1 M_N \Delta\hat{u} \\ \frac{1}{2N(T-1)}\Delta\hat{u}' M'_N (A_2 + A'_2)\Delta\hat{u} & -\frac{1}{2N(T-1)}\Delta\hat{u}' M'_N A_2 M_N \Delta\hat{u} \end{bmatrix} \hat{g}_{NT} = \begin{bmatrix} \frac{1}{2N(T-1)}\Delta\hat{u}' A_1 \Delta\hat{u} \\ \frac{1}{2N(T-1)}\Delta\hat{u}' A_2 \Delta\hat{u} \end{bmatrix} \tag{2.28}$$

Take the derivative of the moment conditions with respect to ρ, we have

$$\hat{J}_{NT} = \hat{G}_{NT}[1, 2\hat{\rho}]' \tag{2.29}$$

The variance of $\hat{\rho}$ is:

$$\Omega_{\hat{\rho}} = \frac{1}{2N(T-1)}(\hat{J}'_{NT}\hat{J}_{NT})^{-1}\hat{J}'_{NT}\Psi\hat{J}_{NT}(\hat{J}'_{NT}\hat{J}_{NT})^{-1} \tag{2.30}$$

$\Psi = (\psi_{r,s})$, $r, s = 1, 2$ is the variance-covariance matrix of moment conditions, where

$$\psi_{r,s} = \frac{\sigma_v^4}{4N(T-1)} tr[G_{T-1}^2] tr[(A_r + A'_r)(A_s + A'_s)] + \frac{\sigma_v^2}{2N(T-1)}\tilde{a}'_r G \tilde{a}_s \tag{2.31}$$

$\tilde{a}$ has a very complex form, which depends on the variance of Δu from the first stage estimation. Notice that the second term on the right side of Equation 2.31 is very small compared with the first term, so we can suppress the second term and simplify the estimation.

Plug the result $\hat{\rho}$ in the regression function:

$$\Delta y = \gamma\Delta y_{-1} + \Delta X\beta + \Delta\hat{u}, \Delta\hat{u} = (I_N - \hat{\rho}M_{N,T-1})^{-1}\Delta\hat{v},$$

$$var(\Delta\hat{u}) = 2\sigma_v^2(I_N - \hat{\rho}M'_N)^{-1}(I_N - \hat{\rho}M_N)^{-1} \tag{2.32}$$

2.3.3 The third stage

After we get the spatial parameter $\hat{\rho}$, we can pre-multiply $(I_N - \hat{\rho}M_N)$ for each time period to eliminate the spatial effect.

Let $Q = I_{T-1} \otimes (I_N - \hat{\rho}M_N)$, so we have:

$$\Delta\tilde{y} = \gamma\Delta\tilde{y}_{-1} + \Delta\tilde{X}\beta + \Delta v \tag{2.33}$$

where $\Delta\tilde{y} = Q\Delta y, \Delta\tilde{X} = Q\Delta X, \tilde{W} = QW$

The new GMM estimator will be:

$$\begin{pmatrix} \hat{\gamma} \\ \hat{\beta} \end{pmatrix} = ([\Delta\tilde{y}_{-1}, \Delta\tilde{X}]'\tilde{W}\tilde{A}^{-1}\tilde{W}'[\Delta\tilde{y}_{-1}, \Delta\tilde{X}])^{-1}[\Delta\tilde{y}_{-1}, \Delta\tilde{X}]'\tilde{W}\tilde{A}^{-1}\tilde{W}'\Delta\tilde{y} \tag{2.34}$$

where $A = (\tilde{W}[G_{T-1} \otimes (I_N - \rho M_N)^{-1}(I_N - \rho M_N')^{-1}]\tilde{W})$

$$var\begin{pmatrix} \hat{\gamma} \\ \hat{\beta} \end{pmatrix} = \hat{\sigma}_v^2([\Delta\tilde{y}_{-1}, \Delta\tilde{X}]'\tilde{W}\tilde{A}^{-1}\tilde{W}'[\Delta\tilde{y}_{-1}, \Delta\tilde{X}])^{-1} \tag{2.35}$$

We can plug $\Delta\tilde{y}$ and $\Delta\tilde{X}$ into 2.29, rearrange the terms and get the following equation:

$$\Delta y = \gamma\Delta y_{-1} + \beta\Delta X + \hat{\rho}M\Delta y - \gamma\hat{\rho}M\Delta y_{-1} - \beta\hat{\rho}M\Delta X + \Delta v \tag{2.36}$$

We find that the structure of spatial error autoregressive model is quite similar as the spatial lag model with exogenous lag variables. The difference is that we impose restriction on the coefficients of exogenous variables.

2.4 Spillovers in growth and convergence

The spatial dynamic panel estimation is actually a process which removes the spatial effects. Using this method in the estimation of international growth and convergence, we can create a counterfactual in which there are no spillovers in the world. The effects of spillovers can be easily separated by comparing the situation of the real world which has spillover effects and the situation in the counterfactual world .

2.4.1 Data description

The panel data comes mainly from two sources: Penn World Table 6.3 and Barro and Lee (2000) education attainment data. We focus on the time span from 1960-2000. The data enters as the five-year average to eliminate the potential business cycle. So there are a total of eight periods. Due to data availability, we can only use 90 countries in our sample.

In the regression, real GDP per capita, investment rate and population growth are from PWT6.3. Real GDP per capita is measured by the chain series. Investment rate and population growth are used as the five-year average. For example, in the period 1960-1965, real GDP per capita is measured at the year 1965 and the lag of it is at the year 1960, while investment and population growth rate are averaged between 1960-1964. Human capital is calculated by the secondary educational attainment of the total population aged 25 and over. Some countries have data starting from 1970. So we extrapolate the early period data by using the later available data and the change rate of total gross enrollment ratio for secondary education from UNESCO.

The data for creating the spatial weights comes from different sources due to the different measures of economic distance. The data of geographic distance is from Conley and Ligon (2002). The countries' pair-wise trade data is from the Center for International Data at UC

Davis.

2.4.2 The canonical Solow model

We can rewrite (12) as:

$$\ln y_{it} - \ln y_{i,t-1} = (\gamma - 1)\ln y_{i,t-1} + \beta_1 \ln s_{k,i,t-1}\beta_2 \ln h_{i,t-1} + \beta_3 \ln(n_{i,t-1} + 0.05) + u_{it} \quad (2.37)$$

The left-hand side is the real GDP growth so as to make our estimation result comparable to the previous research. Here we do not consider the time effect because it does not change the result too much while it increases quite a lot of computational burden.

Table 2.1 shows the results of estimating Solow type convergence model using different estimation procedures such as cross-sectional OLS regression, pooled OLS regression and dynamic panel regression.

In the first two columns, we follow Mankiw et al. (1992) model, in which the growth of income is a function of the steady state determinants and the initial level of income. The dependent variable is the log difference of income per capita over 1960-2000. $\ln(y_0)$ stands for year 1960's real GDP per capita. Growth determinants are averaged over 1960-2000. All the coefficients are of the expected signs and significance level. Our estimated convergence speed is higher than what MRW predict. This inconsistency may come from the different treatment of variables. In MRW paper, they use the real GDP per working-age people instead of real GDP per capita. Meanwhile, they don't use the total population growth but the growth rate of working-age population (aged 16-65).

In columns (3)-(4), we use the pooled OLS method to test the four different specifications of Solow model. Compared with Caselli et al. (1996) (CEL,1996) paper, the convergence speeds calculated from all the four OLS regressions in our estimation are larger than those in CEL's.

Table 2.1: Different Estimations of Solow Type Growth Convergence

	Cross Section	Augmented Cross Section	Pooled OLS	Augment Pooled OLS	Dynamic Panel	Augment Dynamic Panel
Unrestricted						
$\ln(y_0)$	-0.3729	-0.5558	-0.0449	-0.0562	-0.1336	-0.1017
	(0.0764)	(0.0776)	(0.0075)	(0.0092)	(0.0180)	(0.0209)
$\ln(k)$	0.7982	0.5554	0.1165	0.1128	0.0812	0.1022
	(0.1066)	(0.1071)	(0.0105)	(0.0106)	(0.0287)	(0.0273)
$\ln(n+g+\delta)$	-1.9779	-1.5634	-0.1941	-0.1853	-0.0449	-0.0662
	(0.4822)	(0.4383)	(0.0414)	(0.0417)	(0.0812)	(0.0808)
$\ln(h)$		0.4022		0.0160		-0.0217
		(0.0820)		(0.0071)		(0.0113)
λ	0.0156	0.0271	0.0092	0.0116	0.0287	0.0214
Restricted						
$\ln(y_0)$	-0.3000	-0.5323	-0.0396	-0.0538	-0.1414	-0.1186
	(0.0711)	(0.0757)	(0.0070)	(0.0090)	(0.0174)	(0.0219)
$\ln(k) - \ln(n+g+\delta)$	0.8996	0.5889	0.1208	0.1155	0.0825	0.1014
	(0.0992)	(0.1042)	(0.0102)	(0.0104)	(0.0298)	(0.0277)
$\ln(h) - \ln(n+g+\delta)$		0.4276		0.0177		-0.0167
		(0.0799)		(0.0070)		(0.0114)
λ	0.0119	0.0253	0.0081	0.0111	0.0305	0.0252
α	0.7499	0.5253	0.7532	0.6821	0.3684	0.4609
β		0.4455		0.2480		-0.1643
Country	90	89	90	89	85	85

This table tests the growth convergence theory by different estimation method. The dependent variable is first-differenced log per capita real GDP. The first two columns show the cross-sectional results. All the data are averaged data over the year 1960-2000. The next two columns show the results of pooled OLS estimation. We use the five-year averaged panel data. The last two columns show the results of dynamic panel estimation, the data is the same as the column 3 and 4. We test the Solow model in four different forms. In the augmented forms, we include human capital as a growth determinant. λ is the convergence speed, α is the contribution of capital to growth and β is the contribution of human capital to growth. Numbers in the cell show the coefficients and the numbers in the parenthesis show the standard deviation.

It is due to the different treatment of variables. We use the level data while they use the demeaned data. However, both estimations are inconsistent, so we cannot compare these two results.

Finally, we consider the dynamic panel framework. The data availability allows us to have

$\ln(y_0)$, so we only have one time period loss in the estimation. The GMM instruments are created as (17). We assume that growth determinants are predetermined, $E(X_{t-i}u_t) = 0$, for $i = 0, \ldots, t-1$. Specifically, when $t = 3$ (period 1970-1975), the instruments are log real GDP per capita of year 1960, 1965, and the average of capital investment, population growth over the period 1965-1969, 1970-1974. From the result, we can see that capital has a significantly positive effect on growth. Population growth has a negative effect on it, but such an effect is insignificant. In the estimation, the coefficient for the initial income is significantly negative, proving the conditional convergence hypothesis. The convergence speed is 2.87%, 3.15%, 2.34% and 2.77% in the Solow, restricted Solow, augmented Solow and restricted augmented Solow type model respectively, consistent with the previous finding of 2%-3% convergence speed. The contribution of physical capital α is only 0.3612 when human capital is not counted as a growth determinant, just around the suggested 1/3 level. When adding human capital, the calculated convergence speed increases a little. However, the coefficient of human capital is negative and significant, which is inconsistent with the theory and running into the "human capital paradox". We can see that convergence speeds in our period are about 2%-3%, not so large as CHL (1996), in which the convergence speed is as high as 10%. On the one hand, as time goes by, countries are closer to their steady states. So the convergence speed would go down in later periods. On the other hand, the big discrepancy may due to the different assumptions of growth determinants. We assume they are predetermined of current period, for example, X_{it} is predetermined for u_{it}. However, CHL (1996) assumes that X_{it} is predetermined for $u_{i,t+1}$. They reject the Solow model based on the too high convergence speed, while we accept it because of the reasonable convergence speed.

In GMM framework, the invalidity of moment conditions would make the estimation inconsistent. To make sure of the consistency, we perform the Sargan test to check the over-identifying restriction. From Table 2.2, we can see that except for the restricted Solow model, the p-values of Sargan test are insignificant. So we accept the null hypothesis that the instruments are

Table 2.2: Test of Specifications

	Standard Solow	Restricted Solow	Augmented Solow	Restricted Augmented Solow
Sargan	84.9346	76.8841	85.0000	84.7787
p-value	0.3607	0.0221	0.9501	0.3652
m2	0.8000	0.7969	0.7994	0.7968
p-value	0.2118	0.2127	0.2120	0.2128

This table shows the result of test statistics. Sargen test examines the over-identification condition and m2 test examines validity of exogeneity in instrument variables.

strong. Moreover, whether the error terms are series correlated is a big concern. Therefore, we perform the m2 test. From the result, we can find that for all cases, the p-values of m2 test are insignificant even at 20% level, suggesting no first order series correlation among errors. The instrument set is valid. We can confidently conclude that our one-step GMM estimation is consistent and efficient.

2.4.3 Testing the spatial spillovers through geographic distance

Considering the spatial spillover effects in the empirical analysis, the first thing is to identify the spatial correlation in the error terms. So we take a look at the Moran's Scatterplot, which explores the patterns of autocorrelation in space and presents the relation of the variable in one location with respect to the values of the variable in the neighboring locations. It puts the spatial lag of the variable on the vertical axis and the original variable on the horizontal axis. We want to see how productivity of a country is related to the neighbor countries, so we focus on the relationship between u_i and the weighted u_i in the initial period and the latest period, where u_i is obtained from the augmented Solow model.

Figure 2.1 shows the geographic spatial correlation in the productivity of 1960. The scatterplot is divided into four regions. The upper-right region is HH, which means countries

Figure 2.1: Productivity in 1960, by geographic weights

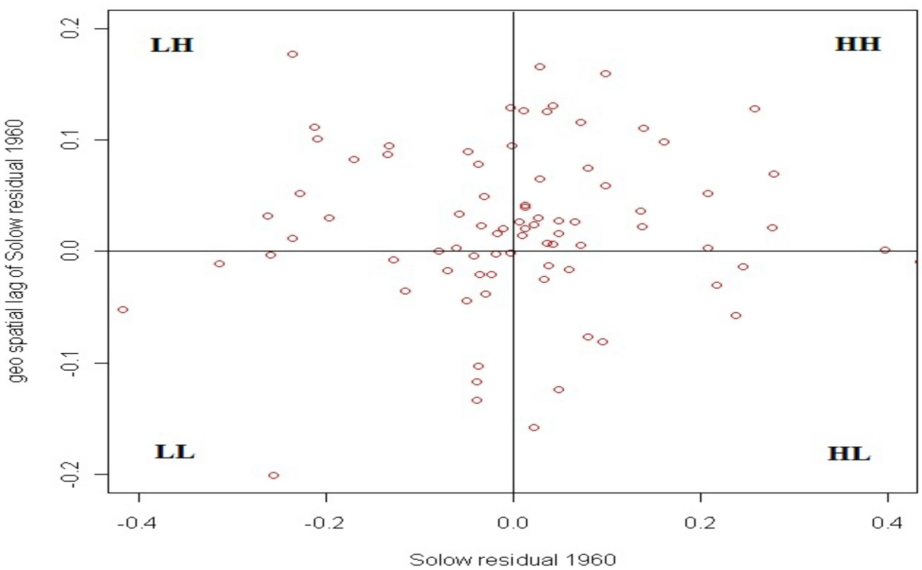
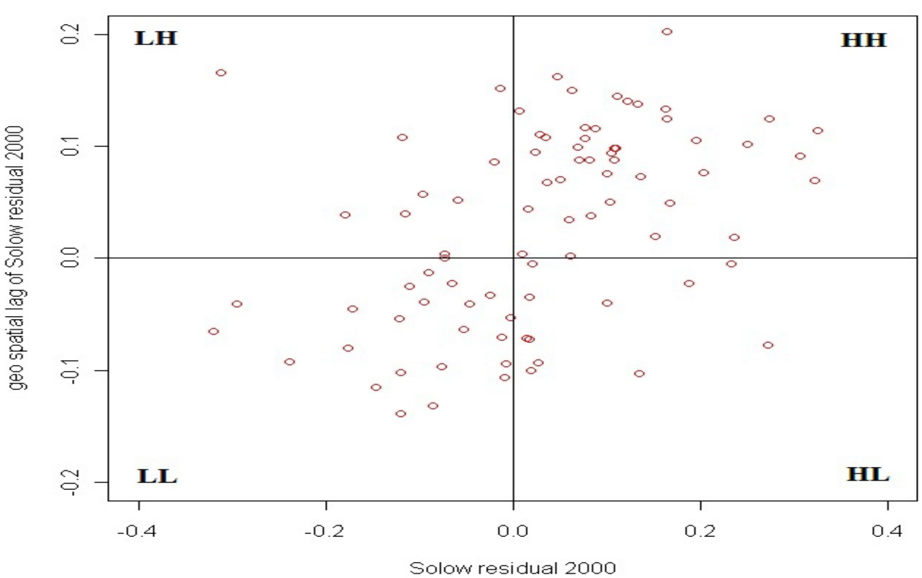


Figure 2.2: Productivity in 2000, by geographic weights



with high productivity are surrounded by high-productive countries. The lower-right region is HL, meaning that high-productive countries are surrounded by low-productive countries. The upper-left region is LH and lower-left is LL. There is no obvious pattern in this scatterplot, but still we can observe that high-productive countries are surrounded by high-productive ones while poor countries are neighbors of poor countries. Some less developed countries may be surrounded by developed ones but it is very rear that developed countries have developing countries as their neighbors.

If we look at the spatial dependence of productivity in 2000 from Figure 2.2, we can see that the pattern changes a lot. There are only a few countries laying into the HL and LH regions. For most of the countries, they are either in HH region or LL regions. It means that developed countries are the neighbors of developed ones while developing countries are the neighbors of their developing counterparts. The preliminary result suggests a positive spatial correlation.

The slop of the Moran's Scatterplot is called Moran's I index, which is written as I:

$$I = \frac{N}{\sum_i \sum_j m_{ij}} \frac{\sum_i \sum_j m_{ij} u_i u_j}{\sum_i \sum_j u_i u_j} \tag{2.38}$$

where m_{ij} is the i, j's element of spatial weighting matrix M_N, N is the number of observations. Especially if M is row standardized, Moran's I index simplifies to I_s:

$$I_s = \frac{\sum_i \sum_j m_{ij} u_i u_j}{\sum_i \sum_j u_i u_j} \tag{2.39}$$

Cautions must be paid to the choice of the spatial weighting matrix M_N. On the one hand, it should reflect the economic relationship between countries. On the other hand, it should not be correlated with the right-hand side variables. In the empirical growth inference, researchers usually avoid using economic indicators as weighting matrix to eliminate the potential endogenous problem (Anselin and Bera (1998)). In this paper, we use several ways to construct the weighting matrix. The first candidate is the geographic distance. It can partly reflect the economic relationship because the nearby countries have a relatively lower transaction cost so they tend to corporate with each other. We choose each country's nearest fifteen countries as neighbors, using the inverse of the squared distance as the non-zero elements in M_N. To guarantee that $|\rho| < 1$, we standardize the spatial weights. The structure of spatial weighting matrix is as follow:

$$m^*_{ij} = \begin{cases} 1/d^2, & if\ \ 0 < d_{ij} < d(15) \\ 0, & otherwise \end{cases} \qquad m_{ij} = \frac{m^*_{ij}}{\sum_j m^*_{ij}} \tag{2.40}$$

Table 2.3: Spatial Analysis Using Geographic Weights

	Standard Solow	Restricted Solow	Augmented Solow	Restricted Augmented Solow
Spatial Analysis				
Moran's I	0.1187	0.1177	0.1122	0.1129
p-value	0.0000	0.0001	0.0001	0.0001
ρ	0.1903	0.1891	0.1822	0.1833
	(0.0024)	(0.0024)	(0.0025)	(0.0025)
σ_v^2	0.0138	0.0137	0.0142	0.0139
JLV's ρ	0.2080	0.2088	0.1854	0.1916
Filtered Regression				
$\ln(y_0)$	-0.1344	-0.1456	-0.1106	-0.1295
	(0.0209)	(0.0209)	(0.0231)	(0.0246)
$\ln(k)$	0.0875	0.0861	0.1008	0.0989
	(0.0290)	(0.0301)	(0.0280)	(0.0284)
$\ln(n+g+\delta)$	-0.0300		-0.0425	
	(0.0797)		(0.0794)	
$\ln(h)$			-0.0171	-0.0125
			(0.0124)	(0.0125)
λ	0.0289	0.0315	0.0234	0.0277
α		0.3715		0.4330
β				-0.1066
Moran's I	-0.0195	-0.0203	-0.0174	-0.0186
P value	0.5463	0.5284	0.5952	0.5665

This table shows the result of spatial analysis by using geographic distance based weights. Moran's I index is the spatial test statistics, ρ and σ_v^2 are the spatial parameters. We compare our result with Jacob's result. The filtering regression is the third step regression, where it doesn't have spatial correlation anymore. Numbers in the cell show the coefficients and the numbers in the parenthesis show the standard deviation.

Table 2.3 shows the results of spatial parameters and growth determinants. The first two rows of Table 2.3 show the Moran's I index when using geographic distance as spatial weights. We can see that in all the four cases, the Moran's I indices are around 0.12, with p-value 0, which indicates a strong spatial correlation.

The rest of Table 2.3 shows the result of the last two stage estimation. In the second stage, we get the spatial parameters ρ and σ_v^2. ρ, which is around 0.19, is quite robust for all four

Table 2.4: Geographic Spatial Correlation in TFP

	US	Japan	Italy	France	U.K	Canada	Australia	Brazil	China	India
US	0	0	0	0	0	0.0982	0	0	0	0
Japan	0	0	0	0	0	0	0	0	0.0251	0.0032
Italy	0	0	0	0.0118	0.0070	0	0	0	0	0
France	0	0	0.0036	0	0.0375	0	0	0	0	0
U.K	0	0	0.0023	0.0411	0	0	0	0	0	0
Canada	0.1161	0	0	0	0	0	0	0	0	0
Australia	0	0.0047	0	0	0	0	0	0	0.0036	0
Netherlands	0	0	0.0018	0.0169	0.0241	0	0	0	0	0
Hong Kong	0	0	0.0114	0	0	0	0	0	0	0
Korea	0	0.0471	0	0	0	0	0	0	0.0690	0.0029
Singapore	0	0.0005	0	0	0	0	0.0004	0	0.0007	0.0008
Taiwan	0	0.0166	0	0	0	0	0.0014	0	0.0250	0.0038
Malaysia	0	0.0005	0	0	0	0	0.0003	0	0.0008	0.0010
Philippines	0	0.0097	0	0	0	0	0.0022	0	0.0107	0.0039
China	0	0.0175	0	0	0	0	0	0	0	0.0054
India	0	0	0	0	0	0	0	0	0.0028	0
Brazil	0	0	0	0	0	0	0	0	0	0
Turkey	0	0	0.0059	0.0026	0	0	0	0	0	0
Malawi	0	0	0	0	0	0	0	0	0	0
Mozambique	0	0	0	0	0	0	0	0	0	0
Kenya	0	0	0	0	0	0	0	0	0	0

This table shows the spatial correlation using geographic weights. Countries in the top row are influencers and countries in the first column are influencees. We choose 10 influential countries and see how they affect other countries in the world. For the countries who are affected, we consider both developed countries and developing countries all around the world in North America, Europe, Asia, Africa and so on. ρ is chosen as 0.1822 from Table 2.3

cases, and it measures the intensity of spatial correlation between countries. The variance of ρ is smaller than 0.01, showing that ρ is significantly positive. Compared the results with those estimated by JLV(2009), the difference is negligible. Both two estimators are consistent, however, mine has a simpler form and an easier-calculating variance.

From the results, the positive ρ means one country would be positively affected by its geographic neighbors' shock (or TFP), which satisfies the conclusion of Coe and Helpman (1995). Now we take a closer look at the spatial correlation of TFPs between country pairs. In Table 2.4, I choose all G7 countries (exclude Germany) and another three G20 countries, and see how their changes in TFP affect the countries in the world. Similar as the time-series correlation where only the early periods can affect the later periods, the spatial correlation is also one-way and asymmetric. The non-zero cell means that the country of that column is the neighbor of the country of that row, but reverse does not necessarily hold. Based on the geographic spatial weights, we can see that the world biggest economy, US, does not have effects on the countries in the continents other than North America. Japan is much more influential, but it only affects the countries in the Asia. Brazil does not have effects on any of the chosen countries. Moreover, we find that the spatial correlation is very small in this case, and we believe that it cannot accurately reflect the economic connections between countries.

We then examine the self-multiplication effect and the higher-order feedback effect. From $u = \rho M u + \epsilon$ from Equation 2.12, these two effects can be presented as follows:

$$u = (I - \rho M)^{-1}\epsilon = \epsilon + \rho M\epsilon + \rho^2 M^2\epsilon + \rho^3 M^3\epsilon + \rho^4 M^4\epsilon + \cdots \qquad (2.41)$$

The Equation 2.41 represents the effects of one country's own R&D plus higher-order spatial effects from other countries' R&D on its TFP. Put spillovers in another way, one country's TPF depends on the effects of its own R&D stock, it is neighbors' R&D stocks, it is neighbors' neighbors' R&D stocks and even higher order indirect effects. We express such effects in Table

Table 2.5: Geographic Spatial Correlation in R&D

	US	Japan	Italy	France	UK	Canada	Australia	Brazil	China	India	all
US	1.0116	0	0	0	0	0.0993	0	0	0	0	0.2109
Japan	0	1.0054	0	0	0	0	0.0003	0	0.0323	0.0050	0.2171
Italy	0	0	1.0039	0.0156	0.0099	0	0	0	0	0	0.2186
France	0	0	0.0047	1.0064	0.0414	0	0	0	0	0	0.2161
U.K	0	0	0.0033	0.0455	1.0060	0	0	0	0	0	0.2166
CAN.	0.1175	0	0	0	0	1.0116	0	0	0	0	0.2110
AUS.	0	0.0062	0	0	0	0	1.0059	0	0.0051	0.0009	0.2166
NLD.	0	0	0.0027	0.0231	0.0288	0	0	0	0	0	0.2109
HKG.	0	0	0.0130	0.0008	0.0005	0	0	0	0	0	0.2218
Korea	0	0.0496	0	0	0	0	0.0002	0	0.0722	0.0047	0.2110
SGP	0	0.0008	0	0	0	0	0.0005	0	0.0012	0.0015	0.1982
Taiwan	0	0.0197	0	0	0	0	0.0017	0	0.0291	0.0058	0.2162
MYS	0	0.0008	0	0	0	0	0.0005	0	0.0013	0.0017	0.1990
PHL.	0	0.0121	0	0	0	0	0.0026	0	0.0143	0.0058	0.2178
China	0	0.0225	0	0	0	0	0.0002	0	1.0078	0.0077	0.2148
India	0	0.0003	0	0	0	0	0	0	0.0038	1.0155	0.2071
Brazil	0	0	0	0	0	0	0	1.0016	0	0	0.2210
Turkey	0	0	0.0066	0.0033	0.0006	0	0	0	0	0	0.2207
Malawi	0	0	0	0	0	0	0	0	0	0	0.2147
MOZ.	0	0	0	0	0	0	0	0	0	0	0.2194
Kenya	0	0	0	0	0	0	0	0	0	0	0.2152

This table shows the feedback effects in R&D using geographic weights. Countries in the top row are influencers and countries in the first column are influencees. The chosen countries are the same as Table 2.4. ρ is chosen as 0.1822 from Table 2.3

2.5. If U.S.'s ϵ increases by 1, it implies that the increase in U.S.'s R&D stock makes the TFP of U.S. increase by 1 unit in the closed economy. However, from Table 2.5 we can see that the TFP of U.S. actually increases by 1.01165. The R&D stock of U.S. may affect the neighbors' TFP and then affect U.S. own TFP indirectly, but such a self-multiplication effect is not very big in this case. For some other countries, the self-multiplication effects are even smaller. Take Brazil as an example, 1 unit increase in ϵ only increases its TFP by 1.0016, such a effect is even negligible. The increase in the R&D of U.S. only has effects on the TFP of Canada, which is similar as the spatial correlation of TFP. However, we surprisingly find that a country's R&D is able to affect the TFP of the country which is not one of its neighbors. For instance, India is not Japan's neighbor, which can be told from Table 2.4. But 1 unit increase in Japan's ϵ can increase the TFP of India by 0.0003. It may due to the fact that Japan's R&D affects its direct neighbor (such as China) then affects India indirectly. In this sense, India is Japan's higher-order neighbor. Similarly, Hong Kong is not France's neighbor, but the marginal effect of France's ϵ on the TFP of Hong Kong is 0.008. Japan, Korean as well as China are not the neighbors of Australia but their TFPs are affected by Australia's R&D. The last column shows how each country's TFP changes with response to 1 unit increase in all its neighbors' ϵ. We can see that for most of the countries, such changes are around 0.21, which is higher than 0.18. It confirms the existence of higher-order feedback effect.

By comparing the results of the last stage with those of the first stage, we can barely observe any big differences. The coefficient of initial income changes from -0.1336, -0.1414, -0.1017 and -0.1186 to -0.1344, -0.1456, -0.1106 and -0.1295, making the convergence speed increase from 2.87%, 3.05%, 2.14% and 2.52% to 2.89%, 3.15%, 2.34% and 2.77%. The coefficients of physical capital change very little without any patterns. The impact of population growth on GDP growth is still negative and insignificant, but the magnitude decreases a lot. The effect of human capital is still negative and insignificant. When turning to test the spatial autocorrelation of errors after spatial filtering, we find that the p-value of Moran's I is over 50%. So we accept the hypothesis that there is no spatial error autocorrelation after we remove the spatial effects.

2.4.4 Consider the spillover effect through trade

We use geographic distance based weighting matrix as the benchmark since the geographic distance is conventionally used to measure the economic distance in the spatial econometric literature . However, trade may be a better proxy because it can reflect the economic relation between countries accurately and dynamically. The only problem of economic factors is that they may be endogenous so the estimation would be inconsistent. We choose the trade flow of specific year to minimize such endogeneity. For example, we use the 1964's trade volume to construct the spatial weighting matrix in the errors for the period 1960-1965, and 1969's trade volume for the period 1965-1970, so on and so forth. In this way, we can reduce the endogeneity in two folds. First, for period 1960-1965, the right-hand side variables are 1960's GDP and the five-year average of growth determinants over 1960-1964. All of them are pre-determined with respect to 1964's trade volume. On the other hand, the left hand side dependent variable-1965's log GDP would not affect 1964's trade, so there is no simultaneous effect. For each five-year period, we choose the trade volume of specific year to present the economic distance of the corresponding period, totally eight years' trades for eight periods. Since the spatial weights should be constant over time to facilitate the estimation, we take the average of these eight years' trade volumes. Due to the pair-wise trade data availability, we only have 85 countries in our sample. Similar as the geographic case, we define each country's biggest fifteen trade partners as neighbors. The fifteen none-zero elements in each row of spatial weighting matrix are the country's log average trade with those fifteen "neighbors". We also make the weights row standardized.

Figure 2.3 and Figure 2.4 shows the spatial pattern of productivity in 1960 and 2000 by using trade volume as weights. In 1960, most of the countries are in the regions of LH and HH. So we can see that both high-productive countries or low-productive countries are tend to trade with countries with high productivity. As time goes by, most of the countries in the

Figure 2.3: Productivity in 1960, by trade weights

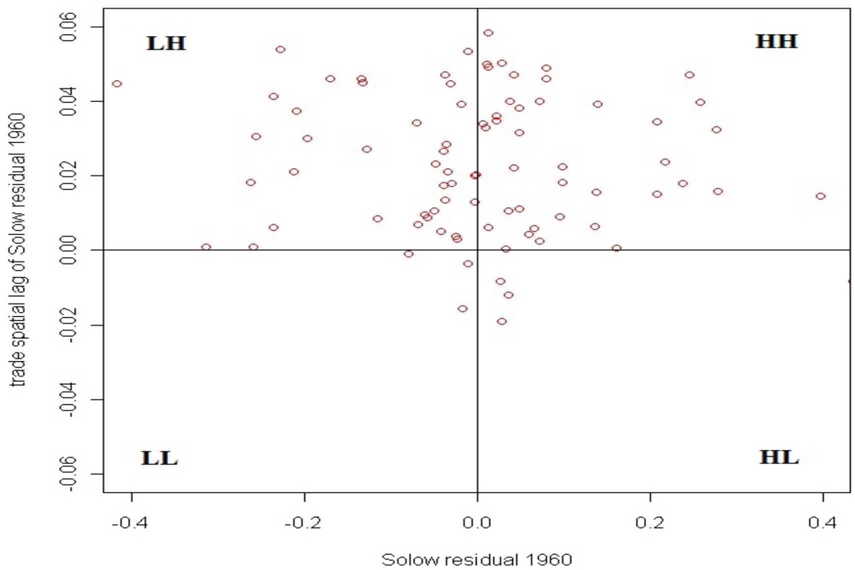
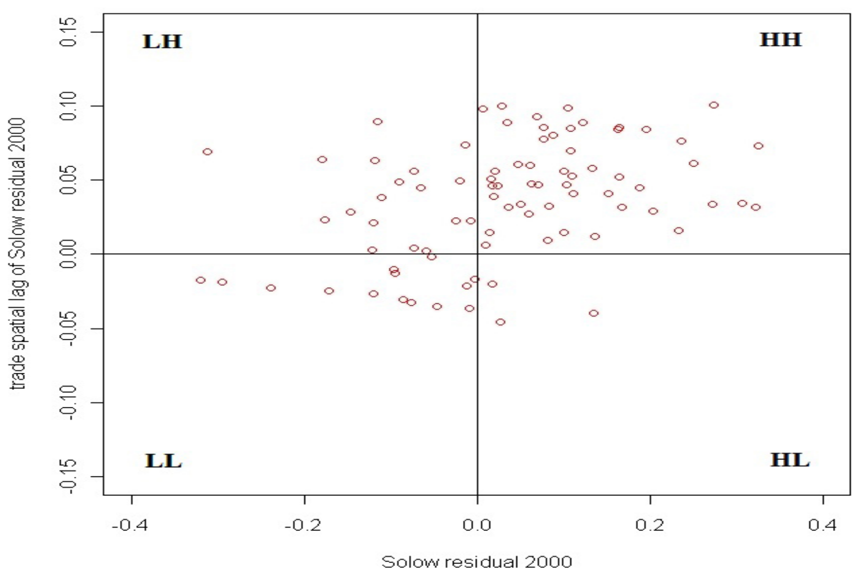


Figure 2.4: Productivity in 2000, by trade weights



HH regions remain in that region while some countries move from LH region to LL region. In 2000, except for 3 outliers, all the developed countries trade a lot with developed countries. Half of the developing countries always trade with developing countries while the rest half are inclined to trade with developed countries. Compared with the situation in 1960, we are still able to find the polarization tendency. Although the patterns of spatial correlation in productivity by geographic weights and by trade weights are quite different, both of them imply the divergence of productivity as time goes by.

Table 2.6 shows the Moran's I index to test the spatial error autocorrelation as well as the results of the last two stages estimation using trade as the spatial weighting matrix. The same

Table 2.6: Spatial Analysis Using Trade Weights

	Standard Solow	Restricted Solow	Augmented Solow	Restricted Augmented Solow
Spatial Analysis				
Moran's I	0.0893	0.0887	0.0858	0.0862
p-value	0.0000	0.0000	0.0000	0.0000
ρ	0.4569	0.4561	0.4449	0.4475
$var(\rho)$	0.0210	0.0211	0.0219	0.0217
σ_v^2	0.0133	0.0131	0.0136	0.0134
$JLV's\rho$	0.4435	0.4477	0.4297	0.4378
Filtered Regression				
$\ln(y0)$	-0.1553	-0.1746	-0.1123	-0.1409
	(0.0332)	(0.0373)	(0.0278)	(0.0311)
$\ln(k)$	0.0696	0.0609	0.1007	0.0922
	(0.0337)	(0.0379)	(0.0293)	(0.0305)
$\ln(n+g+\delta)$	-0.0173		-0.0500	
	(0.0851)		(0.0824)	
$\ln(h)$			-0.0244	-0.0228
			(0.0110)	(0.0110)
implied λ	0.0338	0.0384	0.0238	0.0304
implied α		0.2586		0.3956
implied β				-0.1932
Moran's I	0.0152	0.0151	0.0148	0.0145
P value	0.1397	0.1426	0.1489	0.1586

This table shows the results of spatial analysis by using trade volume based weights. Moran's I index is the spatial test statistics, ρ and σ_v^2 are the spatial parameters. We compare our results of ρ with Jacob's. The filtering regression is the third step regression, where it doesn't have spatial correlation anymore. Numbers in the cell show the coefficients and the numbers in the parenthesis show the standard deviation.

as the previous analysis, the Moran's I indices are significant with nearly 0 p-value, which means that very strong spatial autocorrelation exists in the errors when we use trade weights. The spatial autoregressive parameter ρ is around 0.45 and significant, much higher than that of geographic weights. Using JLV(2009) methods, we still get very similar results. It confirms the previous conclusion: a country can be better off by its neighbor country's technology progress. Higher ρ implies higher intensity of spillovers. Therefore, we can conclude that the spillovers are more effective through the channel of trade, so trade is probably a more appropriate proxy for economic distance.

The pattern of the spatial correlation in TFP using trade weights is quite different from that using geographic weights. Table 2.7 represents the direct relationship of trade partners among countries as well as the correlation between TFPs. From Table 2.7, we can see that U.S., Japan, France and U.K. are among the biggest 15 trade partners of all the selected countries. From the magnitude, we find that U.S. is the biggest trade partner for most of the countries in the list. If the TFP of U.S. increases by 1 unit, the TFP for all the listed countries will increase by about 0.03. Italy, Canada and China also have broad effects on the countries around the world. Compared them with those in the geographic case, we can see the the spillover effects through international trade are much stronger and much more wide-spreading.

Table 2.8 shows the self-multiplication effect and higher-order effect of R&D on TFP in the consideration of spillovers through international trade. ϵ also means the direct effects of a country's R&D on its TFP. Since the intensity of spatial correlation through trade, 0.4457, is much bigger than that through geographic spillovers, the self-multiplication effect in this case is bigger. The increase in the R&D of the U.S., which can only increase its TFP by 1 unit in the closed economy, now can increase its TFP by 1.0238. The magnitudes of the self-multiplication effects for the U.S., Japan, Italy and France are similar and bigger than other countries such as Brazil and India. It suggests that the first four countries are biggest few trade partners of other countries, and the number of countries affected by these four is also big. These two factors make the self-multiplication effects substantial. Moreover, there is no zero entry in the first 10 columns, which implies that the R&D of each of the ten countries has impacts on the TFP of all the listed 21 countries. Direct trade partnership is one of the reasons. However, some countries like Brazil, who is just the trade partner of U.S., Italy and Canada, can affect the TFP of many countries who are not its direct trade partners. With regard to the magnitude, 1 unit increase in U.S.'s ϵ can increase the TFPs of all the

Table 2.7: Trade Spatial Correlation in TFP

	US	Japan	Italy	France	U.K	Canada	Australia	Brazil	China	India
US	0	0.0322	0.0290	0.0296	0.0303	0.0329	0.0281	0.0284	0.0299	0
Japan	0.0335	0	0.0278	0.0287	0.0293	0.0293	0.0298	0	0.0309	0
Italy	0.0317	0.0293	0	0.0329	0.0313	0.0277	0	0.0278	0.0283	0
France	0.0318	0.0297	0.0323	0	0.0319	0.02751	0	0	0.0281	0
U.K	0.0321	0.0299	0.0303	0.0314	0	0.0288	0.0279	0	0	0
Canada	0.0379	0.0326	0.0292	0.0295	0.0313	0	0.0280	0.0279	0.0296	0
Australia	0.0327	0.0334	0.0289	0.0286	0.0307	0.0283	0	0	0.0300	0
Netherlands	0.0317	0.0294	0.0311	0.0320	0.0325	0	0	0	0	0
Hong Kong	0.0325	0.0323	0.0280	0.0278	0.0306	0.0275	0.0279	0	0.0343	0
Korea	0.0340	0.0336	0.0280	0.0284	0.0292	0.0291	0.0295	0	0.0312	0
Singapore	0.0329	0.0324	0	0.0285	0.0294	0	0.0285	0	0.0297	0.0272
Taiwan	0.0339	0.0333	0.0277	0.0285	0.0290	0.0286	0.0289	0	0.0311	0
Malaysia	0.0333	0.0332	0	0.0285	0.0297	0	0.0290	0	0.0293	0.0276
Philippines	0.0344	0.0336	0	0.0280	0.0292	0.0277	0.0285	0	0.0286	0
China	0.0334	0.0332	0.0289	0.0293	0.0287	0.0287	0.0287	0	0	0
India	0.0333	0.0319	0.0293	0.0295	0.0315	0.0281	0.0287	0	0.0281	0
Brazil	0.0341	0.0314	0.0305	0.0303	0.0298	0.0291	0	0	0.0282	0
Turkey	0.0328	0.0299	0.0323	0.0318	0.0316	0	0	0	0.0280	0
Malawi	0.0337	0.0331	0.0274	0.0300	0.0359	0	0.0269	0	0	0.0269
Mozambique	0.0314	0.0316	0.0296	0.0305	0.0306	0.0269	0	0	0	0.0287
Kenya	0.0320	0.0318	0.0304	0.0309	0.0347	0	0	0	0.0274	0.0293

This table shows the spatial correlation in TFP using trade weights. Countries in the top row are influencers and countries in the first column are influencees. The chosen countries are the same as Table 2.4. ρ is chosen as 0.4457 from Table 2.7.

Table 2.8: Trade Spatial Correlation in R&D

isocode	us	Japan	Italy	France	UK	Canada	Aus	Brazil	China	India	all
US	1.0238	0.0539	0.0470	0.0500	0.0511	0.0484	0.0407	0.0331	0.0474	0.0025	0.7485
Japan	0.0562	1.0230	0.0447	0.0490	0.0500	0.0457	0.0453	0.0043	0.0493	0.0026	0.7494
Italy	0.0541	0.0504	1.0216	0.0541	0.0526	0.0412	0.0078	0.0334	0.0435	0.0027	0.7508
France	0.0540	0.0507	0.0528	1.0223	0.0532	0.0409	0.0077	0.0071	0.0432	0.0027	0.7501
U.K	0.0544	0.0510	0.0505	0.0525	1.0224	0.0422	0.0351	0.0054	0.0176	0.0027	0.7499
Canada	0.0605	0.0540	0.0490	0.0501	0.0522	1.0181	0.0387	0.0339	0.0462	0.0010	0.7542
AUS.	0.0554	0.0553	0.0465	0.0489	0.0514	0.0448	1.0165	0.0043	0.0485	0.0026	0.7559
NLD.	0.0538	0.0504	0.0515	0.0532	0.0539	0.0148	0.0079	0.0046	0.0175	0.0028	0.7526
HKG.	0.0551	0.0541	0.0459	0.0484	0.0514	0.0424	0.0416	0.0042	0.0516	0.0033	0.7552
Korea	0.0566	0.0555	0.0448	0.0487	0.0499	0.0455	0.0451	0.0043	0.0496	0.0026	0.7565
SGP.	0.0554	0.0544	0.0183	0.0488	0.0502	0.0171	0.0442	0.0026	0.0475	0.0292	0.7569
Taiwan	0.0565	0.0551	0.0455	0.0489	0.0499	0.0443	0.0436	0.0043	0.0487	0.0026	0.7565
MYS.	0.0558	0.0551	0.0183	0.0487	0.0505	0.0171	0.0447	0.0027	0.0471	0.0296	0.7574
PHL.	0.0570	0.0556	0.0183	0.0482	0.0500	0.0434	0.0442	0.0035	0.0465	0.0026	0.7673
China	0.0560	0.0550	0.0467	0.0496	0.0496	0.0444	0.0434	0.0043	1.0186	0.0025	0.7538
India	0.0558	0.0534	0.0475	0.0502	0.0525	0.0421	0.0412	0.0043	0.0455	1.0042	0.7681
Brazil	0.0567	0.0526	0.0507	0.0512	0.0508	0.0438	0.0091	1.0097	0.0451	0.0017	0.7626
Turkey	0.0551	0.0509	0.0528	0.0531	0.0529	0.0143	0.0081	0.0055	0.0433	0.0035	0.7704
Malawi	0.0558	0.0543	0.0479	0.0512	0.0573	0.0130	0.0345	0.0059	0.0166	0.0307	0.7723
MOZ.	0.0538	0.0529	0.0489	0.0515	0.0519	0.0406	0.0109	0.0061	0.0169	0.0323	0.7723
Kenya	0.0543	0.0531	0.0496	0.0518	0.0559	0.0144	0.0112	0.0036	0.0443	0.0336	0.7723

This table shows the feedback effects using trade volume as weights. Countries in the top row are influencers and countries in the first column are influencees. The chosen countries are the same as Table 2.7. ρ is chosen as 0.4457 from Table 2.4.

listed countries by more than 0.05. When India's ϵ increases by 1 unit, it can only affect its direct trade partners by 0.03 and such effects are even smaller on higher-order indirect trade partners. Overall, feedback effects are significant due to the intensity of spillovers as well as the structures of trade partners. Through international trade, countries are more closely tied together than through the pure geographic spillovers.

The three-stage spatial dynamic panel estimation is actually a process which filters the spatial correlation. By doing this, we create a counterfactual that every country is a closed economy. There is no economic interactivity between countries. In this sense, we can compare the world which has spillovers with the world without spillovers, so as to obtain the effects of spillovers on economic growth and convergence. Compared the results of the third stage with those of the first stage, the coefficients of the initial income increase quite a bit in magnitude. It leads the convergence speed to increase from 2.87%, 3.05%, 2.14% and 2.52% to 3.38%, 3.84%, 2.38% and 3.04% for the standard Solow, restricted Solow, augmented Solow, restricted augmented Solow model respectively. Such an increase in convergence speed is quite robust. The convergence speed increases without spatial correlation, indicating that spillover effect is a factor that slows down the economic convergence.

From Table 2.7, we also find that developed countries are the trade partners of developing countries. Actually, the United States and Japan are every other country's neighbors, United Kingdom and France are the neighbors of 82 countries in the sample. Other countries, such as Netherland, Italy, Spain and China, are the neighbors of over half of the countries in our sample. It suggests that poor countries are able to benefit from the advanced technology spillovers from the developed "neighbors" and enjoy faster growth. However, rich countries grow even faster because of the spillovers, so the gap between the poor and the rich increases and the convergence speed decreases. There are several potential reasons leading to this result. First, the ultimate influences of spillovers are different across countries. It is commonly known that developed countries usually trade more, so they can get more advantages from the technology spillovers. While the gain from the spillovers is less for the developing countries since they trade less and they do not have enough human capital to assimilate the advanced technology from developed countries. Second, the asymmetric spatial relationship is another reason for lower convergence speed. Developed countries are the neighbors of developing countries, but developing countries are too small to be the neighbors of developed countries. In this sense, the negative economic shock such as financial crisis from developed countries would have negative effect on developing countries, but developing countries can hardly do bad to the developed countries. Spillover effects make the developing countries more vulnerable to the external injury so that their "catch up" progress could be impeded. The results of several other papers support our finding. Ertur and Koch (2007) find that international convergence speed increases from 8% to 17% by using mixed regressive, spatial autoregressive model (SAR) and to 12% by using spatial error autoregressive model in the cross-sectional setting. For the regional convergece, Ertur et al. (2006) find that the European convergence speed increases from 0.85% to 1.2% after accounting for the spatial autoregressive errors and confirm the spatial effect on the poor-poor, rich-rich polarization.

Besides the convergence speed, the coefficients of growth determinants also change a lot. The magnitude of change is much bigger than that of the geographic case. The coefficient of capital investment is much smaller in the spatial filtered regression, both in the standard Solow type models and augmented Solow type models. The robust result implies that potential "aggregate capital" due to the spillovers has positive effect on economic growth. The coefficient of population growth is still negative and insignificant, but the magnitude also decrease a lot. The coefficient of human capital is still negative, but the magnitude increases and becomes significant.

2.5 Robustness check

2.5.1 The convergence and spillovers over the period 1960-1985

To make our result comparable to the previous research, we use the same method to analyze the spillover effects of the period 1960-1985.

The top part of Table 2.9 shows the coefficients of the initial income and the convergence

Table 2.9: Convergence 1960-1985

	Standard Solow	Restricted Solow	Augmented Solow	Restricted Augmented Solow
$ln(y_0)$	-0.2143	-0.2304	-0.1302	-0.1615
λ	0.0482	0.0524	0.0279	0.0352
Geographic				
p-Moran's I	0.0634	0.085363	0.254531	0.249129
ρ	0.1256	0.117024	0.082929	0.082238
$var(\rho)$	0.0046	0.0047	0.0054	0.0054
σ_v^2	0.0156	0.015072	0.016854	0.015964
Spatial Filtering				
$ln(y_0)$	-0.2132	-0.2298	-0.13583	-0.16699
λ	0.0479	0.052221	0.029198	0.036542
p-Morans I	0.731	0.753026	0.857821	0.871058
Trade				
p-Morans I	0	5.62E-05	0.007071	0.00493
ρ	0.3325	0.333062	0.200011	0.219291
$var(\rho)$	0.0591	0.0617	0.0789	0.0803
σ_v^2	0.0151	0.014588	0.016551	0.015657
Spatial Filtering				
$ln(y_0)$	-0.2279	-0.23524	-0.13999	-0.17277
λ	0.0517	0.053639	0.030163	0.037935
p-Moran's I	0.1148	0.130813	0.133386	0.127665

This table shows the result of when using shorter sample period. We consider the cases using both types of weights. Numbers in the cell show the coefficients and the numbers in the parenthesis show the standard deviation. All the others are defined similar as the previous tables.

speeds without taking into account spatial effects. We can see that the convergence speed over the period 1960-1985 is much faster than that over the longer period 1960-2000. This is consistent with the convergence theory. As time goes by, countries are closer to their steady state. Therefore, the convergence speed becomes lower, which brings down the overall convergence speed.

The middle part shows the spatial analysis when using geographic distance as the spatial weighting matrix. Notice that Moran's I index is not significant at 5%. For the augmented Solow type model, the Moran's I index is insignificant even at 20% level, which means only very weak spatial autocorrelation exists through the geographic spillovers. The spatial autoregressive scale ρ, which meansures the intensity of spatial autocorrelation, is only around 0.1 but still significant, much less than that over the period 1960-2000. When looking at the convergence speed after eliminating the spillover effects, the result does not have a clear trend. We can say that geographic spillovers during that time were weak and barely had any effect on growth and convergence.

In the bottom part of the table, we use the trade flow as the spatial weighting matrix. Here, we can only use the average of the trade volume over five subperiods. From Moran's I index, there is also strong spatial autocorrelation existed in the error terms, but such a autocorrelation is a little weaker than that over the period 1960-2000. Spatial parameter ρ varies from 0.2 than that over period 1960-2000, which is around 0.45. It confirms that the spillover effects are much smaller in the period 1960-1985. The estimated convergence speed increases from 4.82%, 5.24%, 2.79% and 3.52% before spatial filtering to 5.17%, 5.36%, 3.02% and 3.79% after filtering for the standard Solow, restricted Solow, augmented Solow and restricted augmented Solow model respectively. Although the rise is smaller in magnitude, it proves that technology spillovers through trade make the rich richer and the poor poorer.

2.5.2 Change the number of neighbors

In the previous analysis, each country only has fifteen neighbors in the spatial weighting matrix, which is the standard treatment in the spatial econometric analysis. However, there is no optimal way to choose the number of neighbors. Too many neighbors in the weighting matrix would lower the consistency of estimation, while weighting matrix with too few neighbors cannot reflect the relationship among individuals. What we can do is to change the number of neighbors to see the general pattern of corresponding changes in the spillover effects.

Table 2.10 shows the result using geographic weights, and Table 2.11 shows the result of trade

Table 2.10: Change the Number of Geographic Neighbors

	5 neighbors	10 neighbors	15 neighbors	20 neighbors	25 neighbors
Solow					
ρ	0.1539	0.1788	0.1903	0.1931	0.1941
σ_v^2	0.0138	0.0138	0.0138	0.0138	0.0138
$ln(y_0)$	-0.1338	-0.1342	-0.1344	-0.1341	-0.1338
λ	0.0287	0.0288	0.0289	0.0288	0.0287
Moran's I	-0.0098	-0.0164	-0.0195	-0.0193	-0.0193
p-value	0.8124	0.6339	0.5463	0.5412	0.5355
Augmented					
ρ	0.1469	0.1710	0.1822	0.1849	0.1859
σ_v^2	0.0142	0.0142	0.0142	0.0142	0.0142
$\ln(y_0)$	-0.1082	-0.1100	-0.1106	-0.1104	-0.1100
λ	0.0229	0.0233	0.0234	0.0234	0.0233
Moran's I	-0.0079	-0.0143	-0.0174	-0.0172	-0.0173
p-value	0.8560	0.6828	0.5952	0.5892	0.5820

This table shows the result of when changing the number of geographic neighbors in the spatial weighting matrix. We only show the spatial parameters and the convergence rate in the counterfactual case to make comparisons.

Table 2.11: Change the Number of Trade Neighbors

	5 neighbors	10 neighbors	15 neighbors	20 neighbors	25 neighbors
Solow					
ρ	0.2621	0.3461	0.4569	0.5130	0.5552
σ_v^2	0.0131	0.0134	0.0133	0.0132	0.0131
$ln(y_0)$	-0.1426	-0.1478	-0.1553	-0.1552	-0.1513
λ	0.0308	0.0320	0.0338	0.0337	0.0328
Moran's I	0.0599	0.0269	0.0152	0.0127	0.0111
p-value	0.0013	0.0367	0.1397	0.1561	0.1653
Augmented					
ρ	0.2530	0.3347	0.4449	0.5020	0.5441
σ_v^2	0.0135	0.0137	0.0136	0.0135	0.0135
$\ln(y_0)$	-0.1062	-0.1085	-0.1123	-0.1147	-0.1131
λ	0.0225	0.0230	0.0238	0.0244	0.0240
Moran's I	0.0595	0.0269	0.0148	0.0123	0.0105
p-value	0.0014	0.0367	0.1489	0.1668	0.1841

This table shows the result of when changing the number of trade neighbors in the spatial weighting matrix. We only show the spatial parameters and the convergence rate in the counterfactual case to make comparisons.

weights for both standard Solow and augmented Solow type convergence. Here we only report the changes of the spatial parameters, the convergence speed and the Moran's I index after filtering.

We can clearly see from Table 2.10 that as the number of geographic neighbors increases, the intensity of spillovers increases consistently in both standard Solow and augmented Solow convergence. It is quite intuitive. The more neighbors affecting you, the more spillover effect you would get. However, the convergence speed does not change a lot after filtering the spatial effect because of the small spatial intensity parameter ρ (less than 0.2). The variance is very constant as the number of neighbors increases, which is consistent with the fact that the idiosyncratic shock is not affected by the neighborhood structure. After filtering the spatial effect, the Moran's I index is very insignificant, showing that the spatial effect is cleanly filtered. All the above results show that our results are not affected too much by the choice of number of neighbors.

If we turn our attention to the trade weight in Table 2.11, the situation is quite similar as that of the geographic weight. we can see that the intensity of spillovers increases monotonically in both Solow and augmented Solow type convergence. But the convergence speed does not change a lot. Such a result comes from the irregularity of the shock, which may be good or bad, which may enhance the growth of host country or hurt it. When we look at the Moran's I index after filtering the spatial effect, it is still significant when there are only 5 or 10 neighbors. It implies that a country may receive the spillover effects from at least other ten countries. If we just remove the spillovers from 5 or 10 countries, some spillover effect may still exist. So the proper weighting matrix should include more than 10 neighbors for each individual.

2.5.3 Exogeneity of the trade

To test whether growth determinants are strictly exogenous or at least predetermined to trade, we use the average of trade volumes at the beginning year of each period to construct the weighting matrix. For example, we use the year 1965's trade volume to construct the weighting matrix in the error terms for the period 1965-1970, and 1970's trade volume for the period 1970-1975, then average these eight trade volumes as the element of the spatial weighting matrix. Due to the data availability, we can only choose the year 1962's trade volume for the period 1960-1965. If the result is not quite apart from the section 4.4 result, we can conclude that growth determinants are exogenous to trade. From the Table 2.12, we can see that the

Table 2.12: Using the Trade of the Beginning Year

	Standard Solow	Restricted Solow	Augmented Solow	Restricted Augmented Solow
Moran's I	0.0829	0.0823	0.0794	0.0798
p-value	0.0000	0.0000	0.0000	0.0000
ρ	0.4255	0.4246	0.4133	0.4159
σ_v^2	0.0134	0.0132	0.0137	0.0135
Filtered Regression				
$\ln(y_0)$	-0.1514	-0.1659	-0.1122	-0.1373
	(0.0312)	(0.0343)	(0.0272)	(0.0302)
$\ln(k)$	0.0734	0.0687	0.1009	0.0949
	(0.0325)	(0.0359)	(0.0289)	(0.0300)
$\ln(n+g+\delta)$	-0.0293		-0.0590	
	(0.0844)		(0.0822)	
$\ln(h)$			-0.0224	-0.0202
			(0.0110)	(0.0110)
λ	0.0328	0.0363	0.0238	0.0295
Moran's I	0.0130	0.0144	0.0129	0.0126
P value	0.2009	0.1614	0.2042	0.2130

This table shows the result of when using the beginning year's trade volume in each five-year sample to test the exogeneity of weighting matrix. Numbers in the cell show the coefficients and the numbers in the parenthesis show the standard deviation. All the others are defined similar as the previous tables.

intensity of spillover is a little less when we use the beginning years' trade. That makes the convergence speed increases less after filtering the spatial effect.

Generally speaking, the convergence speed is still larger when the spillover effects are eliminated, the magnitudes and the significant levels for all coefficients are quite similar as the results of Table 2.6. Overall, we can barely observe its difference from the case when using the ending year's trade volume in the spatial weighting matrix. So we can say that trade is at least weak exogenous to the growth determinants, and trade is valid to be used in the spatial weighting matrix.

2.6 Conclusion

This paper considers the spillover effects on international economic growth and convergence. We develop a model which treats the spillovers as the interdependence of TFP through the externalities of R&D between trade partners. To estimate the model empirically, we develop a three-stage GMM estimator in the spatial dynamic panel framework. In the empirical analysis, we estimate the intensity of spillover effects and economic convergence in a "spaceless" environment.

There are three main findings in this paper. First, there exist positive spillover effects. Countries can benefit from their neighbors' newly-developed technologies and enjoy faster economic growth. Second, spillover effects weaken the convergence instead of enhancing it, in both geographic spillover case and the trade spillover case. Third, there was little spillover effect in the early period. Spillovers become more significant as time goes by.

There are several things we can do in the future. First, we can try to make our spatial weighting matrix dynamic so that we can measure the relationship between countries more precisely and dynamically. But new estimation methods are required. Second, we could consider the spillover effect in the club convergence. Since spillovers are among countries with the similar economic structure, for example, the rich-rich and poor-poor spillovers in the geographic case, the spillover club may be quite similar to the convergence club. Third, instead of focusing on the country-wide data, we can examine the industrial level data. It is quite intuitive that the imports of high-technic product may help improve the local technology level by "technology stealing", while the imports of raw material may be not so useful. The export of high-technic product would also stimulate firms' incentive of innovation. To analyze the technology spillovers, we can focus on the trade of product with more technology content, such as the machinery and transport equipment, chemicals and related products instead of food and live animals, crude materials.

Appendix: Simulation procedure and results

We run simulations to prove that our estimator is consistent. We also compare our method with Jacobs et al. (2009) method.

The data generating process is as follows:

$$
\begin{aligned}
y_{it} &= \lambda y_{it-1} + \beta x_{it} + u_{it}, \quad i = 1 \dots N, \quad t = 1 \dots T \\
u_t &= \rho M_N u_t + \mu_i + v_{it}
\end{aligned}
$$

Since it is a panel data, x is generated by two parts. One is the random term from a unified distribution which is time-variant and the other is also the random term from a unified distribution but it is time-invariant to the same individual.

The error term u_t for period t is an $N \times 1$ vector which is spatially correlated and with individual effects from a unified distribution and idiosyncratic term from a normal distribution. We choose the geographic distance to construct M_N.

y_{it} is constructed by a recursive way period by period. We generate 100 periods and delete the first $100 - T$ period to avoid the possibility that the value of y_{it} depends on the initial value setting. We run 1000 times simulation.

We consider two scenarios. In case 1, we have relatively shorter time span, so there are 90 individuals and six time periods. The parameters are specified as follows: $N = 90$, $T = 6$. $\lambda = 0.7$, $\rho = 0.5$, $\beta = 1$, $\sigma_v^2 = 1$. In case 2, we extend the time span and make it 9 periods. We also change the parameter settings a little, so $N = 90$, $T = 9$. $\lambda = 0.5$, $\rho = -0.4$, $\beta = 1$, $\sigma_v^2 = 1$. The result is shown in Table A1.

From Table A1, we can see that for the regression parameters, the estimator in this paper yields the smallest bias and also smallest RMSE. If we look at the spatial parameters from

Table A1. simulation of regression parameter

	Case 1			Case 2		
	First stage	Third Stage		First stage	Third Stage	
	A-B	Liao's	Jocobs's	A-B	Liao's	Jocobs's
β	-0.0259	-0.0179	-0.0182	-0.0190	-0.0153	-0.0158
	(0.0941)	(0.0822)	(0.0826)	(0.0448)	(0.0407)	(0.0407)
λ	-0.0101	-0.0078	-0.0073	-0.0232	-0.0203	-0.0209
	(0.0319)	(0.0272)	(0.0272)	(0.0411)	(0.0381)	(0.0393)

This table shows the simulation results of growth regression. A-B is the Arrellano-Bond estimator. Liao's is the third-stage result developed in this paper and Jocob's is the third-stage result by Jacobs et al. (2009). The numbers in the cell show the bias and the numbers in the parenthesis are the RMSE.

Table A2. simulation of spatial parameter

	Case1		Case 2	
	Liao's	Jocobs's	Liao's	Jocobs's
ρ	-0.0167	-0.0329	-0.0160	-0.0352
	(0.1284)	(0.1164)	(0.0990)	(0.0871)
σ_v^2	-0.0251	0.0384	-0.0264	0.0827
	(0.1017)	(0.5333)	(0.0783)	(0.4013)

This table shows the simulation result of spatial parameters. Liao's is the second-stage result developed in this paper and Jocob's is the second-stage result by Jacobs et al. (2009). The numbers in the cell show the bias and the numbers in the parenthesis are the RMSE.

Table A2, we can see that our estimator still produces the smallest bias in both ρ and σ_v^2. However, the RMSE of ρ is similar to Jocob's estimator while that of σ_v^2 is smaller. From the simulation result, we can see that our estimator is indeed consistent and more efficient than Jocob's estimator. Meanwhile, our method is simpler and we also give the form of the variance of ρ but Jocob's didn't.

Chapter 3

Provincial R&D spillovers in China: Considering the effects of marketization by varying-coefficient model

(ABSTRACT)

This paper comprehensively analyzes the direct and indirect factors in China's technology development, filling in the gaps in the literature by considering the spillover effects and the indirect effects from institutions. Besides the traditional technology determinants such as science and technology (S&T) capital, S&T personnel, human capital and infrastructures, this paper takes into account the spillover effects: provincial spillovers in S&T capital as well as S&T personnel, and international spillovers through trade and FDI. Moreover, this paper examines the multi-channel, nonlinear, indirect effects of institutions (marketization process) by semiparametric varying-coefficient model. Marketization, measured by the share of state-owned enterprises (SOEs) in the economy, may affect the production of technology through changing the efficiency of technology inputs and promoting spillovers. Through the empirical analysis, this paper finds that provincial spillovers are mainly through the externalities of

S&T capital stock while international spillovers occur through trade. Marketization affects the technology development through S&T capital, S&T capital spillovers and trade. Certain share of SOEs is necessary in technology production. In the long run, the marketization process will promote the development of technology in China.

3.1 Introduction

Recent decades have witnessed three seemingly-related trends in the Chinese economy. First, high economic growth. With the nominal GDP growth over 7% for nearly 30 years, China has become the second largest economy in the world. The GDP per capita increased from round $360 in 1990 to more than $4000 in 2010 [1], which is an increase of more than ten times within 20 years. Second, significant improvement in productivity as well as S&T. R&D investment has increased substantially over the last decade. In 1995, R&D expenditure only accounted for 0.5 % of GDP, and this ratio increased to 1.7 % in 2007. This achievement is amazing among developing countries. In 1990 there were only 19,304 patents granted nationwide. This number increased dramatically to 501,786 in 2009 [2]. Third, gradual structure change in the ownership. The ownership reconstruction started at the end of the 1970s. However, the reform until 1990 did not see very prominent achievements. SOEs and collective-owned enterprises (COEs) still accounted for a big portion of China' economy in the early nineties. But the kingdom of SOEs collapsed just in the most recent decade. SOEs now only make up around 20% of the whole economy [3]. Nowadays, individual-owned enterprises, town-and-village-owned enterprises, jointly-operated enterprises and foreign-invested enterprises are active in the Chinese economy. Economists are trying to link the first two trends as well as the

[1] Nominal GDP per capita is calculated by the data from China Statistic Yearbook
[2] The index is calculated by the data from Science and Technology Statistic Yearbook of China
[3] measured by output share, data source: China Statistic Yearbook

first and the last one. However, few papers aim at finding the effects of the ownership reform on technology. Therefore, there are two main objectives in this paper. First, we want to find the determinants of S&T development. Second, we try to build a bridge between economic reform and technology development.

Technology is intangible so it is difficult to measure directly. The widely used indirect approaches are to measure the output (patents) and the effect of technology (productivity). The advantage of using patents is that the patent data has been collected for a longer time even in poorer countries, while the drawback is that it is not internationally comparable. The other indicator of technology, productivity, is usually represented by total factor productivity (TFP), and measures the effects on the output production other than inputs. It is a generated measure so it introduces measurement error and perhaps biases (Wolfgang (2004)). Technology or productivity is considered as the source of sustainable long-run economic growth. As a result, it is important to find the factors which can stimulate technology development. In endogenous growth theory, firms have the incentive to invest resources on R&D since they can obtain the monopoly profit once they develop the new technology successfully. [4] Therefore, R&D investment, R&D personnel as well as the institutions which protect the monopoly profit become the important determinants of technology development. However, in developing countries such as China, the situations are more complicated. If firms develop technology themselves, R&D investment, R&D personnel and good institutions still have influences on technology progress. If firms receive FDI and technology support from multinational corporations, they does not need to do research themselves. What they need are high-skilled technicians who are able to use the advanced technology. In this case, human capital, especially tertiary education, becomes important. R&D investment may still be useful because it is a learning process and it promotes the adaptive capacity (Griffith et al. (2004)). R&D investment could be less relevant due to the "crowding out" effect of foreign technology transfer (Deolalikar

[4]See Jones (1995) and Howitt (1999)

and Evenson (1989)). However, if firms adopt new technology by "stealing" and copying from other domestic or foreign firms, institutions such as patent protection will not do any good. [5] Therefore, comparing with developed countries, the sources of technology progress in China are especially interesting.

Economists have begun to focus on the determinants of technology development in China at province level, industry level or even firm level. Zhang et al. (2003) find that R&D personnel and expenditure will increase R&D output. They also find that the state sector has significantly lower R&D efficiency than the non-state sector by stochastic frontier estimation. Economists also consider human capital a technology determinant and find significant positive effects of it on technology development and redistribution in not only OECD countries (Del Barrio-Castro et al. (2002); Coe et al. (2009)) but also developing countries such as China (Fleisher et al. (2010)). By using innovative ways[6] to measure the technical change (TFP), Shiu and Heshmati (2011) find that both FDI and information and communication technology (ICT) investment are significant factors contributing to the TFP differences. Cheung and Lin (2004) distinguish three types of patents and find that the spillover effect is the strongest for minor innovation such as external design patent, highlighting a "demonstration effect" of FDI. Besides FDI and infrastructures, Fleisher et al. (2010) also take into account both the impact of market reform and direct and indirect effects of human capital on productivity growth in the cross-provincial study.

More than the factors mentioned above, this paper also analyzes the provincial spillovers. It is widely recognized that international technology spillovers play an important role in technology progress. Domestic R&D stock and foreign R&D stock weighted by the corresponding trade share have significant impact on TFP (Coe and Helpman (1995), Coe et al. (2009)).

[5] Fleisher and Zhou (2010) talks about dual effects of patent protections on innovation activities in China. China has benefited from externalities generated through copying innovations generated elsewhere without paying to do so, so patent protection may retard the technological growth. On the other one, patent protection may enhance the innovation because investors in R&D can now reap more of the gains.

[6] Single time trend (TT) approach and general index (GI) approach

Technology transfer from the technology frontier and absorptive capacity can stimulate the productivity growth (Griffith et al. (2004)). In fact, domestic spillovers are much easier and more often happen than international spillovers. With smaller language barrier and shorter geographic distance, researchers have more chances to communicate with each other about the new findings they get.[7] Big corporations usually have branches all over the countries and the branches can share the newest innovations developed by the headquarters. Government policies also encourage the innovation and technology transfer by subsidy and tax holiday. In this sense, we have reasons to believe that domestic spillovers have stronger and more important effects than the international spillovers. Unfortunately, we only find few literature on provincial spillovers in China. Brun et al. (2002) list three possible externalities resulted from provincial spillovers: demand side externalities, trade externalities and supply side externalities. Hu et al. (2005) find that although there is evidence of positive returns to in-house R&D in Chinese firms, the effects of both domestic and foreign technology transfer on firm's productivity are largely conditional on their interaction with in-house R&D. Yet they give a vague description about domestic technology transfer. If beyond the scope of China, there are a lot of papers talking about regional technology spillovers. Bottazzi and Peri (2003) make a detailed analysis on innovation externalities in European regions. They consider several possible ways to measure the spillovers, such as distance intervals, technological distance and border effect. They find that spillovers happen within 300 km. In this paper, we define an explicit form of provincial spillovers in China.

While the effects of provincial spillovers are interesting to investigate, the most fascinating factor of technology development in China is the complicated roles played by institutions. China is a typical country which is experiencing big institution reforms and social structure changes. Institutions affect economic growth and technology progress indirectly through dif-

[7] Krugman (1998) argues that there are geographical boundaries to R&D spillover for tacit knowledge. The marginal cost of transmitting tacit information across regions increases with distance because non-codified knowledge is vague and requires face-to-face interactions.

ferent channels. Financial liberalization enables firms to finance the uncertain innovation activities. It indirectly encourages the innovation activities by stimulating R&D investment. Financial intermediaries are able to identify the best production technologies, boosting the rate of technological innovation by identifying the entrepreneurs with the best chances of successfully initiating the technology breakthrough (Levine (2005)). The enforcement of patent protection plays dual roles on technology growth. China has benefited from the externalities through copying innovations generated elsewhere without paying to do so. IPR protection may slowdown the productivity growth. However, "if innovative activity could be increased because investors in R&D sector can now reap more of the gains obtained then the economic growth may be enhanced."(Fleisher and Zhou (2010)) The effects of nationalization are even more ambiguous. SOEs are known for their overinvestment and low productivity. It seems natural that the higher level of nationalization, the lower the efficiency of innovation activities. [8] Moreover, smaller share of SOEs means higher degree of marketization. Less monopoly power and more market competition would force research institutes to improve the efficiency. In this sense, nationalization hinders technology progress. However, SOEs, with the state government's support, have sufficient funding to conduct big scientific projects. They don't need to worry about the short-term profit much with the state government on the back, so they can focus on the basic research which does not yield immediate profit but has profound impacts on future researches and generates bigger positive externalities. Moreover, the communications between SOEs on the recent technology breakthrough are also encouraged by the government. From this aspect, nationalization could be helpful in technology growth. Until now, we couldn't find any theoretical and empirical papers in the literature systematically analyzing the effects of institutions on technology growth.

This paper fills in several gaps in the literature. First, our paper takes a full consideration

[8] Lai et al. (2006) include government expenditures on science and technology activities to see whether R&D supported by the government is more or less efficient in China. They do not find statistically significant relationship between government S&T expenditures and growth. However, Du et al. (2011) find significant evidence that increases (decreases) in state-invested shares are associated with falling (increasing) productivity.

on the spillover effects, including both domestic spillovers and international spillovers. Concerning the domestic spillovers, we use the weighted S&T inputs of neighbor provinces as the determinants of local technology progress. Regarding the international spillovers, we take into account both technology imitation from imports and the technology transfer through the investment of multinational firms. Second, our paper innovatively analyzes the indirect effects of marketization (measured by the share of SOEs output to total industrial output) on R&D efficiency and technology redistribution. By semiparametric varying-coefficient model, we are able to see that marketization plays different roles the technology process at different stages. Therefore, our paper is the first to systematically analyze the effects of institutions.

The paper is arranged as follows. Section 3.2 describes the basic model specifications. Technology in China is affected by R&D inputs and also spillover effect. Section 3.3 talks about data. Section 3.4 analyzes some basic empirical results and obtains the significant determinants of technology growth. Section 3.5 expands the basic model, making a detailed analysis on the indirect effect of marketization. Section 3.5 summarizes and concludes.

3.2 The models

Research can be taken as a production process. The output is produced by S&T inputs and some other factors. So the production function can be written as:

$$A_{it} = f(K^{ST}_{i,t-1}, L^{ST}_{i,t-1}, X_{i,t-1}, Z_{i,t-1}) \tag{3.1}$$

where technology output for province i at time t is denoted as A_{it}. K^{ST} represents the S&T capital stock, L^{ST} is the S&T personnel. These two are the basic inputs in the production function. X shows other relevant factors such as human capital, spillover effects as well as infrastructures, while Z represents the indirect factors such as institutions. All the factors are all in one-period lag. We have

$$\frac{(\partial A_{it})}{\partial K^{ST}_{i,t-1}} > 0, \frac{(\partial^2 A_{it})}{\partial K^{ST}_{i,t-1} \partial Z_{t-1}} >=< 0 \tag{3.2}$$

$$\frac{(\partial A_{it})}{\partial L^{ST}_{i,t-1}} > 0, \frac{(\partial^2 A_{it})}{\partial L^{ST}_{i,t-1} \partial Z_{i,t-1}} >=< 0 \tag{3.3}$$

$$\frac{(\partial A_{it})}{\partial X_{i,t-1}} > 0, \frac{(\partial^2 A_{it})}{\partial X_{i,t-1} \partial Z_{i,t-1}} >=< 0 \tag{3.4}$$

3.2.1 Baseline model

Although research can be viewed as a production process, it is different from the production of final goods because it yields uncertain outcomes and can only be done by high skilled labors. So high-skilled labors, especially those who have college or higher degree, play an irreplaceable role in the technology production. Meanwhile, good infrastructures, such as highway construction, telecommunication and internet, can facilitate the innovation process. Some provinces are more advanced than others due to historical reasons, so provincial dummies enable us to address the omitted variable bias. We also add year dummy in the regression to capture the potential time trend. By using linear specification, the provincial production function of technological innovations can be expressed as:

$$A_{it} = \beta_1 ST_{i,t-1} + \beta_2 X_{i,t-1} + \mu_i + \tau_t + \epsilon_{it} \tag{3.5}$$

Here we use the number of patents approved each year to measure the technology output A_{it}. Technology output is produced by the previous year's S&T ($ST_{i,t-1}$) inputs: S&T capital stock and S&T personnel. X_{it} includes other factors, such as human capital and the infrastructures. Following the literature, we choose road density and telephone usage to control for the infrastructures.[9]

3.2.2 International spillovers and provincial spillovers

In the global economy, international S&T spillovers as well as domestic provincial spillovers are prevalent. A country assimilates other countries' advanced technologies by attracting foreign investment or importing foreign goods. Within a country, provinces can easily communicate with each other, sharing their achievements. We believe that there should be strong spillover effects among provinces. Therefore, we propose the following technology production function.

$$A_{it} = \beta_1 ST_{i,t-1} + \beta_2 wST_{i,t-1} + \beta_3 F_{i,t-1} + \beta_4 X_{i,t-1} + \mu_i + \tau_t + \epsilon_{it} \tag{3.6}$$

F_{it-1} shows the technology transfer from foreign countries to the provinces of China. Generally there are two forms of technology transfer from developed countries to developing countries such as China. First, technology can be transferred through imitation. Scientists in developing countries try to reverse the production process of high-tech products from developed countries so as to obtain the newly developed technology. Imports, especially the imports of high-tech products, create the potential capability to imitate. Another way spillovers occur is through the investment of multinational firms. By FDI, local affiliates are granted the authority to use the innovations developed by the multinational firms. In addition, upstream industries have the incentive to innovate so that they are able to provide the required intermediate products, while downstream industries can also benefit from FDI since they can use more sophisticated materials in the production. In this paper, we take into account both channels of technology transfer.

In this paper, we go one step further and think of the provincial spillovers in China. We believe that technology development of one province is affected by that of other related provinces,

[9] See Fleisher et al. (2010)

which suggests that other provinces' S&T inputs may contribute to the achievement of the targeted province. Therefore, we use the weighted average of other provinces' S&T inputs to account for the provincial spillovers. It is represented as $wST_{i,t-1}$, which shows the S&T capital spillovers and personnel spillovers. The weight should be chosen properly to reflect the economic relationship among provinces. Geographic distance may be a good example since communication decreases as the distance becomes longer. In this paper, we don't use the pure geographic distance between provinces, while choose the driving time to measure the economic closeness. On the one hand, driving time reflects the geographic distance between provinces. On the other hand, it reflects the transportation cost between provinces. Driving time can be short between two far away provinces if there is a good highway connecting them or a good logistics network between them. Therefore, we think driving time is a better indicator for economic relationship because it reflects the ease of transactions.

3.2.3 The effects of marketization

Economists all agree that institutions are important in economic growth and technology development of developing countries. During the past two decades, the most prominent change in China's economy is the reform of SOEs and the process of marketization. The share of SOEs (noted as R^{SOE}in the paper) drops dramatically, while private and foreign-owned enterprises carry increasing weight in the economy. Market-oriented economy is usually considered to be more efficient than the central-planning economy. However, that may not be necessarily the case in technology development. In China, research is mainly conducted in independent research institutes, large & medium-sized enterprises and institutions of higher education. All the institutions of higher education and the majority of research institutes are state owned. More than half of large & medium-sized enterprises are state-owned or joint state-owned. In short, almost all the research is done in the state-owned sector. It is because innovation requires a big amount of initial investment but yields uncertain outcomes, few individuals are able to afford such a huge investment and bear such a big risk. It is the government that provides enough funds for research. Nationalization becomes a precondition for research. What's more, communications between research sectors are encouraged by the government so that one research institute can access some innovations from other institutes. Researchers have more chances to exchange their new ideas and inventions. In this sense, the nationalization enhances technology spillovers.

However, as the SOEs take more and more share in the economy, problems emerge. With soft-landing, R&D could be over-invested. Managers of the research institutes can hire more researchers than they need since they don't face a solid budget constraint. Principal-agent conflicts result in inefficiency in the technology production. Moreover, when the share of SOEs is too big, it scares away foreign investors and reduces the competition in research sectors. Facing no risk of the competition, state-owned research sectors have even less incentive to improve efficiency and creativity. Bureaucracy will also reduce the efficiency of FDI use. Under this circumstance, nationalization impedes technology progress, while marketization plays a positive role in it.

Therefore, the effects of marketization are complex. It indirectly affects the technology development through many possible ways. It has different effects at different stages. To make a comprehensive consideration of the multiple-channel, nonlinear effects, we use the varying-coefficient semi-parametric model to take account of them.

$$A_{it} = \beta_1(R^{SOE}_{i,t-1})ST_{i,t-1} + \beta_2(R^{SOE}_{i,t-1})wST_{i,t-1} + \beta_3(R^{SOE}_{i,t-1})F_{i,t-1} + \beta_4 X_{i,t-1} + \mu_i + \tau_t + \epsilon_{it} \quad (3.7)$$

Marketization (R^{SOE}) is measured by the share of SOEs' output to the total output of the economy. Higher R^{SOE} means lower level of marketization. From the regression, we can see that the coefficients of technology determinants are nonparametric functions of R^{SOE}. It suggests that at different stages of marketization, the effects of S&T inputs and spillovers on technology are different.

3.3 Data

The major data sources are the *China Statistic Yearbook (CSY)* and the *China Statistic Yearbook on Science and Technology (CSYST)*. The nominal GDP, import, FDI, road and telecommunication as well as patent data come from each year's *CSY*. The science and technology related indices are from *CSYST*. It is a balanced panel data with 29 provinces in the sample (excluding Sichuan and Chongqing)[10] from 1990-2009. Due to the fact that the size of each province is significantly different, we make some changes in the indicators so as to make them comparable across provinces. The summary statistics are shown in Table 3.4 in the Appendix.

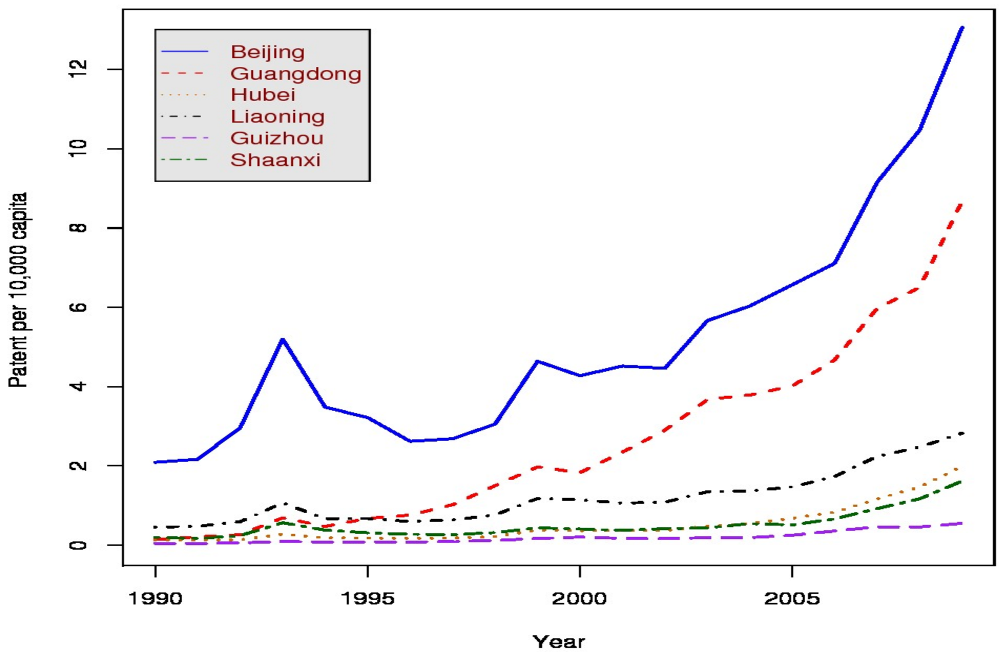
3.3.1 Patent

Productivity and technology achievement(A_{it}) is measured by the number of patents granted per 10,000 capita. In this paper, we use the general definition of patent, which includes innovation, utility model and external design [11]. China's technology has been improving in these 20 years, but regional imbalance is obvious. The patent levels are similar across provinces initially. In 1990, the number of granted patent per 10,000 population is below 3 for all the provinces. As time goes by, regional divergence becomes more significant. In Figure 3.1, we choose some representative provinces from each region and plot the time trend. From Figure

[10] Chongqing was separated from Sichuan in 1998 as a municipality

[11] Innovation is a new technical solution relating to a product, process, or improvement thereof. Utility model means a new technical solutio relating to the shape or structure of a product that is not directly related to its aesthetic properties. External design involves a new design of shape, pattern, or combination or of color or aesthetic properties.Cheung and Lin (2004)

Figure 3.1: Patent per 10,000 Population



3.1, we can observe that eastern provinces such as Beijing and Guangdong have the fastest growth rate as well as highest current patent level. Other provinces such as Jiangsu, Zhejiang and Shanghai (which are not shown in the graph) have even higher growth rates. Northeastern area such as Liaoning province has relatively slower growth rate, and it are ranks below the coastal area. Hubei, the most developed province in the central area has an even smaller growth rate. Western region, including Guizhou and Shaanxi, falls behind other regions.

3.3.2 S&T input

Intuitively, S&T inputs are the basic determinants in technology production, so we hope to see that they have the same trends as the patent. In this paper, we mainly consider two inputs: S&T capital stock and S&T personnel. S&T investment (measured by the current intramural expenditure for S&T) and S&T personnel data can be found the *CSYST*. S&T capital stock is calculated by perpetual inventory method.

$$K_{it}^{ST} = (1-\delta)K_{it-1}^{ST} + E_{it-1} \tag{3.8}$$

where depreciation rate δ is assumed to be 0.05 as Coe et al. (2009) suggest. K is S&T capital stock and E is the real S&T expenditure in terms of 1990 yuan discounted by price index of fixed asset. The initial S&T stocks are calculated as:

$$K_{1990}^{ST} = \frac{E_{1990}}{\delta + g} \tag{3.9}$$

where g is the average annual growth rate of S&T expenditure from 1990 to 2009. It differs for each province. To make all the indices comparable among provinces, we use S&T capital per real GDP in terms of 1990 yuan(denoted as k^{ST}) and S&T personnel per employment (denoted as l^{ST}) in the paper. Unlike A(patent per 10,000 capita) which goes up smoothly, k^{ST} curves are relatively flat. As shown in Table 3.4, Beijing has the highest k^{ST}, which is around 60%. Western provinces such as Guanxi and Tibet, as well as a coastal province Hainan, have the lowest k^{ST}, even lower than 10%. k^{ST} changes in different patterns these years for different provinces. Some provinces enjoy a slightly increasing k^{ST}, such as Tianjin, Shanghai, Jiangsu, Zhejiang and Fujian. Some provinces experience a slowly decreasing k^{ST}, such as: Liaoning, Shangxi and Gansu. For most provinces, we can hardly find significant time trend in the k^{ST}. At this point, we rudimentally predict that k^{ST} can partially explain the regional differences of patent level but cannot predict the time trend of the pattern.

When looking at l^{ST}, we can see that it is more volatile than k^{ST}, while overall it still does not have an explicit time trend. From Table 3.4, we find that Beijing and Shanghai have the highest ratio of S&T personnel to employed people, which is above 20%. Provinces such as Guanxi, Guizhou, Yunan and Tibet in the western region have the lowest ratio. The change pattern of l^{ST} these years is quite similar to that of k^{ST} for most of the provinces, suggesting that these two inputs are complimentary in the patent production. The same as k^{ST}, l^{ST} can only explain the provincial differences of patent level but not the growth of it.

3.3.3 Domestic spillovers

Domestic spillovers are represented by weighted k^{ST} and l^{ST}, calculated as Equation and . The closeness of the economic relationship is inversely related to the driving time, so we use the inverse of the squared driving time (denoted as D) as the weight. We standardize the weight. So

$$wk_{it}^{ST} = \sum_{j=1}^{J} \frac{1}{D_{ij}^2} k_{jt}^{ST}, \qquad wl_{it}^{ST} = \sum_{j=1}^{J} \frac{1}{D_{ij}^2} l_{jt}^{ST} \tag{3.10}$$

$$\sum_{j=1}^{J} \frac{1}{D_{ij}^2} = 1 \tag{3.11}$$

Data of S&T inputs come from the source mentioned in Section 3.3.2. The weights are the driving time between the capital cities of two provinces, which can be found by Google Earth. From the indices, we find that provinces with the highest S&T inputs do not necessarily have the highest weighted S&T inputs. Only the provinces which are surrounded by technology frontiers can get bigger technology spillovers. The structural changes in k^{ST} and l^{ST} can no longer be found in the weighted value of them since the weighted average smooths out the differences.

3.3.4 Infrastructures

Regarding infrastructures, we choose two representations: road density and telephone usage. Road density is measured by the total length of highway per squared kilometer (*road*), and telephone usage (*tel*) is calculated by the ratio of telephone and cellphone subscribers to the total population. We can see that the conditions of infrastructures have a significant improvement during the recent decade. The increase in *road* was still very slow until 2002. But since 2003, the Chinese government dramatically increased the investment on highway and railroad construction. In 2009, one third of the provinces had more than 1 kilometers highway per squared kilometer. For telecommunication, the usage of telephone and cellphone in each province increases continuously for these twenty years, but the growth rate is different for different provinces. *tel* is similar for each province in the early nineties, but the regional disparity enlarges as time goes by.

3.3.5 Human capital

In this paper, human capital is measured by the percent of college graduate in the population. The percent of college graduates is calculated by the share of people who have college or higher degree to the population age 15 and above. The number of college graduates can be found in each year's *National Sample Survey on Population Changes*. Human capital keeps increasing in the sample period. People are more willing to go to college because the returns to college education (college premium) are high. What is more, the policy of university expansion started in 1999 provides more opportunities to study in college. In 1990, there was only 2% of the population that got college or higher degree, while this number increased to 8% in 2009. Although the percent is trending upward, the growth rates are different among provinces. Beijing and Shanghai have the highest initial stock of college graduates as well as the highest growth rate. In 2010, one third people in Beijing had college degree. Data is missing from year 1991 to 1995. We assume that workers have the same distribution of education level as the general population, so we use the education level of the workers to represent that of the whole population for the year 1991 and 1992. For year 1993-1995, we assume that each province has a constant growth (change) in the percent of college graduate. In this way, we are able to extrapolate the missing data. For most provinces, the percentage of college graduates keeps increasing. We find an interesting pattern in the data, where provinces that have more universities experience higher growth rate. It may be due to the fact that people tend to go to nearby universities, or college graduates are inclined to stay in the provinces where they attended colleges.

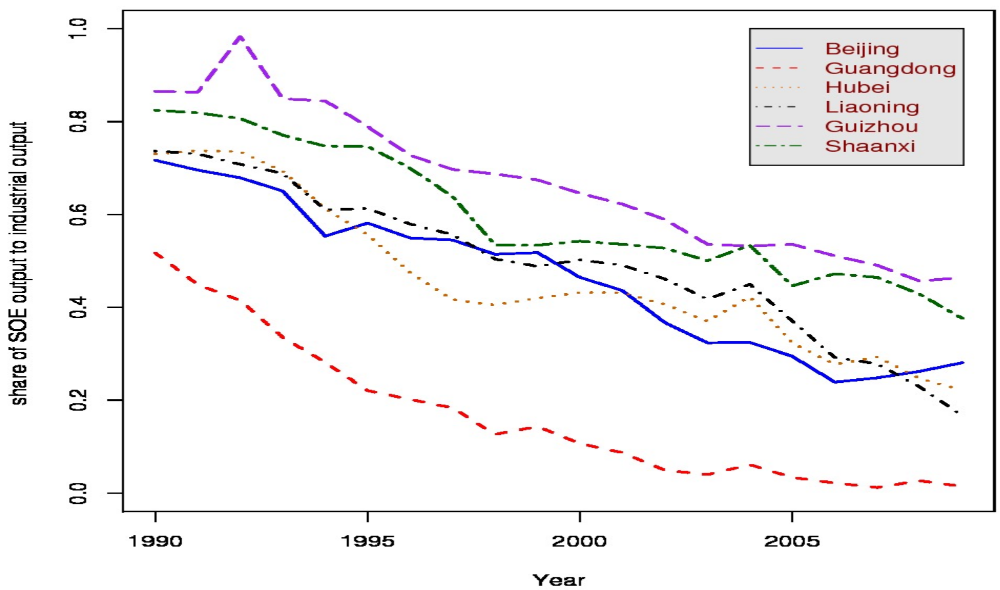
3.3.6 International spillovers

The share of import to GDP (denoted as imp) and the ratio of FDI to GDP (fdi) are used to control the international spillovers. imp is the total value of imports by location in Chinese yuan divided by current GDP, and fdi is the actual used foreign direct investment in Chinese yuan divided by GDP. The actual used FDI is missing since 2004, so we use the total investment by registered foreign funded enterprises to extrapolate it. Not surprisingly, coastal area has the highest import to GDP ratio as well as FDI to GDP ratio. However, we are surprised to find that these two ratios are relatively constant over time. The increase in the imports and FDI are offset by the high growth rate of GDP. Except for Beijing, which has imports to GDP ratio as high as 150%, nearly half of the provinces keep this ratio below 20%. Regarding fdi, most provinces maintain it below 10%.

3.3.7 Marketization

To measure the marketization, we use the ratio of SOEs' output to the total industrial output (Denoted as R^{SOE}). The criterion of the SOEs' output and the industrial output changed in 1998. Before that, the *CSY* included all the state-owned enterprises in summarizing value of the SOEs' output and all the firms of the industry in calculating the value of industrial output. Since 1998, the *CSY* only recorded the enterprises above certain scale. It implicitly ruled out most of the individual-owned enterprises, which were small but prevalent in the industry. In

Figure 3.2: The share of SOE: adjusted



this way, the measure of SOEs share is overestimated. We create a dummy which equates 1 if the year is after 1997 and we allow the dummy to be varied with provinces. Then we regress R^{SOE} on year and the dummies by individual fixed effect estimation. The coefficient for each dummy represents the degree of overestimation for each province. We subtract the dummy from R^{SOE} for each province for the year later than 1997. In this sense, we are able to correct the upward bias of R^{SOE} index. Due to the estimation bias, Jiangsu province has even negative R^{SOE} for year 2007 to 2009, which is obvious impossible. We assign 0.01 to Jiangsu province for these three years. The data is shown in Figure 3.2.

The reform of state-owned enterprises started at the early 1980s. But the speed was very slow until 1992, when Deng Xiaoping made his southern tour[12]. Since 1992, plenty of private-owned and foreign-owned enterprises have emerged and the share of SOEs in the economy decreased dramatically. From Figure 3.2, we can see that all the provinces have decreasing R^{SOE}.

[12]Deng Xiaoping stressed the importance of economic reform in China, making further economic and openness reforms as an national policy. Since that, the pace of transition to a market system has been speeded

Coastal area is the one which receives the highest FDI in these years. Moreover, private-owned enterprises are prevalent in coastal area, with the ratio of total assets to industrial output more than 20%. The above factors result in the lowest R^{SOE} in coastal region. The SOEs share of Guangdong decreases from round 60% to below 10% recently. As a capital city, Beijing has relatively higher share of SOEs, but the share is still lower than most of the central, western and northeast provinces and it keeps on decreasing over time. Northeast region and central region have the similar level of R^{SOE}. Western China has the highest initial R^{SOE} , which is as high as 80%. For some provinces such as Guizhou and Shaanxi, the share decreased slowly while it was still as high as 50% in 2009.

3.4 Estimation results

3.4.1 Baseline regression

In the first step, we consider the basic determinants of technology progress. A_{it} is determined by last year's S&T capital stock per GDP, S&T personnel per employment, college graduate ratio and basic infrastructures. The regional heterogeneity is also considered in the analysis. We run separate regressions for each of the three regions: Coastal, Central and Western [13]. We use panel data two-way fixed effect model which includes provincial dummies and year dummies to control for the omitted provincial characteristics and the time variance. The results are shown in Table 3.1. In the first two columns of Table 3.1, we consider a single input. When k^{ST} increases by 1%, A_{it} significantly increases by 0.396. A= 1% increases in l^{ST} increases A_{it} by 3.915. So we can see that S&T personnel has much bigger effect on patent production than S&T capital. When we consider them together, the coefficients of

[13] In this paper, we group provinces into three regions: Coastal, Central and West. Coastal area includes: Beijing, Tianjin, Heibei, Shanghai, Jiangsu, Zhejiang, Fujian, Shangdong, Guangdong, Hainan, Liaoning, Jilin, Heilongjiang. Central area include: Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan. Western area includes Mongolia, Guangxi,Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

Table 3.1: Basic determinants of patent/10,000 population

	1	2	3	4	5	6	7	8
	National					Costal	Central	Western
$L.k^{ST}$	0.40***		0.30***	0.30***	0.25***	0.44***	-0.009	-0.033
	(0.036)		(0.039)	(0.032)	(0.028)	(0.046)	(0.006)	(0.020)
$L.l^{ST}$		2.47***	3.92***	1.60***	0.222	-0.657	0.264**	-0.361
		(0.414)	(0.437)	(0.354)	(0.327)	(0.455)	(0.134)	(0.315)
$L.col$				47.62***	20.65***	30.03***	0.581	0.795
				(2.847)	(3.276)	(4.895)	(0.806)	(2.287)
$L.road$					1.28***	1.67***	0.51***	0.44***
					(0.325)	(0.587)	(0.118)	(0.167)
$L.tel$					5.27***	5.38***	1.03***	1.55**
					(0.431)	(0.693)	(0.205)	(0.602)
obs	551	551	551	551	551	247	190	114
Adj R^2	0.394	0.365	0.429	0.633	0.722	0.824	0.810	0.845

The table shows the results of basic regressions. The dependent variable is patent per 10,000 capita. We use panel two-way fixed effect model. All the independent variables are lagged by 1 period. The number in each cell represents the coefficients and numbers in parenthesis represent the standard deviation. " *** " $p < 0.01$, " ** " $p < 0.05$, " * " $p < 0.1$

both decrease slightly but remains significantly positive, which means these two inputs are substitute in the technology production. When the percent of college graduates (col) is added in the regression, the coefficient of k^{ST} remains constant but the coefficient of l^{ST} decreases a lot. There may be strong multi-collinearity between col and l^{ST}, which is easy to understand. S&T personnel are usually people with tertiary education, so it is positively correlated to the percent of college graduates in the population. $road$ is significantly positively correlated with the A_{it}, meaning better transportation will facilitate the S&T research. However, after we add tel into the regression, S&T personnel becomes insignificant.

In columns 6, 7 and 8, we take into account the regional heterogeneity, so we run separate regression for each region. In the coastal region, technology growth is mainly due to S&T capital accumulation, human capital and better infrastructures. The coefficients of the related factors in the coastal region are bigger than those of national level, suggesting that the production efficiency is higher in the coastal area. In the central area, S&T personnel turns to be significant but the highly significant variable *col* become insignificant, which confirms the substitution effect between them. S&T capital no longer has an effect on A_{it}. Instead, a 1% higher ratio of S&T personnel will increase A_{it} by 0.264. Infrastructures are still important in the central area. Finally, when we look at the western region, the only significant determinants are infrastructures. Neither S&T inputs nor human capital have positive effects on technology. We suspect that there may be potential determinants which cause the omitted variable bias in the estimation. From the analysis, we can conclude that the patterns of regional technology development are indeed quite different.

3.4.2 Considering the spillover effects, domestic and international

In the global economy, with more and more cooperation, the interdependence between countries or regions becomes stronger and stronger. Spillover effects are a necessary component in the technology development. Omitting it may cause estimation bias in the previous analysis. In this step, we take into account both domestic spillovers and international spillovers. The detailed model description is in Section 3.2.2. The results are shown in Table 3.2.

Similar to the Table 3.1, we focus on the S&T input separately. In Table 3.2, if we just put S&T stock and weighted S&T stock in the regression, the S&T stock has significant positive impact while weighted S&T stock has an even bigger effect. When only considering S&T personnel, we find the similar pattern. Bigger effect from S&T spillovers may result from the assumption of perfect spillovers based on the construction of weight, which may not be true in the reality. When we consider the S&T capital and personnel, human capital as well as spillover effects jointly, all the factors have significantly positive effects except for S&T personnel spillovers. Even with spillovers, human capital still has a big effect on technology growth. It shows that domestic technology spillovers are mainly through S&T investment.

Table 3.2: technology development and spillovers

	1	2	3	4	5	6	7	8
	National					Costal	Central	Western
$L.k^{ST}$	0.29***		0.24***	0.25***	0.25***	0.33***	-0.02**	0.00
	(0.03)		(0.03)	(0.03)	(0.03)	(0.06)	(0.01)	(0.03)
$L.wk^{ST}$	0.72***		0.54***	0.52***	0.52***	0.53***	-0.02	0.02
	(0.06)		(0.06)	(0.06)	(0.06)	(0.10)	(0.02)	(0.05)
$L.l^{ST}$		3.38***	1.34***	1.35***	1.33***	0.36	0.27	-0.07
		(0.39)	(0.32)	(0.32)	(0.33)	(0.51)	(0.17)	(0.34)
$L.wl^{ST}$		7.07***	-0.48	-0.60	-0.62	-1.23	0.38*	-0.85
		(0.76)	(0.70)	(0.69)	(0.69)	(1.13)	(0.21)	(0.78)
$L.col$			42.88***	38.62***	38.71***	46.67***	2.77***	2.89
			(2.89)	(3.19)	(3.20)	(5.31)	(0.73)	(2.41)
$L.imp$				1.12***	1.09***	0.54	-0.08	-2.14
				(0.37)	(0.38)	(0.57)	(0.10)	(2.23)
$L.fdi$				-0.68	-0.62	0.98	-0.65	-5.52**
				(1.79)	(1.80)	(2.54)	(0.94)	(2.75)
$L.road$					0.14	1.48**	0.29**	0.49***
					(0.36)	(0.66)	(0.12)	(0.17)
obs	551	551	551	551	551	247	190	114
AdjR^2	0.521	0.457	0.696	0.700	0.700	0.802	0.781	0.843

The table shows the basic determinants of technology development as well as the spillover effects. The dependent variable is patent per 10,000 capita. We use panel two-way fixed effect model. All the independent variables are in one-period lag term. The numbers in each cell represents the coefficients and numbers in parenthesis represent the standard deviation. " *** " $p < 0.01$, " ** " $p < 0.05$, " * " $p < 0.1$

Higher education is a prerequisite condition for the spillovers of S&T personnel.

If we look at the international spillovers, higher import to GDP ratio will stimulate the technology progress. As a developing country, China tries to get access to the cutting-edge technology by reversing the production process and does obtain better technology by imitation. 1% increases in *imp* can only increase 1.12 patent per 10,000 population. When we look at foreign investment, higher FDI to GDP ratio has no significant effect. The result is consistent with previous findings in the literature. Researchers have analyzed the spillover effects of FDI empirically at different levels: national, industrial and firm level, but they failed to find significant technology transfer from multinational corporations. Multinational firms in China do a good job at protecting their core technologies. The competition they bring into the market does not significantly stimulate the local technology development. When *tel* is added, a lot of key determinants become insignificant. We think the continuously fast increase in telephone usage may result in spur regression, so in the following study, we only consider the road density as the representation of infrastructures. *road* still plays a significant role when domestic and international spillovers exist.

In column 6, 7 and 8 of Table 3.2, we consider the regional heterogeneity so we run a separate regression for each region. In the coastal area, technology development is driven by S&T capital and S&T capital spillovers. S&T personnel has no effects on it. In the coastal area, the effect of college graduate becomes even bigger, suggesting that human capital is extremely important in technology growth. 1% increase in the percent of college graduates can increase patent per 10,000 capita by around 47. Beyond our expectation, neither imports nor FDI has significant effect on technology. High imports in the coastal area are probably used for consumption while FDI stimulates economic growth just by factor accumulation but not technology development. Then we look at the central region, we find that S&T personnel spillovers can slightly increase A_{it} while S&T even has a negative effect on it. Higher human capital level will contribute to technology development, but such an effect is very small compared with its effect in coastal area. In the west region, what surprises us is that neither S&T inputs nor spillovers can benefit technology development. In fact, the technology development is very slow in the west area. No much important research is done there. Better infrastructure has significantly positive effect on A_{it} in all regions, but the magnitude of the effect is different across regions. From the above results, we conclude that China's technology progress is mainly driven by the coastal area.

Table 3.3: determinants of growth of patent

	1	2	3	4	5	6	7	8
	National					Costal	Central	Western
$L.k^{ST}$	0.08***	0.07***	0.15***	0.09**	-0.00	-0.01	0.01	0.01
	(0.02)	(0.02)	(0.04)	(0.05)	(0.00)	(0.01)	(0.01)	(0.01)
$L.wk^{ST}$		0.14***		0.16**		-0.02		0.03
		(0.03)		(0.08)		(0.02)		(0.03)
$L.l^{ST}$	0.24	0.21	-0.16	-0.04	0.08	0.13	-0.03	0.11
	(0.18)	(0.18)	(0.36)	(0.39)	(0.12)	(0.14)	(0.14)	(0.18)
$L.wl^{ST}$		-0.45		-0.62		0.07		-0.06
		(0.39)		(0.84)		(0.17)		(0.41)
$L.col$	9.04***	9.32***	11.30***	12.10***	0.38	0.36	-0.17	0.48
	(1.47)	(1.78)	(3.03)	(4.12)	(0.57)	(0.59)	(1.14)	(1.26)
$L.road$	0.49**	0.36*	1.07**	1.34***	-0.03	-0.02	0.12	0.14
	(0.19)	(0.20)	(0.47)	(0.50)	(0.09)	(0.10)	(0.09)	(0.09)
$L.imp$		-0.18		-0.42		-0.07		-0.43
		(0.21)		(0.42)		(0.08)		(1.17)
$L.fdi1$		0.96		2.14		-0.73		-1.74
		(1.00)		(1.91)		(0.75)		(1.44)
obs	551	551	190	190	190	190	114	114
Adj R2	0.301	0.324	0.426	0.432	0.403	0.398	0.674	0.669

The table considers the potential factors which may stimulate the patent growth. The dependent variable is number of first-difference of patents per 10,000 capita. We use panel two-way fixed effect model. All the independent variables are lagged by 1 period. The number in each cell represents the coefficients and numbers in parenthesis represent the standard deviation. " *** " $p < 0.01$, " ** " $p < 0.05$, " * " $p < 0.1$

3.4.3 Determinants of growth of patent

The factors which affect the growth of patent are shown in this section. We use first-differenced patent per 10,000 capita (ΔA) as the dependent variable. We adopt this specification for two reasons. First, we can see from Figure 3.1 that patent per 10,000 capita is upward trending. Even we control the year dummies, we are still worried about the unit-root in it. After the first-difference, we can get stationary dependent variable and are free of spur regression. Second, we are able to find whether the technology determinants have increasing or decreasing marginal returns, and whether technology production is economy of scale. We not only look at the national level, but also consider the regional disparity. The results are shown in Table 3.3.

Column 1 and 2, we can tell that S&T capital, and S&T capital spilovers from neighbor provinces, human capital and infrastructures accelerate the growth of patent production in the national level. It suggests that these factors not only contribute to the technology development, but the marginal benefit also increases. S&T personnel, which is a significant input in the technology production, has no effects on technology growth, implying the constant marginal returns. Then turning our attention to the coastal area, we observe that similar pattern. The increase in the marginal return are even bigger since the corresponding coefficients are larger in magnitude. If looking at the central and western regions, we cannot find any factors which have significant effects on the growth of A_{it}. We believe that technology determinants in the central region have constant marginal return while technology development in west region is resulted from other factors (government policy) but not the S&T input and spillover effects.

3.5 Indirect effect of marketization

As analyzed in Section 3.2.2, marketization affects technology progress through many possible channels. Different degrees of nationalization also affect technology development differently. The difficulty is that we are not sure through which channels R^{SOE} affects technology growth and what forms such effects are. In this sense, simple linear specification cannot capture all the features. We assume that the coefficients of some technology determinants may vary with the degree of marketization (or nationalization). Therefore, we use the semi-parametric specification.

3.5.1 Partial linear varying-coefficient model

The varying-coefficient models are proposed by Hastie and Tibshirani (1993) and the non-parametric estimation method is developed by Li et al. (2002). Later researches extend it into the panel data framework (Cai and Li (2008), Sun et al. (2009)) using fixed effect specification. In this paper, we think R^{SOE} has indirect effects through some technology determinants but not all, so we use the partial linear varying-coefficient model specification. To capture the individual omitted effect as well as the potential time trend, we use two-way fixed effects specification, which is consistent with the previous analysis. We need to modify their method to accommodate the panel error structures. We briefly introduce the estimation method here.

$$Y_{it} = X_{it}\beta(Z_{it}) + W_{it}\gamma + \mu_i + \tau_t + v_{it} \quad i = 1...N, t = 1...T \tag{3.12}$$

The indirect factor Z_{it} affects dependent variable through direct factors X_{it}. W_{it} are control variables. μ_i, τ_t and v_{it} represents individual effect, time effect and idiosyncratic errors. Writing the formula in the matrix form and doing some rearrangement, we have

$$Y - W\gamma = X\beta(Z) + Z_\mu\mu + Z_\tau\tau + v \tag{3.13}$$

where Y and Z is $NT \times 1$ vector. X is $NT \times k1$ and W is NT*k2. Using the projection matrix Q, we can eliminate the time and individual effect. We then solve the optimization problem:

$$min_{\beta(z)}((Y - W\gamma) - X\beta(z))QM_H(z)Q((Y - W\gamma) - X\beta(z))' \tag{3.14}$$

where

$$Q = (I_N - J_N J_N'/N) \otimes (I_T - J_T J_T'/T)$$

$$M_H(z) = diag(K_H(Z_1 - z), \ldots K_H(Z_N - z))$$

$$K_H(Z_i - z) = diag(K_H(Z_{i1} - z), \dots K_H(Z_{iT} - z))$$

where K is the Gaussian kernel function, and h is the bandwidth by least squares cross-validation [14]. Denote QY as $\tilde{Y}$, QX as $\tilde{X}$,QW as $\tilde{W}$,Qv as $\tilde{v}$, $\tilde{v}$ is i.i.d. disturbance term. Take the first derivative of β_z, we can get

$$\begin{aligned} \tilde{X} M_H(z)(\tilde{Y} - \tilde{W}\gamma) &= \tilde{X} M_H(z) \tilde{X} \beta(z) + \tilde{X} M_H(z) \tilde{v} \\ E\left(\sum_{i=1,j=1}^{I,T} \tilde{X}_{it} M_H(Z_{it} - z) \tilde{v}_{it} | Z_{it} \right) &= 0 \end{aligned} \tag{3.15}$$

Then

$$\begin{aligned} \hat{\beta}(Z_{it}) = &\left[\sum_{i=1,j=1}^{I,T} \tilde{X}_{it} \tilde{X'}_{it} K(\frac{Z_{it} - z}{h}) \right]^{-1} \sum_{i=1,j=1}^{I,T} \tilde{X}_{it} (\tilde{Y'}_{it} - \tilde{W}_{it}\gamma) K\left(\frac{Z_{it} - z}{h} \right) \\ = &\hat{\beta}_y(Z_{it}) - \hat{\beta}_w(Z_{it})\gamma \end{aligned} \tag{3.16}$$

where

$$\hat{\beta}_y(Z_{it}) = \sum_{i=1,j=1}^{I,T} \tilde{X}_{it} \tilde{X'}_{it} K(\frac{Z_{it} - z}{h})]^{-1} \sum_{i=1,j=1}^{I,T} \tilde{X}_{it} \tilde{Y'}_{it} K(\frac{Z_{it} - z}{h})$$

$$\hat{\beta}_w(Z_{it}) = \sum_{i=1,j=1}^{I,T} \tilde{X}_{it} \tilde{X'}_{it} K(\frac{Z_{it} - z}{h})]^{-1} \sum_{i=1,j=1}^{I,T} \tilde{X}_{it} \tilde{W}_{it} K(\frac{Z_{it} - z}{h})$$

Replacing $\hat{\beta}(Z_{it})$ into the original regression function, we get

$$\tilde{Y}_{it} - \tilde{X}_{it} \hat{\beta}_y(Z_{it}) = (\tilde{W}_{it} - \tilde{X}_{it} \hat{\beta}_w(Z_{it}))\gamma + \tilde{v}_{it} \tag{3.17}$$

We can get γ by regressing $\tilde{Y}_{it} - \tilde{X}_{it} \hat{\beta}_y(Z_{it})$ on $\tilde{W}_{it} - \tilde{X}_{it} \hat{\beta}_w(Z_{it})$ by OLS. Plug $\hat{\gamma}$ into Equation 3.17, we can get the semiparameric estimatior of the coefficients. Confidence bands are

[14] See the first two chapters of Li and Racine (2007)

obtained by bootstrap method [15].

3.5.2 Scenario 1: base case

We consider the following two scenarios. In the first case, share of SOEs can only affect the efficiency of provincial S&T stock and S&T personnel on technology growth. The estimation model is specified as follow:

$$A_{it} = \beta_1(R^{SOE}_{it-1})ST_{it-1} + \beta_2 wST_{it-1} + \beta_3 F_{it-1} + \beta_4 X_{it-1} + \mu_i + \tau_{t-1} + \epsilon_{it-1} \tag{3.18}$$

The result of parameter estimation is shown below:

$$\begin{aligned} A_{it} =& \beta_1(R^{SOE}_{it-1})ST_{it-1} + \underset{(0.056)}{0.343} wk^{ST}_{it-1} + \underset{(0.634)}{0.846} wL^{ST}_{it-1} + \underset{(0.004)}{0.01} imp_{it-1} \\ & - \underset{(0.016)}{0.01} fdi_{it-1} + \underset{(2.836)}{38.89} col_{it-1} + \underset{(0.316)}{0.028} road_{it-1} \end{aligned} \tag{3.19}$$

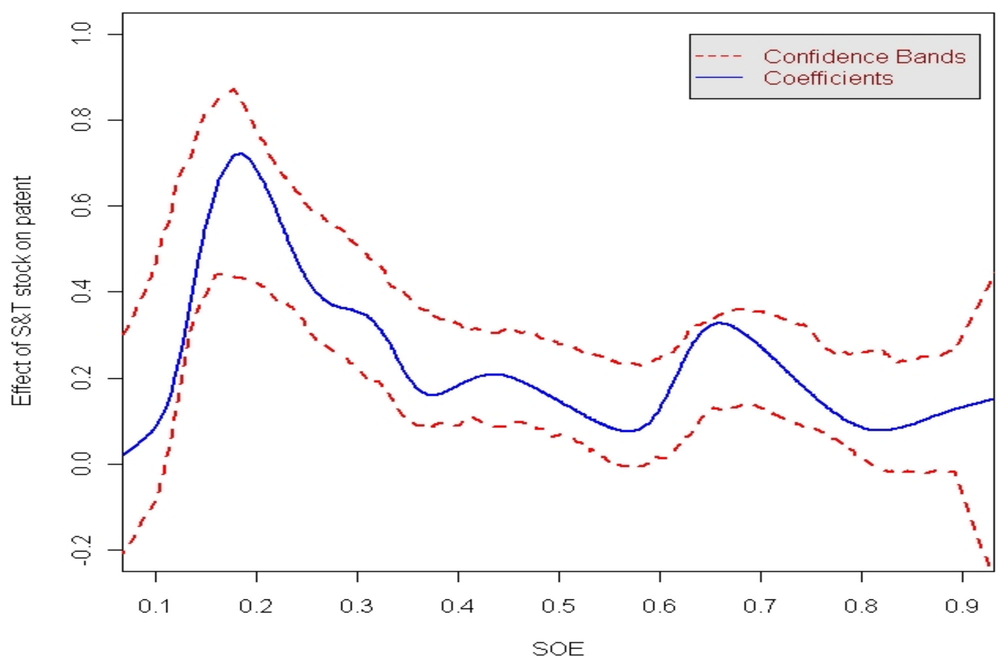
In this case, domestic spillovers are mainly through S&T stock externalities. Weighted S&T personnel of neighbor provinces has a positive effect of 0.846 on patent production, but such an effect is insignificant. International spillovers are only through imports, but the effects are still very small. 1% increase in import to GDP ratio can only increase the number of patent per 10,000 capita by 0.01 unit. Human capital has a big and significant effect on patent production. If 1% percent more people get college degree, there will be nearly 39 more patents per 10,000 capita. The infrastructures is not significantly relevant in this case.

Then we want to look at the indirect effect of R^{SOE} through S&T input. The coefficients of

[15] See the Appendix 3.6

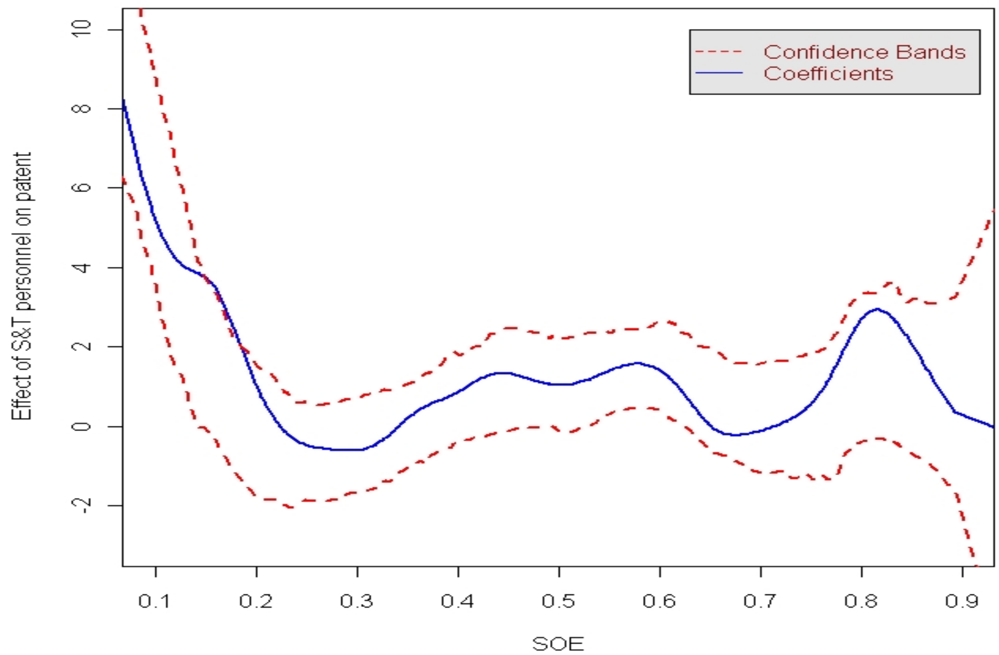
S&T stock and personnel on A vary with R^{SOE}. We do not assume a functional form, so we can only show the result by plotting the coefficients with R^{SOE}. The results are shown in Figure 3.3 and Figure 3.4. The solid line presents the coefficients β, which is the function of R^{SOE}, while the dash lines are the 95% confidence bands. Since for the majority provinces, R^{SOE} is scattered from 0.1 to 0.9, so we can neglect the extreme value with big confidence intervals.

Figure 3.3: Partial effect of R^{SOE} through S&T capital without spillovers



From Figure 3.3, we can see that when the share of SOEs is very low (below 0.2), higher R^{SOE} actually facilitates the efficiency of S&T stock on technology progress. It is commonly known that researches require huge initial investments and produce semi-public goods which have positive externalities. Private sectors are either incapable to conduct researches or unwilling to do that. Government, which is represented by SOEs in the economy, has responsibilities to participate in research activities. By the support of government, SOEs are able to launch

Figure 3.4: Partial effect of R^{SOE} through S&T personnel without spillovers



big projects and take the risk of failures. Therefore, a certain degree of nationalization is the precondition of technology development. However, once the share of SOEs increases beyond the necessary level, side-effects appear. The inconsistency between the government and the managers of SOEs results in principal-agency problem. Lack of monitoring leads to the overuse of resources and the inefficiency of production. Without competition and encouragement mechanism, SOEs have no incentive to innovate and improve the productivity. Negative effect counteracts the benefit brought by nationalization. In this stage, higher degree of nationalization has negative effects on patent production. No matter what, S&T stock always has positive effect on A.

Figure 3.4 represents the effects of R^{SOE} on technology through S&T personnel. The coefficient drops quickly as R^{SOE} increases until 0.2 then slightly increases with it. It contradicts with our expectation that higher ratio of nationalization actually increases the efficiency of S&T

personnel. However, we still find that as long as R^{SOE} is below 0.2, the coefficient of l^{ST} on patent will always be bigger that that when R^{SOE} is at a higher level. From the confidence interval, we can see that S&T personnel does not have significant effect on technology when R^{SOE} is bigger than 0.2. Therefore, S&T personnel is more efficient and only efficient when the share of R^{SOE} is small.

3.5.3 Scenario 2: more general specification

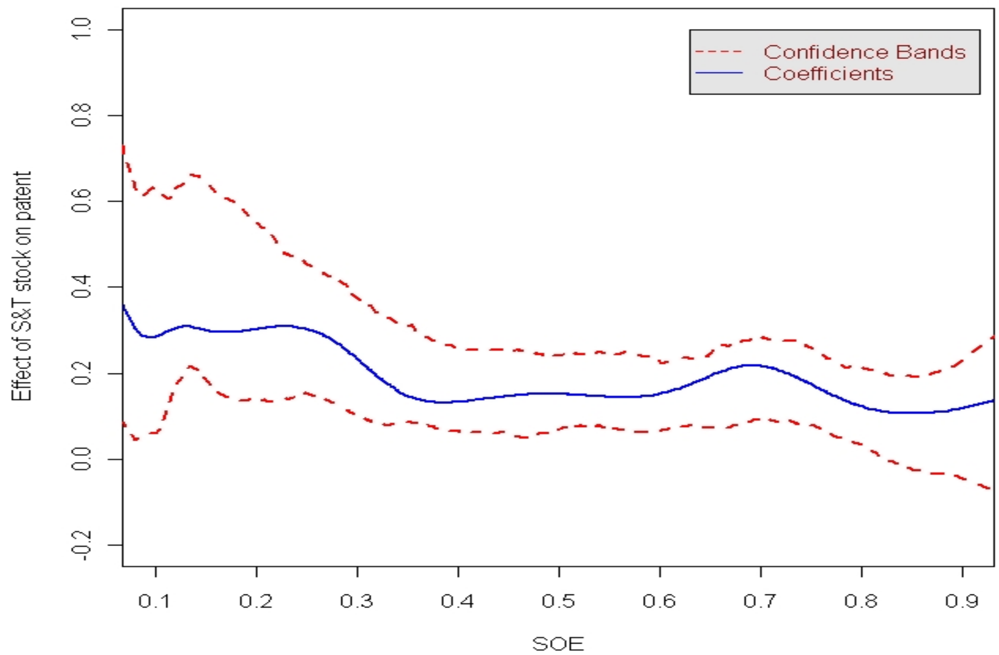
In this section, we look at a more general specification which assumes that domestic spillovers and international spillovers can also be affected by the degree of marketization so the coefficients of them are also the functions of R^{SOE}. Then we have the following result:

$$A_{it} = \beta_1(R_{it-1}^{SOE})ST_{it-1} + \beta_2(R_{it-1}^{SOE})ST_{it-1}^{w} + \beta_3(R_{it-1}^{SOE})F_{it-1} + \underset{(11.082)}{32.37}col_{it-1} - \underset{(0.114)}{0.034}road_{it-1} \tag{3.20}$$

Human capital still has a positive effect on patent production while infrastructure is irrelevant in this scenario, which is the same as the previous analysis. Next, we look at the indirect effects of R^{SOE} through S&T input, provincial and international spillovers. The results are shown from Figure 3.5 to Figure 3.10.

After we consider the complicated effects of R^{SOE}, from Figure 3.5, we can see that the effects of R^{SOE}on the coefficients of S&T stock change quite a lot. There is no positive relation between R^{SOE} and the coefficient anymore. Contrast to the previous case where nationalization can promote the efficiency of S&T capital when R^{SOE} is small, nationalization always plays an negative role on the S&T capital efficiency. But the negative effect is very minor. When R^{SOE} increases from 0.1 to 0.9, the efficiency of S&T capital only decreases from

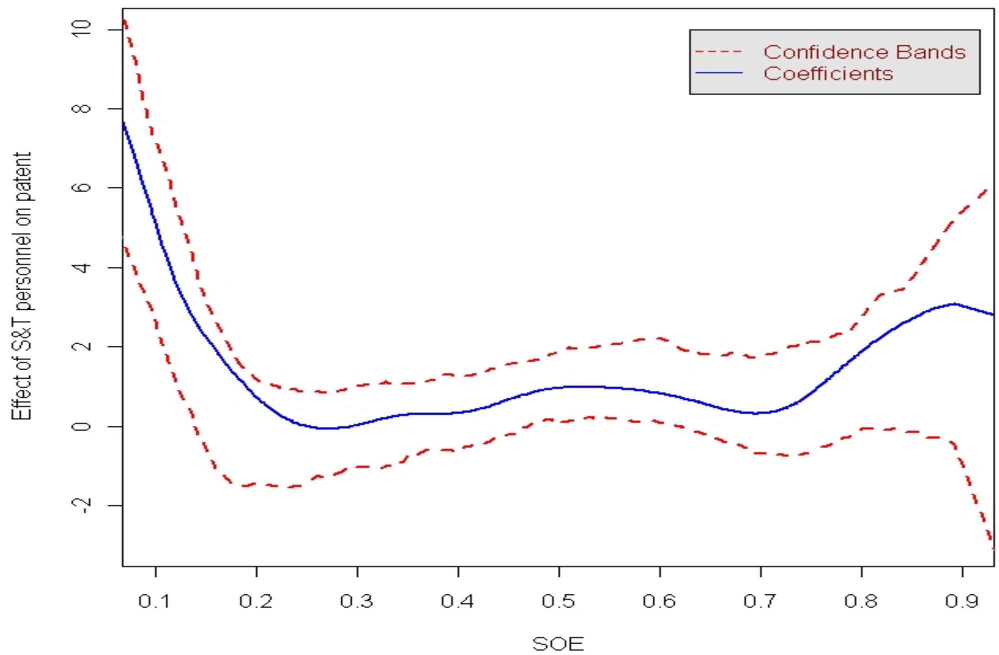
Figure 3.5: Partial effect of R^{SOE} through S&T capital with spillovers



around 0.4 to 0.2. We suspect that the previous positive effect may be due to the positive effect of R^{SOE} through some channels which are omitted in the specification. Figure 3.6 shows the indirect effect of marketization through S&T personnel with spillovers. We can see that the result is similar compared to Figure 3.4, but the relation curve becomes smoother. Except for the extreme value, zero is always cross the confidence bands. It implies that S&T personnel does not have a significant effect on technology development no matter how economic structure changes, which is consistent with the previous finding.

It is also intuitive to think that the provincial spillover effects can be affected by institutions. Better institutions can break the obstacle and facilitate the communication between the same industry or even upstream and downstream industries in two related provinces. Government can provide subsidies to research institutes so that they are willing to provide the semi-public goods and generate positive externalities to the neighbor provinces. We want to see what

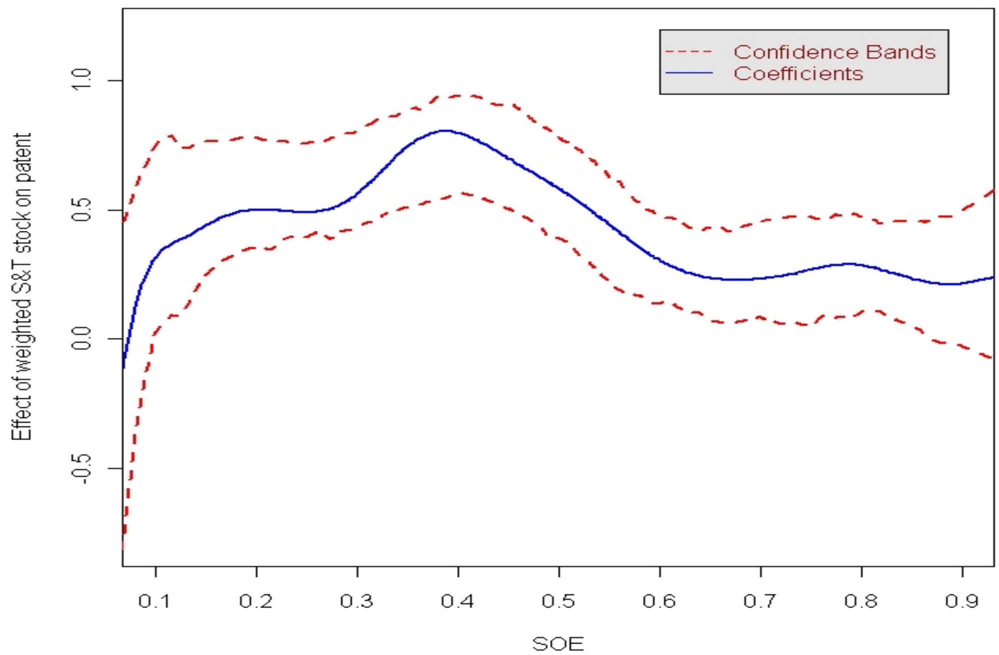
Figure 3.6: Partial effect of R^{SOE} through S&T personnel with spillovers



exactly the effects look like, therefore, we plot spillover effects with R^{SOE} in the following two figures.

The indirect effect of marketization on the S&T capital spillovers is obviously nonlinear in Figure 3.7. When R^{SOE} is below 0.4, it can largely promote the spillovers. When the share of SOEs increases by 10%, the coefficient of S&T capital spillover will increase by 0.2. We can conclude that, with certain level of nationalization, state government is capable to promote the positive externalities of S&T capital probably through research subsidy or tax reduction so that research institutes can internalize the positive externalities. Moreover, big state-owned enterprises have branches in several nearby provinces. Technology achievements are shared among branches so the S&T capital in the province where the headquarter is located can contribute to the technology development of the provinces where branches are built. However, once beyond the threshold, higher share of SOEs actually hurts the spillovers because

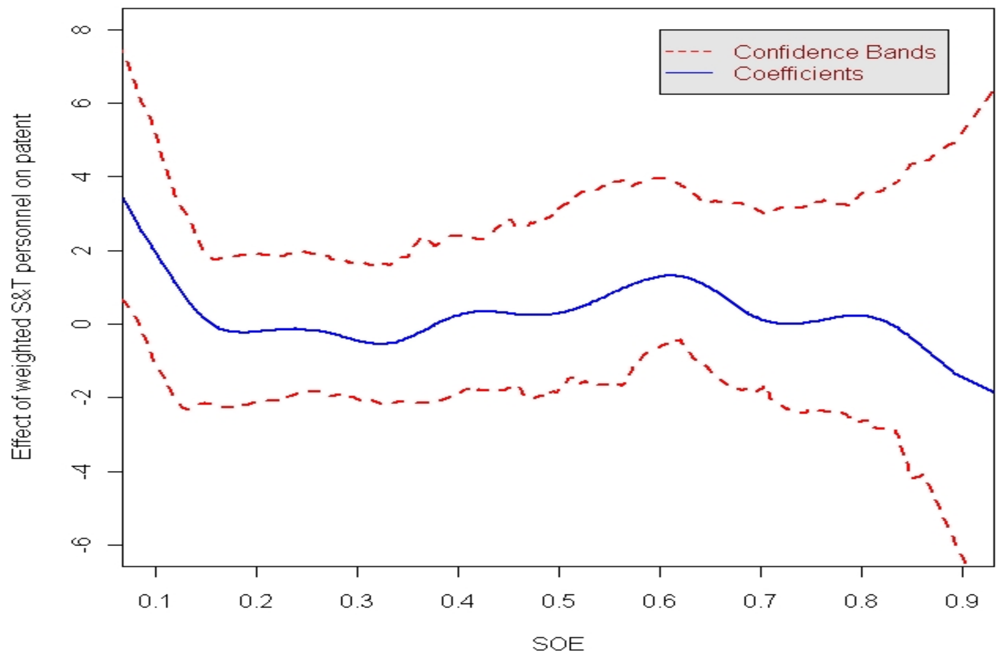
Figure 3.7: Partial effect of R^{SOE} through weighted S&T capital



of the traditional problem of bureaucracy. The spillovers disappear after R^{SOE} reaches 0.8. Therefore, as long as we keep the R^{SOE} below the threshold, nationalization actually benefits the S&T capital spillovers.

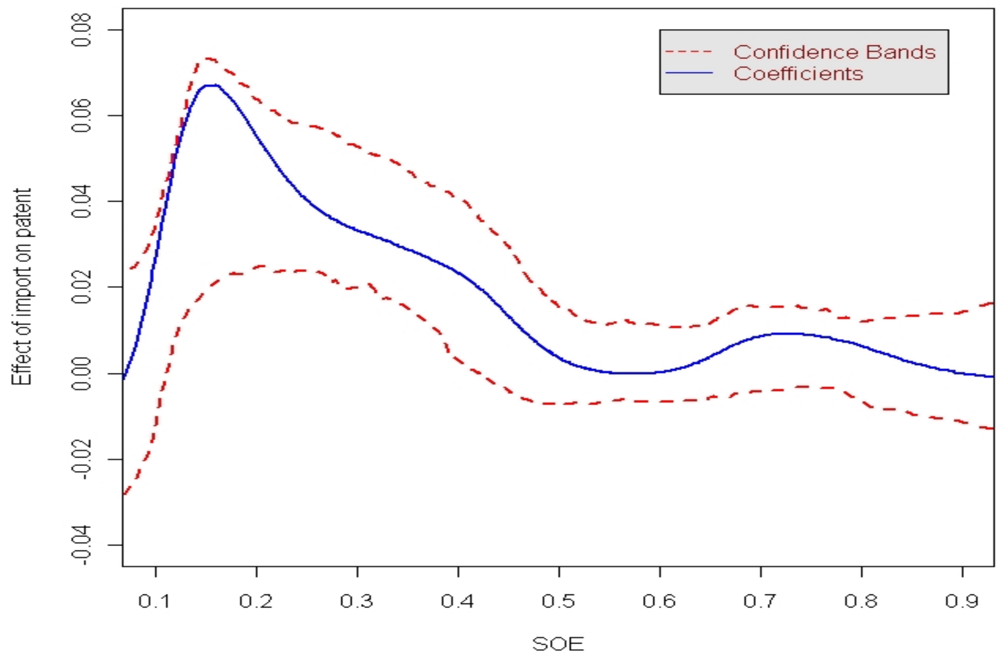
With respect to the spillovers of S&T personnel in Figure 3.8, generally it always falls down as R^{SOE} increases. Therefore, higher share of SOEs does not necessarily encourage the communications between researchers in different provinces. The side effects of nationalization, such as principal-agent problem and corruption offset the possible benefits it can bring. The confidence intervals tell us that weighted S&T personnel does not have significant effects on technology progress for most of the provinces at most stages of marketization. We conclude that R^{SOE} does not have any net effect through either own S&T personnel or weighted S&T personnel of neighbor provinces. The indirect effects of R^{SOE} are basically through the channel of S&T capital and weighted S&T capital.

Figure 3.8: Partial effect of R^{SOE} through weighted S&T personnel



When we take a look at the effects of R^{SOE} through imports in Figure 3.9, we find that higher R^{SOE} stimulates the technology spillovers from imports when R^{SOE} is below 0.2. We know that to imitate the advanced technology requires a certain level of research skills and R&D investment. The process to get the newly developed technology by reversing the production process is still uncertain, which is similar as the research activities. Big state-owned enterprises or research institutes are more capable to afford that. Therefore, a certain degree of nationalization actually does good to the international spillovers. We also find that the increase in the share of SOEs reduces the possibility of international spillovers when R^{SOE} is big. High share of state-owned enterprises impedes the market competition, scares away foreign capital and good inflows, and hurts the spillovers. Turning our attention to the FDI spillovers in Figure 3.10, we can see that it is not significant no matter how much the share of SOEs is. It confirms the previous conclusion that international spillovers in China are mainly

Figure 3.9: Partial effect of R^{SOE} through imports

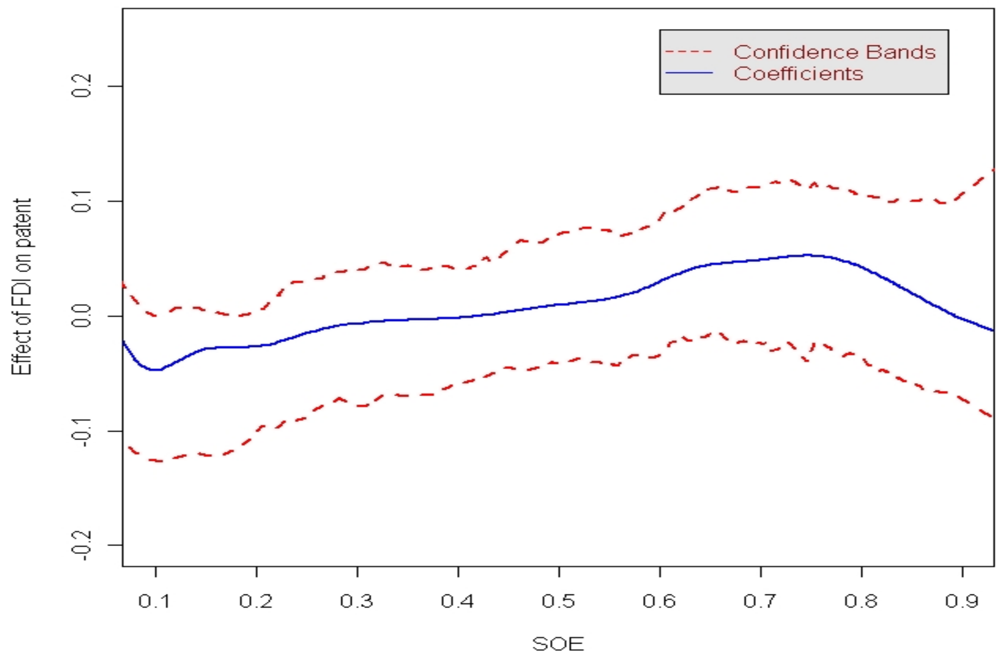


through imitation instead of foreign investment.

3.6 Conclusion

This paper comprehensively considers the direct and indirect determinants of the technology development in China since 1990. When only the basic S&T inputs, capital and personnel, are considered, both of them have significant positive effects on the patent production. Human capital and infrastructures have positive effects as well. If we go furthur and consider the technology spillovers between provinces, we find that S&T capital spillovers can stimulate the local technology progress but there are no significant provincial S&T personnel spillovers found in China. International spillovers are mainly through imitation of the imported high-technic good but not through the investment from foreign enterprises. Finally, we account for the indi-

Figure 3.10: Partial effect of R^{SOE} through FDI



rect effects of institutions, in particular, the marketization in China. Using varying-coefficient semiparametric estimation, we find that a small degree of nationalization does contribute to the technology progress through S&T capital spillovers and spillovers from imported good. But a high share of SOEs hinders technology development.

Appendix 1: Summary statistics

Table 3.4: Figure A1: Summary Statistics

	A	k^{ST}	l^{ST}	wk^{ST}	wl^{ST}
Coastal					
Beijing	5.17 (2.19)	64.03 (2.90)	3.41(0.28)	13.12(1.40)	1.17(0.23)
Tianjin	2.24 (1.29)	17.50 (1.95)	1.77 (0.36)	39.28(1.81)	2.11(0.18)
Heibei	0.43 (0.18)	5.08 (0.62)	0.28 (0.07)	18.73(1.26)	1.12 (0.15)
Liaoning	0.32 (0.14)	8.75(2.06)	0.52 (0.16)	13.20 (0.70)	0.74 (0.10)
Jilin	0.29 (0.13)	4.99 (0.27)	0.34 (0.05)	19.40 (1.10)	1.12 (0.14)
Heilongjiang	1.19 (0.51)	13.94(1.24)	0.85(0.10)	15.87(0.89)	0.99(0.13)
Shanghai	0.58 (0.24)	9.72(0.63)	0.63(0.12)	13.63(0.61)	0.82 (0.09)
Jiangsu	0.61 (0.26)	9.63 (0.42)	0.57 (0.06)	12.46(0.62)	0.78 (0.11)
Zhejiang	4.94(4.18)	25.61 (2.28)	2.38 (0.22)	7.78 (2.44)	0.55 (0.22)
Fujian	1.77 (1.68)	9.79 (2.58)	0.75 (0.25)	11.22 (1.81)	0.82 (0.12)
Shandong	3.13 (2.87)	5.97 (3.18)	0.49 (0.29)	17.71(1.92)	1.51 (0.16)
Guangdong	0.28(0.19)	5.54 (1.77)	0.25 (0.06)	11.20(1.78)	0.80 (0.17)
Hainan	1.01 (0.67)	4.30 (2.15)	0.34 (0.15)	10.04 (1.18)	0.67 (0.12)
Central					
Mongolia	0.25(0.11)	4.76 (0.42)	0.29 (0.04)	9.55 (1.25)	0.57(0.12)
Guangxi	0.98 (0.70)	6.74 (1.35)	0.43 (0.13)	16.15 (1.09)	1.02 (0.14)
Guizhou	0.34 (0.22)	6.14 (0.79	0.25(0.05)	12.58 (0.92)	0.71 (0.11)
Yunnan	0.51 (0.36)	10.39(0.96)	0.56 (0.11)	9.41(0.87)	0.51 (0.09)
Tibet	0.46 (0.23)	7.71 (0.43)	0.28 (0.06)	9.52(0.91)	0.55 (0.10)
Shaanxi	2.60 (1.94)	5.06 (1.27)	0.51 (0.24)	8.14 (0.83)	0.45 (0.08)
Gansu	0.23 (0.09)	4.98 (0.81)	0.18 (0.03)	7.55 (0.72)	0.43(0.09)
Qinghai	0.27 (0.13)	2.30 (0.41)	0.18 (0.06)	7.83 (0.89)	0.44 (0.10)
Ningxia	0.19 (0.11)	6.43 (0.45)	0.18 (0.02)	9.21 (0.63)	0.43(0.07)
Xinjiang	0.26 (0.11)	6.33 (0.31)	0.19 (0.04)	8.61 (0.54)	0.40 (0.05)
West					
Shanxi	0.13 (0.14)	2.44 (0.30)	0.16(0.09)	11.23(0.67)	0.60 (0.08)
Anhui	0.51 (0.24)	24.75 (2.04)	0.74 (0.04)	10.66 (0.89)	0.59 (0.09)
Jiangxi	0.20 (0.08)	13.94 (2.06)	0.45(0.05)	10.76(0.81)	0.54 (0.03)
Henan	0.20 (0.09)	9.29 (1.20)	0.48 (0.08)	13.27 (1.18)	0.52 (0.04)
Hubei	0.40 (0.21)	10.02 (0.55)	0.40(0.05)	12.86 (0.52)	0.62 (0.07)
Hunan	0.37(0.17)	5.35 (0.50)	0.39(0.04)	11.72(0.62)	0.63 (0.08)

The table summarizes the basic statistics. The number in each cell shows the mean of the variable and the number in parenthesis is the standard deviation

Table 3.5: Figure A1: Summary Statistics(continued)

	col	*imp*	*fdi*	*road*	*tel*	*soe*
Coastal						
Beijing	0.20 (0.06)	0.97 (0.37)	0.051(0.019)	0.86(0.17)	0.76 (0.54)	0.46(0.08)
Tianjin	0.11(0.04)	0.37(0.11)	0.076(0.038)	0.66(0.27)	0.48(0.34)	0.38(0.11)
Heibei	0.04(0.02)	0.03(0.01)	0.012(0.006)	0.40(0.16)	0.24(0.21)	0.44(0.11)
Liaoning	0.05(0.02)	0.03(0.01)	0.009(0.003)	0.39(0.16)	0.25(0.23)	0.49(0.09)
Jilin	0.05(0.02)	0.05(0.01)	0.007(0.003)	0.06(0.02)	0.26(0.24)	0.60 (0.08)
Heilongjiang	0.07(0.03)	0.14(0.03)	0.037(0.009)	0.38 (0.12)	0.37 (0.29)	0.63(0.06)
Shanghai	0.06(0.02)	0.09(0.02)	0.017(0.008)	0.24(0.09)	0.30(0.24)	0.37(0.09)
Jiangsu	0.05(0.01)	0.05(0.01)	0.010(0.005)	0.16(0.06)	0.28(0.23)	0.18(0.08)
Zhejiang	0.14(0.05)	0.54(0.22)	0.073(0.023)	0.44(0.18)	0.74(0.50)	0.15(0.08)
Fujian	0.05(0.02)	0.22(0.13)	0.057(0.015)	0.58(0.35)	0.37(0.29)	0.22(0.10)
Shandong	0.05(0.03)	0.12(0.05)	0.025(0.007)	0.50(0.20)	0.49 (0.40)	0.33(0.09)
Guangdong	0.03(0.02)	0.04(0.02)	0.010(0.004)	0.48(0.25)	0.18(0.16)	0.17(0.08)
Hainan	0.04(0.02)	0.22(0.03)	0.082(0.041)	0.47 (0.10)	0.39 (0.32)	0.47(0.15)
Central						
Mongolia	0.04(0.02)	0.03(0.01)	0.018(0.006)	0.37(0.17)	0.18(0.16)	0.63(0.15)
Guangxi	0.04(0.02)	0.09(0.03)	0.026(0.012)	0.59(0.32)	0.26(0.23)	0.51(0.10)
Guizhou	0.03(0.02)	0.02(0.00)	0.008(0.003)	0.57(0.35)	0.19(0.17)	0.67(0.08)
Yunnan	0.05(0.02)	0.04(0.01)	0.017(0.006)	0.47(0.22)	0.23(0.20)	0.66(0.08)
Tibet	0.04 (0.02)	0.02 (0.005)	0.014(0.006)	0.42(0.17)	0.19(0.17)	0.66(0.12)
Shaanxi	0.05(0.02)	0.68 (0.08)	0.087(0.042)	0.60 (0.18)	0.52 (0.42)	0.60(0.05)
Gansu	0.03(0.02)	0.04(0.02)	0.023(0.013)	0.24(0.07)	0.18(0.17)	0.65(0.03)
Qinghai	0.04(0.02)	0.21(0.09)	0.129(0.067)	0.50(0.08)	0.26(0.22)	0.72(0.06)
Ningxia	0.03(0.01)	0.02(0.00)	0.004(0.002)	0.31(0.16)	0.13 (0.13)	0.62(0.11)
Xinjiang	0.02(0.01)	0.04(0.01)	0.010(0.007)	0.31(0.14)	0.17(0.15)	0.68(0.02)
west						
Shanxi	0.010(0.004)	0.14(0.14)	0.003(0.005)	0.03(0.01)	0.17(0.18)	0.55(0.07)
Anhui	0.05(0.02)	0.04(0.01)	0.015(0.007)	0.29(0.13)	0.25(0.23)	0.40(0.09)
Jiangxi	0.03(0.01)	0.04(0.02)	0.005(0.003)	0.11(0.05)	0.19(0.17)	0.55(0.13)
Henan	0.05(0.02)	0.01(0.01)	0.005(0.005)	0.04(0.02)	0.23(0.21)	0.49(0.12)
Hubei	0.06(0.02)	0.03(0.01)	0.009(0.008)	0.18(0.06)	0.26(0.23)	0.46(0.08)
Hunan	0.08(0.03)	0.05(0.02)	0.003(0.002)	0.04(0.02)	0.28(0.25)	0.49(0.11)

The table summarizes the basic statistics. The number in each cell shows the mean of the variable and the number in parenthesis is the standard deviation

Appendix 2. Boostrap

We use regular boostrap method to find the confidence band. First, we get the fitted value by plugging the estimated coefficients into equation (13) and eliminate the individual effect and time effect:

$$\tilde{v} = \tilde{Y} - \hat{\tilde{Y}}$$

$$\hat{\tilde{Y}} = \tilde{W}\hat{\gamma} + \tilde{X}\hat{\beta}(Z_{it})$$

Then we resample the residuals without replacement, add them back to the fitted value and get new $\tilde{Y}$. We use the new $\tilde{Y}$ in the estimation and get new estimated parameters. We repeat the process 199 times. For each evaluation point, we pick up the 5th and the 195th value and use them as the lower bond and the upper bond of the confidence interval. We get the confidence bond by connecting the lower bond and upper bond of all the evaluation points.

Chapter 4

Provincial Technology Transfer and Absorptive Capacity in China

(ABSTRACT)

While technology transfer and absorptive capacity have been theoretically proven and empirically tested in OECD countries, this paper aims at examining whether they exist in developing countries such as China. First, this paper defines the potential of technology transfer from the frontier in two ways: technology distance because of the structural discrepancy in the patent portfolio and technology gap due to the difference in the patent level. Empirical analysis shows that the factors such as S&T investment(expenditure), road density and international spillovers through imports and FDI have positive effects on patent growth. It also shows that technology transfer due the technology distance can stimulate patent growth. However, it fails to find the robust evidence of technology transfer due to technology gap. The finding suggests that the provincial technology convergence does not exist in China.

4.1 Introduction

Walking toward a knowledge-driven economy, China has begun to develop its high-tech industries and leaped into the information episode since the early 1990s (Lu (2000)). In 2006, the global share of China's high-tech exports [1] surged to 16.9%[2], followed by the US's 16.8%, EU-27's 15% and Japan's 8% (Meri (2009)). "In the past 15 years, China has moved from 14th place to 2nd in the world in published research articles, trailing only the U.S. now[3]." China's R&D spending has been increasing dramatically for decades. Its R&D intensity (R&D/GDP ratio) increased to 1.7% in 2007, which is amazing among developing countries. Literature has identified some factors of technology development in China, such as R&D input (Cheung and Lin (2004); Lai et al. (2006)), FDI (Cheung and Lin (2004); Fleisher et al. (2010); Lin et al. (2009); Lin and Kwan (2011); Liu (2008)), information and communication technology (ICT) investment (Shiu and Heshmati (2011)) and institutions (Fleisher and Zhou (2010); Du et al. (2011)). However, it neglects the interactions among the provinces. In this paper, we specifically consider the technology spillovers (provincial technology transfer and absorptive capacity) among the provinces in China:

Absorptive capacity is first discussed in the literature of business administration. Cohen and Levinthal (1989) suggest that R&D not only generates new information, but it also enhances the firm's ability to assimilate and exploit existing information. They call it "the two face of R&D". In Cohen and Levinthal (1990), they formally specify this idea as absorptive capacity, which is "a firm's ability to recognize the value of new information, assimilate it, and apply it to commercial ends". They empirically evaluate the importance of absorptive capacity for innovation by considering the responsiveness of R&D activity to learning incentives. Ex-

[1]Based on OECD definition, high-tech products are defined, in this case, using Standard International Trade Classification (SITC) codes. For that latter study, high-tech manufactures include the following SITC codes: 524, 541, 712, 716, 718, 751, 752, 759, 761, 764, 771, 774, 776, 778, 792, 871, 874, and 881.

[2]However, 82% of the high-tech exports was processed/assembled high-tech products, mainly made of imported parts and components from industrialized economies (Xing (2011))

[3]Source: News " U.S. Falling Behind China in High-Tech Manufacturing"

tending the idea to the country level, international trade literature considers the absorptive capacity in the analysis of international technology spillovers. Instead of economic growth convergence, some studies consider the productivity convergence in which labor productivity growth tends to vary inversely with productivity level (Abramovitz (1986), Madsen (2007)). Griffith et al. (2003) present a structural model of Schumpeterian endogenous growth and provide the microeconomic foundations for the reduced-form equation of productivity convergence. Griffith et al. (2004) empirically examine the assumption of productivity convergence (technology transfer) as well as the two faces of R&D (innovation and absorptive capacity). They find that R&D is economically important in both technological catch-up and innovation in OECD countries. Girma (2005) analyzes the absorptive capacity of FDI in UK manufacturing industry by endogenous threshold model, and finds that the productivity benefit from FDI increases with technology until some threshold level. Lai et al. (2009) adopt the similar method and finds two thresholds in the technology gap of China's industry sector. The purpose of this paper is to find whether provincial technology transfer and convergence exist in China and whether R&D can help enhance the technology transfer.

The rest of the paper is arranged as follows: Section 5.2 reviews the literature and propose some possible factors of technology development. Section 5.3 focuses on the provincial technology transfer and absorptive capacity, describing the model specifications. Section 5.4 talks about the data. Section 5.5 examines two different forms of technology transfer and absorptive capacity, and identifies the determinants of technology growth. Section 5.6 considers the regional heterogeneity to see whether different provinces have different growth patterns. Section 5.7 summarizes and concludes.

4.2 Determinants of S&T development

4.2.1 S&T inputs

Following the literature, we treat the technology development as a production process. Two basic inputs are capital and labor, which are measured by S&T expenditure and S&T personnel (or R&D expenditure and R&D personnel). The difference between the production of final product and the production of S&T is that more inputs will result in more outputs in the production of final product but uncertainty exists in the technology production. There are always risks in the development of technology. A lot of inputs may produce no technology output if the innovation fails. Therefore, S&T inputs are always considered the basic determinants of technology progress but they enter the production functions in different ways. S&T inputs can be represented by S&T expenditure, S&T capital stock, S&T personnel, S&T expenditure to GDP ratio, in lag term, in linear or log linear specification. They are either at country level, or province and regional level, or even as small as industrial and firm level (Coe and Helpman (1995), Coe et al. (2009), Hu et al. (2005), Zhang et al. (2003), Cheung and Lin (2004), Griliches (1998)). S&T expenditure may be endogenous since there potentially exist factors that affect both the technology progress and S&T expenditure. Fleisher and Zhou (2010) instrument the current R&D stock with the previous R&D stock, patent law, export, FDI and so on, and then use the fitted value as the explanatory variable of innovation patent applications. Among these empirical analyses, most of them find significant positive effects of R&D stock (or expenditure) on technology progress in China or other countries in the world. However, some studies, such as Cheung and Lin (2004), find insignificant effects of S&T expenditure on patent application. In this paper, we use both S&T expenditure and S&T personnel as the technology inputs, and see how they affect the growth of patent application.

4.2.2 International spillover effects

As the connections between countries become stronger and stronger, no country in the world is now isolated. Developing countries can benefit from the advanced technology created by developed countries through international trade and foreign investment due to the non-rival and non-excludable nature of technology. By imports, especially the imports of high-tech products, developing countries are able to reverse the production process so as to imitate the new technology.

Since the enforcement of the Open-door policy[4], China has received unprecedented amount of foreign investment. In 2009, more than 200 billion (USD) FDI was invested in China, which was nearly 20 times as much as that in 1990. The actually used FDI, which reflects the FDI efficiency, also increases from 3.5 billion in 1990 to more than 90 billion recently. The effects of FDI on economic growth and technology development are still under debates. A plethora of papers have studies on it (Cheung and Lin (2004); Fleisher et al. (2010); Lin et al. (2009); Lin and Kwan (2011); Liu (2008)). Theoretically, when receiving FDI, local affiliates are granted the authority to use the innovation developed by the multinational firms. Moreover, other local firms have more chances to "steal" the technology by either "copying" it or hiring technicians trained by multinational firms. FDI also boosts competition. Through these channels, FDI can potentially increase the productivity of local industries. However, empirical works either fail to find the positive correlation between FDI and productivity growth or fail to construct the causal relationship between them. Researches argue that it may be wrong to look at horizontal spillovers since multinationals have an incentive to prevent information leakage, so vertical spillovers are more likely to happen (Javorcik (2004)). When we look at the special case of China, things become more optimistic. Fleisher et al. (2010) consider the two-period lag of FDI and find that it significantly improves TFP growth after Deng Xiaoping's "South

[4] The new policy designed by Deng Xiaping since 1978. It is a capitalist-inclined system that promoted market forces, committed China to adopting policies which promote foreign trade and economic investment.

Trip". Cheung and Lin (2004) find that FDI inflow has positive effects on general patent application as well as three types of patent application: invention, utility model, external design. Shiu and Heshmati (2011) innovatively calculate TFP growth by time trend (TT) approach and general index (GI) approach and find positive but insignificant effects of FDI. Industrial and Firm level data are needed to examine the horizontal or vertical spillovers. Lin et al. (2009) investigate the FDI spillovers to the firms over certain scale and find positive and heterogeneous backward and forward spillovers by different firm types and different sources of FDI. The effects of imports on technology spillovers have been talked a lot among OECD countries (Coe and Helpman (1995), Coe et al. (2009), Engelbrecht (1997), Guellec and Van Pottelsberghe de la Potterie (2004), Madsen (2007) and Acharya and Keller (2008)) following the seminal paper of Coe and Helpman (1995). However, only a few (Yu (2009)) have been found on the studies of China.

4.2.3 Infrastructures

Infrastructures are the foundation of economic development and technology progress. "At the beginning of reform, transportation and communications infrastructure were poor, but governments at various levels have invested heavily in the construction of highways, expansion of rail systems, and development of electronic communication facilities(Fleisher et al. (2010))." Better infrastructures facilitate the research activities. It takes an irreplaceable position in technology production and transfer. Fleisher et al. (2010) take road density and telecommunication as two representative infrastructures and find that two period lag of telecommunication has significant positive effects on TFP growth. Besides these two, Shiu and Heshmati (2011) also take into account the ICT (information and communication technology) and find the significant effects of it.

In this paper, we loot at the road density and the telecommunication as well. Since the infrastructures have been improved these years, the two variables may have upward time trend or unit root which makes them nonstationary. More than using the variables directly, we group the provinces into four categories: excellent, good, medium and bad, and compare the effects of different groups on technology development.

4.3 Provincial spillovers and absorptive capacity

Domestic spillovers, or we can say provincial spillovers, have seldom been studied compared with the international spillovers. By using the same language, provinces can easily communicate with each other, sharing their achievements with lower cost. Central government also has the policies that eastern developed provinces should help the western less developed provinces. In this sense, there should be strong spillover effects among provinces. The measure of provincial spillovers is challenging. Lin and Kwan (2011) use the spatial weighted FDI of nearby neighboring counties to measure the spillovers and find that FDI which presences in one county will generate negative spillovers to domestic private firms in the same locality. Liao (2011) use driving-time weighted average of S&T inputs of the neighbor provinces to show the spillovers.

In this paper, we model the provincial spillovers in another way. Following Griffith et al. (2004), we use the technology difference between the targeted province and the frontier province to represent the potential of technology transfer and technology catch-up. The interaction terms of S&T inputs and technology distance present the absorptive capacity. Therefore, the technology development can be written as:

$$\Delta A_{it} = \underbrace{\beta_1 ln\left(\frac{A_F}{A_i}\right)_{t-1}}_{technology \quad transfer} + \underbrace{\beta_2 \left[ln(R_{i,t-1}) ln(\frac{A_F}{A_i})\right]_{t-1}}_{absorptive \quad capacity} + \beta_3 ln(R_{i,t-1}) + \beta_4 X_{it-1} + \mu_i + \tau_t + v_{it} \tag{4.1}$$

where A_{it} represents the technology level of province i at time t, and A_{Ft} represents the technology level of the frontier province at time t. $R_{i,t-1}$ is the R&D investment of i at $t-1$. X_{it-1} shows one-period lag of the control variables. Notice that there is no technology transfer from the frontier to itself.

In Branstetter (2001), he uses the degree of similarity in individuals' patent portfolios to measure the "distance" in "technology space". If two individuals have very different patent structures, the technology distance between them is big. In this paper, we use technology distance from the frontier to show the potential to assimilate the advanced different technology from the frontier. Assume that $\mathbf{f}_i = (f_{i,1}, f_{i,2}, ...)$ represents the technology portfolio of province i. Technology distance can be represented as follows:

$$ln(T_{ij}) = ln\left(\frac{A_j}{A_i}\right) = ln\left[\frac{[(\mathbf{f}_i\mathbf{f}_i')(\mathbf{f}_j\mathbf{f}_j')]^1/2}{(\mathbf{f}_i\mathbf{f}_j')}\right], \ \ where \ \ j = F \tag{4.2}$$

In this paper, we not only consider the technology distance in individuals' patent portfolios, but also take into account of the difference in the magnitude of patent portfolios, which is called "technology gap". We use Equation 4.3 to present that. If a province has much smaller number of patents compared with the frontier, the technology gap to the frontier is very big. The further the technology gap, the more technologies can be assimilated from the frontier. It reflects a province's potential to assimilate advanced technology from the frontier and also shows the possibility of technology convergence.

$$ln(MT_{ij}) = ln\left(\frac{A_j}{A_i}\right) = ln\left[\frac{[(\mathbf{f}_j\mathbf{f}_j')]}{(\mathbf{f}_i\mathbf{f}_i')}\right], \ \ where \ \ j = F \tag{4.3}$$

In Griffith et al. (2004), they assume frictionless technology transfer without cost no matter how far the distance is. However, knowledge and information flow more easily among agents located in the same area due to social bonds that foster reciprocal trust and promote frequent face-to-face contacts (Breschi and Lissoni (2001)). In our paper, we consider the economic closeness which may also affect the technology transfer. If a province has a closer relationship with the frontier provinces, technology transfer may be stronger. Closer geographic distance reflects a closer economic relationship. In this paper, we don't use the geographic distance directly. Instead, we adopt the driving time because it not only represents the geographic distance but also shows the road condition and transportation ability.

$$\Delta A_{it} = \beta_1 \frac{1}{ln(D_{Fi})} ln\left(\frac{A_F}{A_i}\right)_{t-1} + \beta_2 \frac{1}{D_{Fi}} \left[ln(R_{i,t-1}) ln(\frac{A_F}{A_i})\right]_{t-1} + \beta_3 ln(R_{i,t-1}) + \beta_4 X_{it-1} + \mu_i + \tau_t + v_{it} \tag{4.4}$$

where D_{Fi} represents the closeness between the frontier province and province i. To make the results comparable, we standardize the $ln(D_{Fi})$ so that $\sum_i 1/ln(D_{Fi}) = N$, where N is the total number of provinces.

Regional heterogeneity is a big issue in the analysis of China's economic growth and technology development. The coastal region has the fastest economic growth, accounts for more than 60% of national GDP and owns around 70% of the total S&T capital stock. The central region and the western region are far more behind. It is highly possible that the three regions follow different patterns in technology development and spillovers. Therefore, we run regressions for different regions separately. For central and western regions, the distances between the national frontier (usually in coastal area) and themselves are usually long, which makes the technology transfer weak. In this sense, we assume that each region may have its own technology frontier, and the provinces in different regions can assimilate advanced technology from local frontier.

$$\begin{aligned}\Delta A_{i,s,t} =& \beta_1 ln\left(\frac{A_{F,s}}{A_{i,s}}\right)_{t-1} + \beta_2 \left[ln(R_{i,s,t-1}) ln(\frac{A_{F,s}}{A_{i,s}})\right]_{t-1} + \beta_3 ln(R_{i,s,t-1}) \\ &+ \beta_4 X_{i,s,t-1} + \mu_{i,s} + \tau_t + v_{i,s,t}\end{aligned} \tag{4.5}$$

where s represents the region and $A_{F,s}$ is technology level of the regional technology frontier.

4.4 Data

The data mainly comes from China Statistic Yearbook (CSY) and China Statistic Yearbook on Science and Technology (CSYST). It is annual data from 1990-2009. There are 29 provinces in the sample, excluding Sichuan, Chongqing and Tibet. Summary statistics are shown in Table 4.1

Technology output is measured by the number of patent applications each year of each province. We use the grow of patent applications to measure the technology development. There are three categories of patents in China: inventions, utility models and designs [5]. Figure 4.1 shows the provincial average growth of patent applications for each region. We are surprised to find that different regions have pretty similar technology growth patterns. It has an obvious drop from 1990 to 1995 and then fluctuatingly increases afterward. However, if we take a deeper look at it, we can still find the coastal area has the highest patent growth and northeast has lowest one.

R&D investment and R&D personnel are generally used as technology inputs. Due to the data limitation in China, only intramural expenditure for Science and Technology (S&T expenditure) and S&T personnel for provinces are available. S&T indices are broader defined than R&D indices but still related to the technology development, so they are proper to use in this paper. We use $ln(ste)$ to show the log of S&T expenditure and $ln(stp)$ to show the log

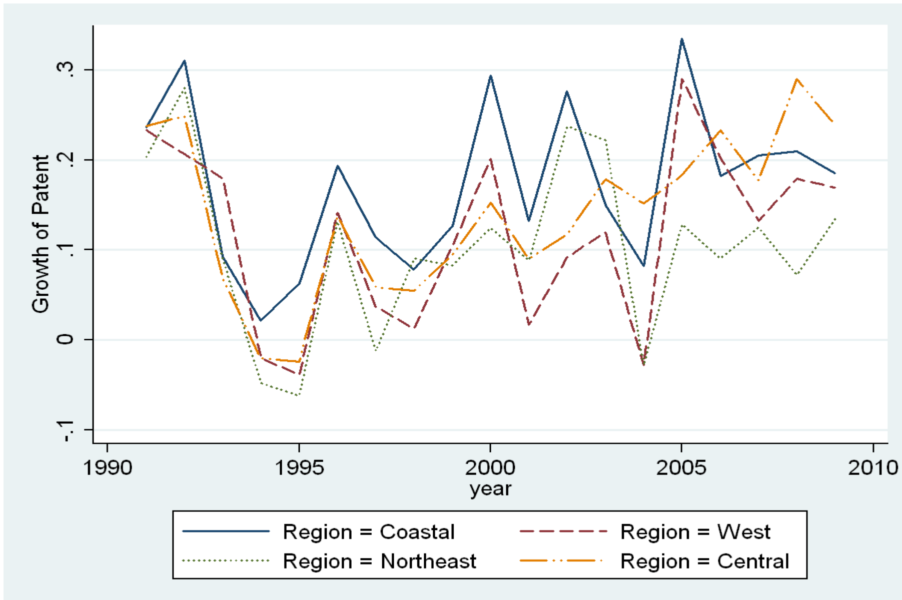
[5] Invention refers to the new technology for product, production method or its improvement. According to the general international standard, it is the core indicator for the independent intellectual property rights. Utility model refers to the improvement in the shape of products, the structure of product or both. It reflects the achievement with certain technology content. Design refers to the new industrial design for products' shape, pattern, color or combination which increases the aesthetic feeling. It reflects the achievements of exterior design.

Table 4.1: Summary Statistics

Variable	Region	Mean	Std. Dev.	Min	Max
$\Delta ln(patent)$	Eastern	0.1731	0.0894	0.0213	0.3344
	Western	0.1174	0.0969	-0.0384	0.2896
	Northeasten	0.1028	0.0940	-0.0618	0.2800
	Central	0.1404	0.0893	-0.0237	0.2897
$ln(ste)$	Eastern	3.4664	0.9733	2.2074	5.1537
	Western	1.8649	0.7063	1.0700	3.3133
	Northeasten	3.1408	0.6939	2.3396	4.4383
	Central	2.9544	0.8695	2.0054	4.6151
$ln(stp)$	Eastern	11.5188	0.4250	11.0860	12.4221
	Western	10.4187	0.1526	10.2353	10.8518
	Northeasten	11.5245	0.1639	11.2605	11.8882
	Central	11.4164	0.2955	11.0299	12.0642
$road$	Eastern	0.5589	0.2416	0.3188	1.0401
	Western	0.1761	0.0899	0.1038	0.3711
	Northeasten	0.2592	0.1177	0.1716	0.4948
	Central	0.4486	0.2870	0.2328	1.0198
tel	Eastern	0.4523	0.3975	0.0264	1.1172
	Western	0.2168	0.2332	0.0091	0.6924
	Northeasten	0.3148	0.2934	0.0169	0.8411
	Central	0.2033	0.2149	0.0069	0.6320
$ln(imp)$	Eastern	15.8091	1.2786	13.0109	17.4514
	Western	12.5707	1.1575	10.0072	14.2537
	Northeasten	14.6085	0.9398	12.5337	15.9192
	Central	13.4933	1.1686	11.1397	15.3035
$ln(fdi)$	Eastern	14.2305	1.2004	10.8719	15.3553
	Western	10.5539	1.8394	6.3082	12.5138
	Northeasten	12.9602	1.2070	9.9401	14.1040
	Central	12.5042	1.4590	8.3955	13.8036

The table shows the summary statistics of the main variables used in this paper. Each variable is the average level of the region.

Figure 4.1: Growth of Patent



of S&T personnel. From Table 4.1, we can see eastern area[6] is always ranked first during the whole sample years, followed by central and Western.

Import is the total value of provincial import by location of China's Foreign Trade Managing Units. In this paper, we use the log value of import in RMB as one way of international spillovers. Regarding FDI, we use the actually used foreign direct investment in RMB by provinces. Coastal region has the highest average log imports as well the the log FDI, followed by the northeast, central. West region always has the lowest level for both.

Considering the infrastructures, we mainly focus on the road density and telecommunication. Road density is measured by the total length of highway per squared kilometer. The far west areas such as Qinghai and Xinjiang have the lowest road density, even below 0.1 in 2009. For the eastern provinces with high population density, the road density is also high.

[6]In Statistic Yearbook of China, provinces are divided into four regions: Eastern, Central, Northeast and West. Eastern area includes: Beijing, Tianjin, Heibei, Shanghai, Jiangsu, Zhejiang, Fujian, Shangdong, Guangdong, Hainan. Liaoning, Jilin, Heilongjiang are considered northeast region. Central area include: Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan. Western area includes Mongolia, Guangxi,Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

Telecommunication is calculated by the ratio of telephone and cellphone subscribers to the total population. Twenty years ago, there was only 1 telephone for more than 10 people. In the contrast, right now everybody has at least one telephone (cellphone) for most of the provinces. There are obviously upward trends in the time series of infrastructures. The possible spur-regression renders the credit of the results. To avoid this problem, we rank each province's infrastructure resources and divide provinces into four groups: high, median high, median low and low. There are seven provinces belonging to each group. Bejing, Tianjin, Shanghai, Zhejiang and Guangdong are always among the first tier. Guanxi, Guizhou and Gansu are ranked in the low group for the whole sample period. The middle two groups have a lot of variations.

4.5 Basic empirical result

To estimate the technology transfer and absorptive capacity, we first need to define the technology frontier. In this paper, we define the technology frontier as the province with the highest number of patent applications each year. From the data, we find that from 1990-1994, Beijing is the technology frontier. However, it changes to Guangdong from year 1995-2007. In 2008 and 2009, Jiangsu is the frontier province. Technology distance and technology gas are defined as Equation 4.2 and 4.3. There are three types of patents so we treat them as three items in the technology portfolio. The bigger difference in the technology structure (portfolio) between itself and the frontier, the bigger technology distance it is. The technology distance from frontier to itself is 0. The technology distance fluctuates a lot. For most of the provinces, the initial difference is negligible. The difference goes bigger first and then goes smaller, finally becomes bigger in the recent years. In the following analysis, we want to see the effects of technology distance on the provincial technology development. Meanwhile, we want to see whether S&T puts can help to assimilate the advanced technology from the frontier province.

4.5.1 Frictionless technology transfer

First, we adopt the specification of Griffith et al. (2004) and consider the frictionless technology transfer because of the difference in the patent portfolio (or structure). For a province, the technology distance between the frontier province and itself reflects the potential of technology transfer no matter whether it is far away from the frontier or whether it has any economic connection with the frontier. We also consider some other factors which may affect the technology growth. The results of baseline regression are shown in Table 4.2.

In regression 1, we just consider the basic S&T inputs and technology transfer. We see that more S&T expenditure will lead to higher patent growth. If S&T expenditure increases by 1%, the growth of patents can be accelerated by 0.07%. The average growth rate of S&T expenditure after 2000 is about 20% every year, which leads to 1.4% increase in patent growth. Higher level of S&T personnel yields lower technology growth, suggesting the decreasing marginal returns but the magnitude is not very big. The coefficient of technology transfer is significantly positive. It means that bigger difference in the structure of technology with frontier, higher technology growth.

Next step we want to see the absorptive capacity, so we interact the technology distance with the S&T inputs. It reflects the capability to assimilate the new technology from the frontier. From regression 2 to regression 4 we can see that the coefficients of technology transfer are still significantly positive. Meanwhile, the magnitudes increase nearly twice compared with regression 1. The coefficient of interaction term of technology difference with S&T investment is also positive, suggesting the positive absorptive capacity. And the magnitude shows that the absorptive capacity of S&T investment has bigger effects than the effects of S&T investment itself on patent growth. However, the interaction term with S&T personnel is negative. It may due to the multicollinearity with S&T personnel. About the infrastructures, road density positively affects patent growth while the telephone usage has insignificant effects. If we group

Table 4.2: Baseline Regression: Frictionless Technology

	1	2	3	4	5	6
$L.ln(ste)$	0.0709**	0.0525*	0.0421	0.0473	0.0114	0.0171
	(0.0296)	(0.0315)	(0.0318)	(0.0319)	(0.0326)	(0.0327)
$L.ln(stp)$	-0.0568*	-0.0228	-0.0316	-0.0162	0.0058	0.0116
	(0.0324)	(0.0381)	(0.0384)	(0.0387)	(0.0394)	(0.0395)
$L.ln(t_{ij})$	0.0818*	1.4915*	1.4764*	1.5565*	1.6175**	1.6192**
	(0.0469)	(0.8061)	(0.8046)	(0.8117)	(0.8038)	(0.8108)
$L.ln(t_{ij}) * ln(ste)$		0.1077**	0.1103*	0.1145*	0.1033	0.0968
		(0.0669)	(0.0667)	(0.0674)	(0.0676)	(0.0683)
$L.ln(t_{ij}) * ln(stp)$		-0.1526*	-0.1505*	-0.1590*	-0.1617*	-0.1611*
		(0.0872)	(0.0871)	(0.0878)	(0.0871)	(0.0879)
$L.road$			0.1056**		0.0994**	
			(0.0489)		(0.0507)	
$L.tel$			0.0128		-0.0144	
			(0.0480)		(0.0491)	
$L.tier2$				-0.0364		-0.0142
				(0.0294)		(0.0301)
$L.tier3$				-0.0356		-0.0095
				(0.0362)		(0.0368)
$L.tier4$				-0.0263		-0.0055
				(0.0423)		(0.0425)
$L.ln(imp)$					0.0393**	0.0442***
					(0.0163)	(0.0158)
$L.ln(FDI)$					0.0131**	0.0105*
					(0.0063)	(0.0061)
LLC	-0.9178***	-0.9288***	-0.9513***	-0.9387***	-0.9823***	-0.9690***
obs	532	532	532	532	532	532
Adj R2	0.275	0.277	0.281	0.275	0.297	0.291

The table shows the results of baseline regression when technology transfer is frictionless. The dependent variable is growth of patent. We use panel two-way fixed effect model. ste is the S&T expenditure and stp is S&T personnel.$ltij$ is the technology distance. $road$ is the length of road per km^2 while tel is the telephone subscriber per person. imp is the value of imports in RMB and FDI is the utilized FDI in RMB. $tier2$, $tier3$ and $tier3$ are the dummies for good, median and bad infrastructures. All the independent variables are lagged by 1 period. The number in each cell represents the coefficient and the number in parentheses represents the standard deviation. “ *** ” $p < 0.01$, “ ** ” $p < 0.05$, “ * ” $p < 0.1$

the provinces into four categories based on the infrastructure conditions, we find that provinces with worse infrastructures have slower patent growth, but such a relationship is insignificant. From the analysis, we do find technology transfer and absorptive capacity in the technology development in China. We do panel cointegration test by doing Levin et al. (2002) test on the residuals. All the coefficients are significant, so we can reject the null that there is panel root root and conclude that the regressions are cointegrated.

When considering the international spillovers, both imitation from imported goods and the technology transfer from foreign direct investment can stimulate patent growth. However, after taking into account the international spillovers, the effects of S&T inputs become insignificant. After taking a second thought, we find that the correlation of S&T expenditure with FDI is above 0.5 and even as high as 0.8 with imports. Actually FDI contributes a lot to China's S&T investment. More than 1200 foreign R&D centers have been set up in China by 2009[7]. The effects of S&T investment has been diluted. However, the adjusted R^2 shows that these variables can only explain 30% of the technology growth in China. Even after including provincial and year characteristics, the analysis only explains half of China's technology growth.

4.5.2 Technology transfer: decay with distance

In this section, we release the assumption of frictionless technology transfer. Some technologies are tacit to codify. "Diffusion will tend to be more geographically localized the higher is the non-codified share in total technology (Keller (2004))." Even technology transfer may happen without cost, transfer to a far distance will induce the application lag (Eaton and Kortum (1999)). In this sense, the technology spillovers decay with distance. We use the inverse of log driving time to the frontier province as the weight of each province. To make the results

[7]See "Managing foreign R&D in China: some lessons"

Table 4.3: Technology Transfer: Decay with Distance

	1	2	3	4	5	6
$L.ln(ste)$	0.0721**	0.0507*	0.0421	0.0455	0.0096	0.0136
	(0.0297)	(0.0316)	(0.0320)	(0.0321)	(0.0327)	(0.0329)
$L.ln(stp)$	-0.0598*	-0.0223	-0.0339	-0.0160	0.0068	0.0156
	(0.0325)	(0.0378)	(0.0381)	(0.0383)	(0.0392)	(0.0392)
$L.ln(t_{ij})2$	0.0844*	1.7154**	1.6176*	1.7910**	1.8929**	2.0002**
	(0.0489)	(0.8223)	(0.8265)	(0.8280)	(0.8261)	(0.8287)
$L.ln(t_{ij})2 * ln(ste)$		0.1249*	0.1190*	0.1317*	0.1168*	0.1205*
		(0.0670)	(0.0671)	(0.0674)	(0.0679)	(0.0684)
$L.ln(t_{ij})2 * ln(stp)$		-0.1758**	-0.1643*	-0.1831**	-0.1880**	-0.1991**
		(0.0881)	(0.0886)	(0.0887)	(0.0887)	(0.0889)
$L.road$			0.0994**		0.0929*	
			(0.0489)		(0.0503)	
$L.tel$			0.0174		-0.0112	
			(0.0480)		(0.0492)	
$L.tier2$				-0.0376		-0.0157
				(0.0294)		(0.0299)
$L.tier3$				-0.0371		-0.0116
				(0.0361)		(0.0366)
$L.tier4$				-0.0291		-0.0087
				(0.0423)		(0.0423)
$L.ln(imp)$					0.0417**	0.0458***
					(0.0164)	(0.0159)
$L.ln(FDI)$					0.0135**	0.0112*
					(0.0063)	(0.0061)
LLC	-0.9189***	-0.9312***	-0.9525***	-0.9415***	-0.9833***	-0.9714***
obs	532	532	532	532	532	532
Adj R2	0.275	0.278	0.282	0.276	0.299	0.293

The table shows the results when technology transfer is decaying with distance. The dependent variable is the growth of patent. We use panel two-way fixed effect model. *ste* is the S&T expenditure and *stp* is S&T personnel.t_{ij} is the technology distance and $ln(t_{ij})2 = \frac{1}{ln(D_{ij})} * ln(t_{ij})$ where $\frac{1}{ln(D_{ij})}$ is the standardized inverse log of driving distance.. *road* is the length of road per km^2 while *tel* is the telephone subscriber per person. *imp* is the value of imports in RMB and FDI is the utilized FDI in RMB. $tier2$, $tier3$ and $tier3$ are the dummies for good, median and bad infrastructures. $\frac{1}{ln(D_{ij})}$ is the standardized inverse log of driving distance. All the independent variables are lagged by 1 period. The number in each cell represents the coefficient and the number in parentheses represents the standard deviation. " *** " $p < 0.01$, " ** " $p < 0.05$, " * " $p < 0.1$

comparable, we standardize the weights so that $\sum_i 1/ln(D_{Fi}) = N$. By this way, we put higher weight to the provinces which are closer to the technology frontier. Even with the same technology distance, a province which is far away from the frontier is more difficult to assimilate the new technology. Take Gansu as an example. Its patent structure is quite different from the frontier province Guangdong, so it has a big potential to assimilate different technologies from Guangdong. However, it is far away from Guangdong, so such a potential is discounted. We can estimate the Equation 4.4 to see how distance affects technology spillovers and the results are shown in Table 4.3.

Similar as Table 4.2, we consider only the basic S&T inputs and technology transfer first and then consider the absorptive capacity and other control factors. If we just look at the in house S&T inputs, we can see that the results are robust no matter whether technology transfer decays with distance or not. S&T investment still has positive and partial significant effects on patent growth while S&T personnel shows decreasing marginal return. Technology transfer is more significant in this case. The magnitudes of the coefficients are bigger than those in Table 4.2. It means that the effects of technology transfer is stronger after we consider the distance-discounted potential of technology spillovers. Higher road density can still lead to higher patent growth, and international technology spillovers also have positive contribution. Therefore, the determinants of S&T development are robust to different specifications.

4.5.3 Robustness check: another measurement of technology transfer

Instead of considering the technology distance, we take technology gap into account. It reflects the magnitude difference in the patent level. By this measurement, we mainly consider the absolute difference in the technology level. Bigger $ln(MT_{ij})$ when j is the frontier province means that province i is less developed in technology. Positive coefficient suggests technology convergence. The results are shown in Table 4.4.

Table 4.4: Another Measurement of Technology Transfer

	1	2	3	4	5	6	7	8
$L.ln(ste)$	0.091***	0.195***	0.128***	0.109***	0.073**	0.099***	0.064	0.047
	(0.029)	(0.039)	(0.041)	(0.042)	(0.030)	(0.037)	(0.040)	(0.040)
$L.ln(stp)$	-0.022	-0.111**	-0.054	-0.040	-0.055*	-0.107**	-0.094**	-0.067
	(0.033)	(0.044)	(0.046)	(0.046)	(0.032)	(0.045)	(0.045)	(0.045)
$L.ln(mt_{ij})$	0.043***	0.030	0.118**	0.082				
	(0.010)	(0.057)	(0.060)	(0.063)				
$L.ln(mt_{ij}) * ln(ste)$		-0.021***	-0.010*	-0.011*				
		(0.005)	(0.006)	(0.006)				
$L.ln(mt_{ij}) * ln(stp)$		0.008	-0.000	0.003				
		(0.006)	(0.006)	(0.006)				
$L.ln(mt_{ij})2$					0.006	-0.097**	-0.063	-0.070
					(0.005)	(0.048)	(0.050)	(0.049)
$L.ln(mt_{ij})2 * ln(ste)$						-0.004	0.001	-0.002
						(0.004)	(0.005)	(0.005)
$L.ln(mt_{ij})2 * ln(stp)$						0.011**	0.007	0.008
						(0.005)	(0.005)	(0.005)
$L.road$			0.210***	0.189***			0.117**	0.112**
			(0.057)	(0.057)			(0.051)	(0.052)
$L.tel$			0.142***	0.105*			0.070	0.042
			(0.054)	(0.056)			(0.055)	(0.055)
$L.ln(imp)$				0.034**				0.042***
				(0.015)				(0.016)
$L.ln(FDI)$				0.009				0.014**
				(0.006)				(0.006)
LLC	-0.868***	-0.847***	-0.860***	-0.888***	-0.918***	-0.928***	-0.953***	-0.981***
obs	532	532	532	532	532	532	532	532
Adj R2	0.299	0.321	0.341	0.350	0.274	0.279	0.285	0.304

The table shows the results when technology transfer due to the technology gap. The dependent variable is the growth of patent. We use panel two-way fixed effect model. ste is the S&T expenditure and stp is S&T personnel.$ln(mtij)$ is the technology gap and $ln(mtij2) = \frac{1}{ln(D_{ij})} * ln(mtij)$ where $\frac{1}{ln(D_{ij})}$ is the standardized inverse log of driving distance. $road$ is the length of road per km^2 while tel is the telephone subscriber per person. imp is the value of imports in RMB and FDI is the utilized FDI in RMB. $tier2$, $tier3$ and $tier3$ are the dummies for good, median and bad infrastructures. All the independent variables are lagged by 1 period. The number in each cell represents the coefficient and the number in parentheses represents the standard deviation. " *** " $p < 0.01$, " ** " $p < 0.05$, " * " $p < 0.1$

Regression 1-4 show the frictionless technology transfer because of the technology gap. We can see that S&T investment always plays a significantly positive role in patent growth and the effect on patent growth is bigger compared with that in Table 4.2. While S&T personnel have negative but insignificant effects. In regression 1, the coefficient of technology gap is significantly positive, which suggests that the lower the technology level, the higher the growth of patent. It is a technology convergence process. However, if we add absorptive capacity by interacting the technology gap with S&T inputs, the convergence disappears. The absorptive capacity of S&T investment is always negative and is robust to different specifications, which is surprising. Regression 5-8 consider the distance-decaying technology transfer. From regression 5, we can see bigger technology gap leads to higher patent growth. But such an effect disappears after we add the interaction terms. In summary, we find neither robust technology transfer due to the technology gap, nor positive absorptive capacity. In this sense, it is the difference in technology structure instead of technology level that leads to the technology transfer. Therefore, we cannot observe technology convergence in China.

4.6 Regional heterogeneity

Since the regional imbalance is so strong in China, it is highly likely that different regions have different paths of technology development. We want to examine the regional heterogeneity, so we run regressions separately for each region[8].

4.6.1 Technology transfer from the national frontier

In this section, we split the sample into three regions. However, provinces in different regions share the same frontier: the national frontier. For instance, Beijing has the highest number of patent applications in 1990, so it is the national frontier. It is also the frontier province for all the coastal, central and western regions. Regression 1-3 show the results of frictionless technology transfer because of the technology distance. And regression 4-6 show the distance-decaying technology transfer.

[8] In the analysis, we group eastern region and northeast region as one region: coastal region.

Table 4.5: Technology Transfer and Regional Heterogeneity: National Frontier

	1	2	3	4	5	6
$L.ln(ste)$	0.0068	0.0778	0.0024	-0.0004	0.0144	0.0113
	(0.0491)	(0.0946)	(0.0687)	(0.0492)	(0.0942)	(0.0706)
$L.ln(stp)$	0.0408	-0.0270	-0.1247	0.0484	0.0031	-0.1214
	(0.0523)	(0.1266)	(0.1029)	(0.0527)	(0.1251)	(0.1025)
$L.ln(tij)$	3.7412**	-1.4195	-0.4776			
	(1.4835)	(3.3185)	(1.5393)			
$L.ln(tij) * ln(ste)$	0.2219**	-0.1395	-0.1681			
	(0.0984)	(0.2291)	(0.1564)			
$L.ln(tij) * ln(stp)$	-0.3783**	0.1569	0.0926			
	(0.1519)	(0.3406)	(0.1743)			
$L.ln(tij)2$				4.6335***	1.0687	-0.5146
				(1.6058)	(3.0581)	(1.6796)
$L.ln(tij)2 * ln(ste)$				0.2559**	0.0113	-0.1981
				(0.1091)	(0.2008)	(0.1745)
$L.ln(tij)2 * ln(stp)$				-0.4650***	-0.0810	0.1070
				(0.1656)	(0.3100)	(0.1914)
$L.road$	0.0602	-0.1347	0.0923	0.0436	-0.0724	0.1139
	(0.0801)	(0.1217)	(0.2156)	(0.0795)	(0.1193)	(0.2164)
$L.tel$	0.0151	0.1174	0.1951	0.0161	0.1211	0.1937
	(0.0680)	(0.3356)	(0.2967)	(0.0677)	(0.3318)	(0.3004)
$L.ln(imp)$	0.0674***	0.0071	-0.0100	0.0747***	0.0115	-0.0061
	(0.0259)	(0.0499)	(0.0326)	(0.0260)	(0.0501)	(0.0332)
$L.ln(FDI)$	0.0293	0.0369	0.0074	0.0320	0.0218	0.0075
	(0.0210)	(0.0292)	(0.0087)	(0.0205)	(0.0294)	(0.0087)
Region	Coastal	Central	Western	Coastal	Central	Western
LLC	-0.9618***	-0.6375***	-0.8622***	-0.9580***	-0.7456***	-0.8515***
obs	247	114	171	247	114	171
Adj R2	0.342	0.413	0.255	0.348	0.421	0.255

The table shows the results of technology transfer and regional heterogeneity with a unified frontier for different regions. The dependent variable is the growth of patent. We use panel two-way fixed effect model. ste is the S&T expenditure and stp is S&T personnel. $ln(tij)$ is the technology distance and $ln(tij2) = \frac{1}{ln(D_{ij})} * ln(tij)$ where $\frac{1}{ln(D_{ij})}$ is the standardized inverse log of driving distance. $road$ is the length of road per km^2 while tel is the telephone subscriber per person. imp is the value of imports in RMB and FDI is the utilized FDI in RMB. $tier2$, $tier3$ and $tier3$ are the dummies for good, median and bad infrastructures. $\frac{1}{ln(D_{ij})}$ is the standardized inverse log of driving distance. All the independent variables are lagged by 1 period. The number in each cell represents the coefficient and the number in parentheses represents the standard deviation. “ *** ” $p < 0.01$, “ ** ” $p < 0.05$, “ * ” $p < 0.1$

From Table 4.5, we find that for coastal area, S&T inputs have insignificant effects on patent growth due to the multicollinearity. It is similar to the national-wide case. Technology transfer is significant, and the absorptive capacity from the S&T investment is also significant. Compared with the national case, the magnitudes are bigger. If we look at the central and western regions, we cannot find anything which affects the patent growth. Actually, researches are usually taken in coastal regions. After 2000, coastal region owns more than 80% of the patents in China while the other two regions only have less than 20%. Therefore, patent growth in these two regions may due to some other factors, such as government policy. The results are also robust to different specifications of technology transfer.

4.6.2 Technology transfer from the regional frontier

From section 4.6.1, we cannot find significant factors for patent growth of central and western regions. As we mentioned, only a small portion of research is done in those area, which could be a reason. Another reason could lie in the hypothesis that they have their regional technology frontiers and they can assimilate advanced technology from their own frontiers. In this section, we assume that each region has a technology frontier and we want to see whether it makes difference in the analysis.

Since the national frontier is always in the coastal region, so national frontier is also the regional frontier of eastern. From the data, we can see that the frontier of the central region is always Shaanxi. The frontier of the western region is Human for the first ten years. It changes to Henan in 2000 and then becomes Hubei afterward. We adopt the same strategy as section 4.6.1, first consider the frictionless technology transfer and then consider the distance-decaying technology transfer. The result is shown in Table 4.6.

From regression 1-4 in Table 4.6, we can see that results are the same as the corresponding regressions in Table 4.5. That's intuitive because national frontier is also the frontier of eastern.

Table 4.6: Technology Transfer and Regional Heterogeneity: Regional Frontier

	1	2	3	4	5	6
$L.ln(ste)$	0.0068	0.0467	-0.0088	0.0010	0.0561	-0.0139
	(0.0491)	(0.0791)	(0.0685)	(0.0494)	(0.0784)	(0.0683)
$L.ln(stp)$	0.0408	-0.0872	-0.1145	0.0414	-0.0626	-0.1107
	(0.0523)	(0.1296)	(0.0900)	(0.0526)	(0.1259)	(0.0902)
$L.ln(tijreg)$	3.7412**	-41.6429	-0.6634			
	(1.4835)	(41.3151)	(10.3001)			
$L.ln(tijreg) * ln(ste)$	0.2219**	-0.7198	-0.0177			
	(0.0984)	(1.7156)	(1.0878)			
$L.ln(tijreg) * ln(stp)$	-0.3783**	3.8354	(dropped)			
	(0.1519)	(4.0224)				
$L.ln(tijreg)2$				4.1066***	-27.3421	2.1533
				(1.5669)	(24.3562)	(9.2893)
$L.ln(tijreg)2 * ln(ste)$				0.2258**	-0.7357	0.2566
				(0.1068)	(1.0674)	(0.9987)
$L.ln(tijreg)2 * ln(ste)$				-0.4130**	2.5720	-0.2819
				(0.1620)	(2.3782)	(1.0907)
$L.road$	0.0602	-0.0692	0.1131	0.0395	-0.1241	0.1179
	(0.0801)	(0.1341)	(0.2119)	(0.0795)	(0.1336)	(0.2112)
$L.tel$	0.0151	0.0163	0.1494	0.0135	0.0808	0.1294
	(0.0680)	(0.3466)	(0.2969)	(0.0679)	(0.3302)	(0.2904)
$L.ln(imp)$	0.0674***	0.0115	-0.0186	0.0735***	0.0122	-0.0192
	(0.0259)	(0.0498)	(0.0332)	(0.0260)	(0.0501)	(0.0334)
$L.ln(FDI)$	0.0293	0.0378	0.0086	0.0332	0.0430	0.0085
	(0.0210)	(0.0290)	(0.0089)	(0.0206)	(0.0287)	(0.0089)
Region	Coastal	Central	Western	Coastal	Central	Western
obs	247	114	171	247	114	171
Adj R2	0.342	0.421	0.227	0.342	0.421	0.225

The table shows the results of technology transfer and regional heterogeneity with different frontiers for different regions. The dependent variable is the growth of patent. We use panel two-way fixed effect model. ste is the S&T expenditure and stp is S&T personnel.$ln(tijreg)$ is the regional technology distance and $ln(tijreg)2 = \frac{1}{ln(D_{ij})} * ln(tijreg)$ where $\frac{1}{ln(D_{ij})}$ is the standardized inverse log of driving distance $road$ is the length of road per km^2 while tel is the telephone subscriber per person. imp is the value of imports in RMB and FDI is the utilized FDI in RMB. $tier2$, $tier3$ and $tier3$ are the dummies for good, median and bad infrastructures. $\frac{1}{ln(D_{ij})}$ is the standardized inverse log of driving distance. All the independent variables are lagged by 1 period. The number in each cell represents the coefficients and number in parentheses represents the standard deviation. “ *** ” $p < 0.01$, “ ** ” $p < 0.05$, “ * ” $p < 0.1$

However, when we look at the central and western region, we still did not find anything significant. There are no significant technology spillovers from either national frontier nor region frontier.

4.7 Conclusion

This paper analyzes the factors of provincial technology development in China. Besides the traditional factors such as S&T investment, S&T personnel, infrastructures and international spillovers, we specially consider the domestic technology spillovers. Less developed provinces can assimilate advanced technology from the frontier province, and the technology differences (in two forms) show the potential of technology transfer. S&T endowment can help assimilate the advanced technology and suggesting the absorptive capacity. Technology transfer can be due to the difference in the technology structure as well as the gap in the technology level. Through the empirical analysis, we can see that S&T investment has positive effects on patent growth while S&T personnel has negative but insignificant effects. Technology transfer is resulted from the difference in the technology structure. No robust evidence of the technology transfer is found due to the gap in the technology level. It implied that there may be no technology convergence in China. Regional heterogeneity is very significant. We can see strong technology transfer and absorptive capacity from S&T investment in coastal region. However, we cannot find significant factors which contribute to technology growth in the central and western regions.

There are some other unexplored issues. First, the explanatory power of the proposed factors is less than 50%. There should be some other factors which can explain the technology development in China. Second, to construct a better technology portfolio, we may need industrial level or even firm level data. Third, government intervention may be a reason of technology development in central and western regions. We leave them for the future research.

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