The role of education in regional innovation activities and economic growth: spatial evidence from China

Wei Chi and Xiaoye Qian

Tsinghua University, China

June 2009

First draft: March 2009

The Role of Education in Regional Innovation Activities and Economic Growth: Spatial Evidence from China

Wei CHI (Corresponding Author)
Associate Professor
School of Economics and Management
Tsinghua University
Beijing, China 100084
Email: chiw@sem.tsinghua.edu.cn
Tel.: (8610) 62795072
Fax: (8610) 62772021

Xiaoye QIAN
School of Economics and Management
Tsinghua University
Beijing, China 100084
Email: qianxy.08@sem.tsinghua.edu.cn

The Role of Education in Regional Innovation Activities and Economic Growth: Evidence from China

Abstract:

This study examines one of the channels through which education may contribute to economic growth, specifically, innovation. Endogenous growth theory has long suggested that human capital lead to greater innovation and, through technology innovation and diffusion, contribute to economic growth. However, there is little evidence on the role of human capital in innovation. Using the Chinese provincial data from 1997 to 2006, we show that workers' tertiary education is significantly and positively related to provincial innovative activities measured by invention patent applications per capita. This result does not vary when spatial dependence is allowed in the estimation. Thus, we find strong and robust evidence for the prediction of endogenous growth theory regarding the effect of human capital on innovation. However, we do not find the consistently significant effect of innovation on growth. This finding may, however, relate to the growth pattern in China.

JEL code: O1, O3

Keywords: Education, Human Capital, Innovation, Patent, Economic Growth, Spatial Analysis

1. Introduction

There is a large literature on the role of education in a country or region's economic growth. A number of studies have shown that the East Asian growth miracle, such as that of Singapore and Hong Kong, may be related to the significant investment in human capital and consequently highly educated workforce of these countries and regions (Ahlburg and Jensen, 2001; McMahon, 1999, 1998; Ito and Krueger, 1995; World Bank, 1993). It is less conclusive with respect to China as to whether fast economic growth in the last several decades was driven by human capital or physical capital investment. The stereotyped view is that China's economic growth is mostly due to high fixed asset investment, while the contribution of human capital is relatively small. Several studies have found concrete evidence in support of this view (Arayama and Miyoshi, 2004; Wei et al., 2001, Chen and Fleisher, 1996). However, there are also studies that have found some measures of human capital, such as secondary and higher education enrollment, the number of science and technology workers in the labor force and per capita spending on education and science, are significantly related to the growth rate (Ding and Knight, 2008; Song et al. 2000; Yao and Zhang, 2001). Reconciling the different evidence, Chi (2008) suggests that the higher education of workers contributes to economic growth, but the effect may be indirect, which explains the insignificant direct effect of education on growth. Despite the large literature, there is still much to learn how the education of workforce contributes to growth which remains largely a black box. This paper explores one mechanism by which human capital and growth may be linked, specifically through regional innovation activities.

Using the provincial panel data from 1996 to 2006, the study describes the large differences in the workforce educational attainment, innovation activities, and economic growth across regions, and then examines the impact of education on regional innovation activities and the impact on economic growth. A feature of the study is the use of spatial econometric method to account for spatial dependence across regions. Spatial dependence refers to the correlation across neighboring areas in economic variables which widely exists in geographic data and can pose a serious problem to the simple OLS estimates. We estimate the Spatial Error Model (SEM) and Spatial Lag Model (SLM) in contrast to the OLS model, and Spatial General Method of Moment (GMM) in the case of two stage IV (instrument variable) estimation.

The main findings of the paper include: innovation activities have significantly increased across the country in China from 1996 to 2006, and the spatial correlation of innovation activities has also been rising, suggesting increasing knowledge spillovers in the neighboring provinces. Estimates of OLS, SEM, and SLM models unanimously suggest that the percentage of college educated workers in the labor force is a significant predictor of regional innovation intensity. Over time, the impact of education on innovation activities has been increasing.

The structure of the paper is as follows: In section 2, we review theoretical and empirical studies regarding the role of education in technological innovation and economic growth. Section 3 describes data and variables. Section 4 presents the spatial econometric methods used in the study. Section 5 reports the empirical estimates. A summary and conclusion is contained in section 6.

2. Related Studies

According to Endogenous Growth Theory represented by the work of Nelson and Phelps (1966), Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992), human capital is of crucial importance to economic growth. The enhancement of workers' educational attainment will lead to economic growth by means of technological innovation and diffusion. Following the theoretical research, a large number of empirical studies have used cross-country data to test the effect of human capital on economic growth (Barro, 1991, 2001; Benhabib and Spiegel, 1994; Barro and Sala-i-Martin, 1995; Barro, 2001; Gemmell, 1996; Bils and Klenow, 2000). These empirical studies have generally found that the initial stock of human capital played a significant role in economic growth, while Gemmell (1996) showed that both the initial stock and accumulation of human capital were significant determinants of growth. Although the key argument of Endogenous growth theory is that human capital first leads to innovation and knowledge spillover and then to economic growth, most empirical work so far has focused on the impact of human capital on growth, while relatively fewer studies have estimated the effect of human capital on innovation (Simonen and McCann, 2008; Badinger and Tondl, 2005).

Similarly, in China studies on human capital and economic growth are abundant, however, much less is known about the role of human capital in innovation activities. Several Chinese authors have studied how foreign direct investment (FDI) affects the host country's innovation activities. Cheung and Lin (2004) found the positive effect of FDI on the number of domestic patent applications in China. This result supports the argument articulated in Grossman and Helpman (1990, 1991) that international trade serves as a channel of knowledge spillover which generates endogenous economic growth. In this argument, human capital is considered to affect the capability of the host country to absorb foreign knowledge. Two recent studies, Lai et al. (2006) and Kuo and Yang (2008), use Chinese provincial data and include the interaction of human capital with FDI or with foreign R&D to explain domestic GDP growth. Both studies found that the benefit of foreign knowledge to China depends on the Chinese domestic human capital levels. Workers with college education are especially important as they are more capable to absorb foreign knowledge embodied in FDI or R&D.

Our study significantly differ from the previous two studies in that they emphasize the role of human capital in absorbing foreign knowledge, while our research examines the effect of workers' human capital on knowledge creation concerning the country's own innovative ability. Moreover, we take into consideration spatial dependence and spillover effects across provinces, and examine both the impact of human capital on innovation and that on economic growth.

3. Data

Data used in this study are drawn from China Statistics Yearbooks and China Labor Statistical Yearbooks from 1997 to 2006. Provincial GDP, population, the size of labor force, educational attainment of labor force, fixed capital investment (FCI), patent applications are selected. Workers' education attainment is reported in labor statistics yearbooks only from 1996. Also in 1996, Chongqin became the fourth municipal city directly under the central government following Beijing, Tianjin, and Shanghai, and reported data separately from Sichuan province. Since the Spatial models, SEM, SLM and GMM, require a geographic matrix that consists of the fixed number of sub-areas, we use data from 1997. Two spatial matrixes are used in the estimation: one is generated based on whether any two provinces are neighboring provinces, where neighboring provinces are defined as those who share a common border line; the other is the spatial coordinate matrix obtained from the database constructed by the National Geomatics Center of China.

Human capital is measured by two variables: the percentage of workers with tertiary, secondary, or primary education, and the average years of schooling. Following Chi (2008), we use workers' educational attainment to measure human capital because it is a better measure of a province's human capital level than the widely used school enrollment data and it has fewer measurement errors. The average years of schooling are imputed based on the percentage of workers with different educational attainment.

Since the direct measure of innovation does not exist, a common approach has been to use the number of patent applications or patent grants as the proxy for innovation. We use the patent applications rather than patent grants to measure innovation due to the concern that patent grants may be biased by different granting standards across provinces. The same as many other countries, the Intellectual Property offices in China classify patent applications into three categories: invention patent, utility model patent and design patent. An invention patent refers to any new technical solution relating to a product or process. Utility model patents refer to the shape, structure, or their combination of a product, which enhances the practical use of the product. A design patent means any new design of the shape, pattern, color, or their combinations that serves for the ornamental purpose. Since invention patents most reflect new knowledge and technology creation, we choose the number of invention patent application as the proxy of innovation activities. To ensure the robustness of the estimates, we also use the total patent applications as the measure of innovation in the estimation. The results do not vary by different measures.[1] Definition and summary statistics of the variables used in the study are given in Appendix.

4. Econometric Methods

In the geographically coded data, neighboring areas often share more common characteristics than those that are far apart due to the interaction and spillover effects across regions. A recent study shows that spatial interaction does occur in terms of innovation. Using the U.S. county level data, Monchuk and Miranowski (2004) found that a county's innovative behavior is influenced by the innovative activity of the neighboring counties. GDP, employment, and fixed capital investment data are also likely subject to spatial dependence. OLS regression assumptions imply that the individual observations be independent and uncorrelated. Spatial dependence clearly violates these assumptions, thus causes conventional OLS analysis invalid and

[1] Results are available for the authors.

requires special spatial methods.

The spatial econometric methods used in this study include the Moran's I test to evaluate whether there is the spatial clustering effect in the Chinese provincial data. The Moran's I test statistic is calculated as follows:

$$MoranI = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}},$$

where $S^2 = \frac{1}{n}\sum_{j=1}^{n} W_{ij}(Y_j - \bar{Y})$, and $\bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$.

Y_i represents the observation of sub-area i, e.g. the patent applications of province i. n represents the total number of subareas. W_{ij} denotes the binary spatial weight matrix, which defines the adjacent relationship between provinces i and j. W_{ij} equals one if the two provinces have a common border line and zero otherwise.

If spatial correlation exists, that is if the p-value of Moran's I is significant, the spatial effect should be incorporated in the regression models. The commonly used spatial regression models are the Spatial Lag Model (SLM) and Spatial Error Model (SEM). The difference between SLM and SEM lies in whether spatial dependence is modeled by the spatially lagged dependent variable or induced in the disturbance term.

We begin with the OLS estimation as a benchmark, modeling the relations between human capital and innovation.

$$\ln patent = \beta_1 + \beta_2 HC + \beta_3 \ln FCI + \beta_4 \ln employee + \varepsilon \qquad (1)$$

$\ln patent$: Logarithm of the number of invention patent applications per 10,000 population.

HC: human capital variables. Specifically, “High”, “Secondary”, and “Primary” denotes the percentage of workers with primary, primary, secondary, and tertiary educational attainment. *S* represents the average years of schooling in a year.

ln*FCI*: Logarithm of fixed capital investment.

ln*employee*: Logarithm of the number of employees in the labor force.

Then, we estimate the Spatial Lag Model and Spatial Error Model, and compare the results of the OLS estimation. The Spatial Lag Model is specified as follows:

$$\begin{aligned} &\ln patent = \rho W \ln patent + \beta_1 + \beta_2 HC + \beta_3 \ln FCI + \beta_4 \ln employee + \varepsilon \\ &\varepsilon \sim N(0, \sigma^2) \end{aligned} \qquad (2)$$

W is the $n \times n$ spatial weight matrix to capture the neighboring relations. ρ is the parameter reflecting the degree of spatial dependence between observations in the sample.

The Spatial Error Model is as follows:

$$\begin{aligned} &\ln patent = \beta_1 + \beta_2 HC + \beta_3 \ln FCI + \beta_4 \ln employee + \varepsilon \\ &\varepsilon = \lambda W \varepsilon + \mu \\ &\mu \sim N(0, \sigma^2) \end{aligned} \qquad . \qquad (3)$$

The Spatial Error Model uses the same weight matrix W as that in the Spatial Lag Model. λ is the parameter for the spatial error term. The rest of the variables and parameters in (3) are the same as those in equation (2).

Finally, we model the indirect relationship between human capital and economic growth through innovation, using the two-stage instrument variable (IV) method. Human capital is used to instrument for innovation to estimate the effect on economic growth. To obtain correct standard error estimates for the IV model with spatial dependence, we adopt the Conley Generalized method of Moments (GMM) method (Conley, 1999). Spatial coordinates (x- and y-coordinates) are used in the IV estimations. They are obtained from the National Geomatics Center of China.

5. Results

5.1 Spatial Maps of Innovation across the Country

We begin our analysis by showing spatial distribution of innovation across the country from 1997 to 2006. Each year, a province is classified into one of the five quantiles based on the number of invention patent applications per 10,000 population, with the lowest 20% of the provinces forming the first quantile and the top 20% forming the fifth quantile. The map shows five shades of blues from light to deep blues, corresponding to the five levels of innovative intensity from low to high. As shown by the maps, innovation activities have been rising rapidly all over the country during 1997 to 2006. In 1997, for the bottom 20% of provinces in terms of innovation intensity, the number of invention patent applications per 10,000 people ranges from 0.004 to 0.05, while for the highest 20% of provinces the number ranges from 0.11 to 1.35. In 2006, the number of invention patent applications per 10,000 people for the two groups ranges from 0.07 to 0.26 for the land 2.29 to 9.00 respectively.

Despite the overall increase in innovative activities in China, there still exists a large variation across the country. By 1997, China has seen the rise of several innovation centers that have had a considerably higher number of per capita invention patent applications than the rest of the country; The two most significant centers of innovation were Beijing and Shanghai and the city’s surrounding areas; Another important area of innovation is the northeast region including four provinces, Heilongjiang, Jilin, Liaoning, and Inner Magnolia (to a lesser degree).

What is interesting is that the highlighted centers of innovation have been changing over time. Beijing and Shanghai remain the most innovative cities in China. However, the northeast region has lost its lead in innovation, falling from the first-tier innovative provinces to the third tier. In contrast to the northeast region, Guangdong, has moved up one class from the third class to the second class in terms of innovation.

Coastal areas such as Guangdong, Fujian, and Zhejiang have had the fastest economic growth in the last decades but are not the most innovative regions. It is not surprising because the three provinces have attracted most FDI and become the centers of Chinese exporting industries characterized by the large-scale labor-intensive manufacturing with relatively unsophisticated technology. The key factors driving the fast growth of the three coastal provinces are scale of economy and low costs of unskilled labor, not technology and product innovation.

One last point from figure 1 is that after evolving over the 10-year period, by 2006, two knowledge and innovation zones have emerged in China, one is along the east coast, and the other is in the center of china including Hunan, Hubei, and Shaanxi. The wide area between these two regions and the area in the west are almost in white color, suggesting very low innovative activities.

Table 1 reports the Moran's *I* statistics and Z-value from 1997 to 2006. For most of the years, Moran's *I* is significant at the 5 percent level or lower, suggesting the existence of clustering in innovation activities across provinces. The high level of innovation in one province tends to spatially correlated to the high level innovation of nearby provinces, which is likely due to knowledge spillover across regions. The extent of knowledge spillover tends to decrease with the distance between the two provinces. Also, Tables 1 shows some evidence of the increased spatial correlation between provinces in innovative activities. This result suggests the need for spatial regression models to estimate impact of education on innovation.

5.2 Spatial Regression Estimates

We employ the OLS, SEM, and SLM models introduced in section 4 to estimate the effect of human capital on innovation activities. The results are reported in Table 2. The first four columns report the OLS estimates with each column using a different human capital measure. The SEM and SLM estimates are reported in the rest columns with similar specifications to the OLS. All the models in Table 2 include control variables, logarithm of fixed capital investment and logarithm of the number of employees in the labor force. In a separate estimation, we estimate the models without the control variables, while the results do not vary much. Due to the limited length, these results are not reported but available from the authors upon request.

Several important findings emerge from Table 2: educational attainment of workers appears to be a crucial factor explaining the degree of innovation of a province. The workers with tertiary and secondary education lead to greater innovative effort. Tertiary educational attainment of workers is even more important to innovation than secondary education. For example, in 2006, on average, the percentage of workers with tertiary education is 8.2 percent in China, while the province with the lowest educational attainment has only half percent, and the province with the highest educational attainment has 36 percent of workers with tertiary education. The regression estimates suggest that one percentage point increase in the fraction of workers with tertiary education is associated with a 9 percent increase in the number of invention patent applications per 10,000 population. Also, as can be seen from the OLS estimates, after controlling for the size of labor force and fixed assets investment, adjusted *R* square is around 0.8, suggesting the model has a good explanatory power. Even without control variables, education variables can still explain 60-70 percent of innovation activities, suggesting education is a key factor explaining innovation.

However, we need to be aware of the declining effect of tertiary education on innovation. Both OLS and spatial regression estimates show that the marginal effect of tertiary education of workers on provincial innovation outputs have evidently declined from 1997 to 2006. This finding is consistent with the decreasing marginal productivity of input factors assumed in the classical production theory. The number of college-educated workers has increased significantly in the last decades. As the result of college expansion effort starting from 1999, the number of college graduates has almost tripled from 0.8 million in 1998 to 3.08 million in 2005. [2] As the number of college-educated workers increases, the marginal contribution of college education to innovation declines, suggesting the declining marginal productivity of human capital in the production of innovation.

[2] Data source: China Education Statistics Yearbooks, 2006.

From the econometric perspective, Table 2 shows that the OLS estimates are comparable to the SEM and SLM estimates. This result indicates that the estimates are rather robust and do not vary by different econometric models. However, we also estimate the model without correcting spatial dependence using the maximizing likelihood method, and report log likelihood; we compare the log likelihood of the model without correcting spatial dependence with that of spatial error and spatial lag models. The results suggest that the spatial regression models perform better than the OLS models as the log likelihood of spatial models is a little larger. The more rigorous diagnostic tests for spatial dependence in OLS regression are reported in Table 3. The test statistics are significant for several years, which also suggest the use of spatial models.

Table 4 reports the estimates of two-stage IV model of the effect of innovation on economic growth. Economic growth is measured by the change of logarithm of GDP from year *t-1* to *t*. For the comparison purpose, we also report the OLS estimates of the impact of innovation on growth. Table 4 does not show strong evidence that greater innovation has led to faster economic growth during 1997-2006. The effect of innovation is significant in both OLS and IV estimates only in 2005. This finding may be related to the lack of commercializing the patents so as to limit the new technology generating economic growth. In the broader context, this finding confirms the view that China's economic growth so far has been mostly driven by exporting labor-intensive products in large scales and that technology and product innovation have not become the major driver of the Chinese economy. Regarding spatial methods,

Table 4 shows an interesting point that spatial GMM standard error estimates are not necessarily larger than the 2SLS standard error; in many cases, they are actually smaller. This important point has been explained in Conley (1999).

6. Summary and Conclusion

This paper addresses the important question of how human capital contributes to economic growth. Although endogenous growth theory has long suggested that human capital lead to greater economic growth through technology innovation and diffusion, there is very little empirical evidence on the effect of human capital on innovation. With respect to China, several studies have examined the role of human capital in absorbing foreign knowledge and turn it into domestic productivity. However, this research has not explicitly studied the effect of human capital on the country's own knowledge generation. To address this issue, we use detailed provincial education and patent applications data, and employ spatial econometric methods to allow spatial dependence in observations.

We find that workers' educational attainment is highly related to provincial innovation activities, measured by the number of invention patent applications per 10,000 people. Higher education contributes more to innovation than primary and secondary education. However, we also find two less positive results: first, the effect of workers' tertiary educational attainment on innovation has declined in the last ten years. Second, the contribution of innovation to economic growth has not been evident in recent years. We give two policy recommendations in light of these findings: one is to enhance commercialization of the patents, and the other is to improve the pattern of economic growth and strengthen the role of technology and product innovation in economic development.

References:

Aghion, P., Howitt, P., 1998. Endogenous Growth Theory. Cambridge, MA: MIT Press.

Ahlburg, Dennis A., Jensen, Eric R., 2001.Education and the East Asian Miracle. In: Mason, Andrew, (Eds.), Population Change and Economic Development in East Asia: Challenges Met, Opportunities Seized, Stanford University Press, pp. 231-54.

Arayama, Y., Miyoshi, K., 2004. Regional Diversity and Sources of Economic Growth in China. World Economy, 27(10), 1583－1607.

Badinger, Harald; Tondl, Gabriele, 2005. The Factors behind European Regional Growth: Trade, Human Capital and Innovation. Review of Regional Research, 25(1) pp. 67-89.

Barro, R. J., 1991. Economic Growth in a Cross Section of Countries. Quarterly Journal of Economics, 106(2), 407－443.

Barro, R. J., 2001. Human Capital and Growth. American Economic Review, 91(2), 12－17.

Barro, R. J., Sala-i-Martin, X., 1995. Economic Growth. NY: McGraw-Hill.

Benhabib, J., Spiegel, M. M., 1994. The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-country Data. Journal of Monetary Economics, 34(2), 143－174.

Bils, M., Klenow,P. J., 2000. Does Schooling Cause Growth? American Economic Review, 90(5), 1160－1183.

Chen, J., Fleisher, B. M., 1996. Regional Income Inequality and Economic Growth in China. Journal of Comparative Economics, 22(15), 141－164.

Chi, W., 2008. The Role of Human Capital in China's Economic Development: Review and New Evidence. China Economic Review, 19, 421-436.

Cheung, K., Lin, P., 2004. Spillover Effects of FDI on Innovation in China: Evidence from the Provincial Data, China Economic Review 15, 25-44.

Conley, T.G., 1999. GMM Estimation with Cross Sectional Dependence. Journal of Econometrics 92, 1-45.

Ding, S., Knight, J., 2008. Why has China Grown So Fast? The Role of Physical and Human Capital Formation. University of Oxford, Department of Economics, Economics Series Working Papers: 414.

Gemmell, N., 1996.Evaluating the Impacts of Human Capital Stocks and Accumulation on Economic Growth: Some New Evidence. Oxford Bulletin of Economics and Statistics, 58(1), 9－28.

Grossman, G. M., Helpman, E., 1990. Trade, Knowledge Spillover, and Growth. NBER working paper No. 3485.

Grossman, G. M., Helpman, E., 1991. Innovation and Growth in the Global Economy, MIT Press, Cambridge, MA, USA.

Ito, T., Krueger, A.O.(Eds), 1995. Growth Theories in Light of the East Asian Experience. Chicago and London: University of Chicago Press and NBER.

Kuo,C., Yang, C., 2008. Knowledge Capital and Spillover on Regional Economic Growth: Evidence from China, China Economic Review 19, 594－604.

Lai, M., Peng, S., Bao, Q., 2006. Technology Spillovers, Absorptive Capacity and Economic Growth, China Economic Review 17, 300-320.

McMahon, Walter W., 1998. Education and Growth in East Asia. Economics of Education Review, vol. 17, no. 2, April 1998, 159-172.

McMahon, Walter W., 1999. Education and Development: Measuring the Social Benefits. Oxford and New York: Oxford University Press, pp. xiv, 299.

Miranowski, J., Monchuck, D. C., 2004. Spatial Labor Markets and Technology Spillovers: Analysis from the US Midwest, Working Paper 04022, Iowa State University, Department of Economics, Working Papers Series.

Nelson, R. R., Phelps, E. S., 1966. Investment in Humans, Technological Diffusion, and Economic Growth. American Economic Review, 56(1), 69－75.

Romer, P. M., 1990. Endogenous Technological Change. Journal of Political Economy, 98(5), S71－S102.

Simonen, Jaakko; McCann, Philip. 2008. Firm Innovation: The Influence of R&D Cooperation and the Geography of Human Capital Inputs. Journal of Urban Economics, 64(1), pp. 146-54.

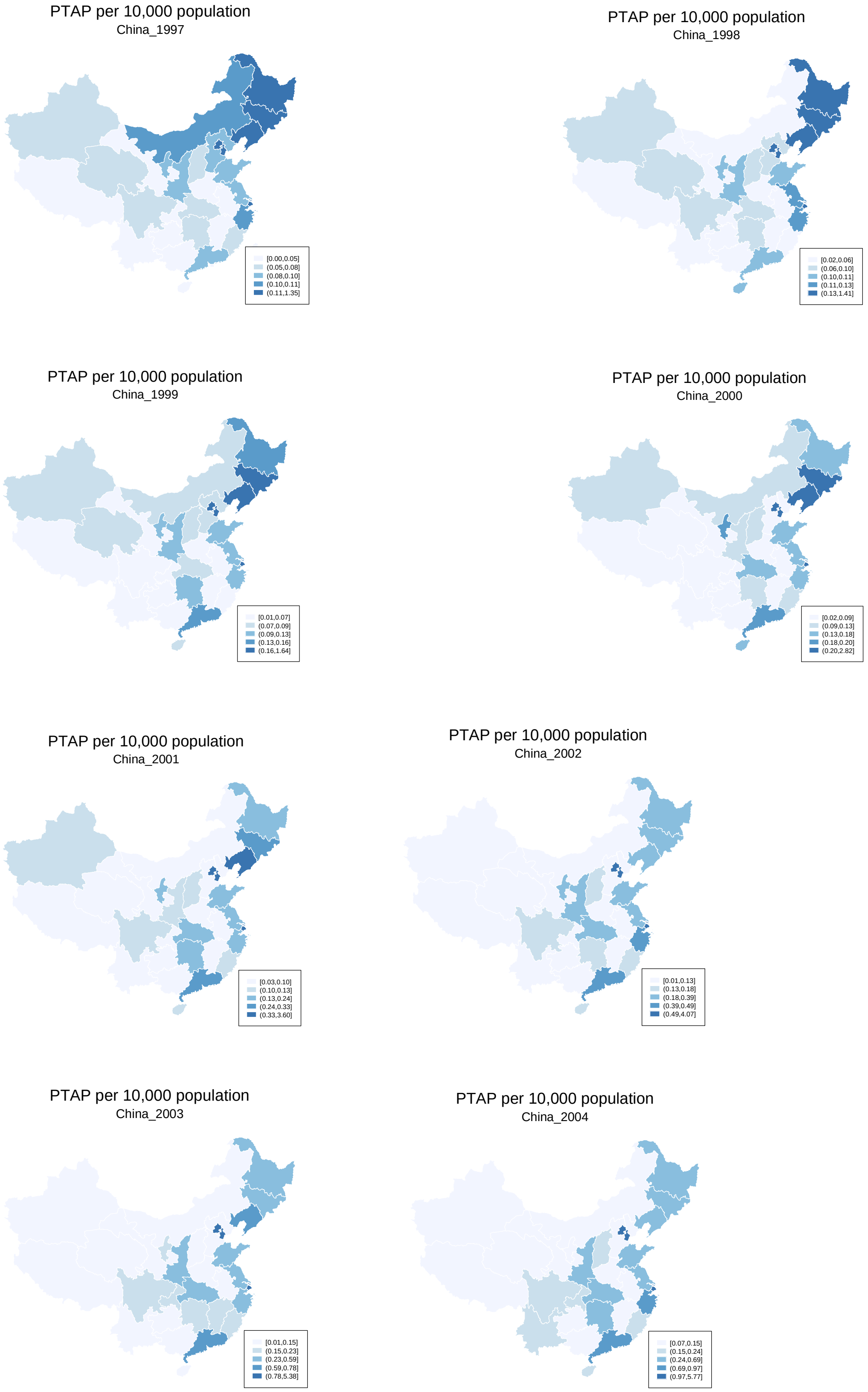
Song, S., Chu, George S. -F., Cao, R., 2000. Intercity regional disparity in China. China Economic Review, 11, 246－261.

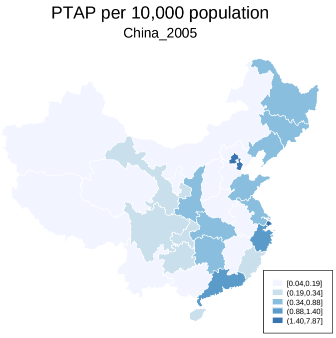
World Bank, 1993. The East Asian Miracle: Economic Growth and Public Policy, Policy Research Report. pp. 369, Policy research Department, The World Bank.

Wei, Y., Liu, X., Song, H., Romilly, P., 2001. Endogenous Innovation Growth Theory and Regional Income Convergence in China. Journal of International Development, 13, 153－168.

Yao, S., Zhang, Z., 2001.On Regional Inequality and Diverging Clubs: A Case Study of Contemporary China. Journal of Comparative Economics, 29, 466－484.

Figure 1: Spatial Map of Regional Innovation Activities, 1997-2006




PTAP per 10,000 population
China_2005
[0.04,0.19]
(0.19,0.34]
(0.34,0.88]
(0.88,1.40]
(1.40,7.87]

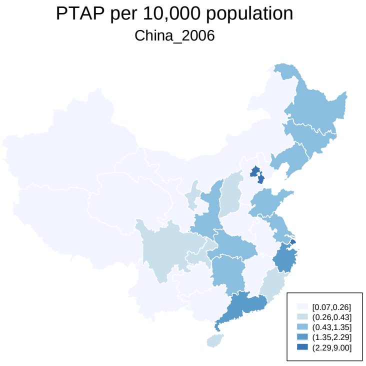

PTAP per 10,000 population
China_2006
[0.07,0.26]
(0.26,0.43]
(0.43,1.35]
(1.35,2.29]
(2.29,9.00]

Table 1: Spatial Correlation of Innovation Activities, 1997-2006

Year	Moran's *I*	Z-value
1997	0.088	2.355
1998	0.068	1.970
1999	0.062	1.473
2000	0.054	1.026
2001	0.085	1.562
2002	0.176	2.397
2003	0.190	2.441
2004	0.202	2.519
2005	0.178	2.290
2006	0.174	2.241

Note: Moran's I is calculated for provincial Patent Applications Per Capita. The statistics show spatial correlation of innovation activities over time.

Table 2: The Impact of Education on Regional Innovation Activities, 1997-2006

Dependent Variable: Regional Innovation Activities, measured by Logarithm of Patent Applications per capita

Year	**OLS**				**Spatial Error**				**Spatial Lag**			
1997	Model(1)	(2)	(3)	(4)	Model(1)	(2)	(3)	(4)	Model(1)	(2)	(3)	(4)
high	0.210***				0.207***				0.201***			
secondary		0.039***				0.037***				0.040***		
primary			-0.036***				-0.035***				-0.036***	
s				0.972***				0.879***				0.963***
Adjusted R^2	0.87	0.73	0.79	0.76								
Log likelihood	-6.318	-17.033	-14.453	-15.982	-5.417	-15.648	-12.503	-13.788	-4.062	-16.222	-12.557	-14.958
1998												
high	0.179***				0.261***				0.178***			
secondary		0.032***				0.032***				0.036***		
primary			-0.032***				-0.031***				-0.035***	
s				0.963***				0.948***				1.024***
Adjusted R^2	0.83	0.81	0.87	0.90								
Log likelihood	-4.876	-15.647	-12.353	-9.024	-3.082	-13.490	-10.385	-7.411	-5.534	-13.324	-10.021	-7.200
1999												
high	0.155***				0.146***				0.153***			
secondary		0.043***				0.042***				0.048***		
primary			-0.040***				-0.039***				-0.043***	
s				1.113***				1.110***				1.164***
Adjusted R^2	0.83	0.81	0.87	0.90								
Log likelihood	-10.935	-13.768	-9.251	-3.856	-9.431	-12.045	-7.018	-3.213	-9.917	-11.161	-5.643	-2.416
2001												
high	0.134***				0.115***				0.131***			
secondary		0.031***				0.032***				0.034***		
primary			-0.029***				-0.030***				-0.032***	
s				0.847***				0.839***				0.893***
Adjusted R^2	0.86	0.84	0.86	0.88								
Log likelihood	-13.132	-14.937	-13.241	-11.024	-11.582	-13.806	-11.264	-9.609	-11.865	-13.580	-11.106	-9.564
2002												
high	0.139***				0.118***				0.130***			
secondary		0.040***				0.042***				0.036***		
primary			-0.037***				-0.037***				-0.034***	
s				1.029***				1.004***				0.939***
Adjusted R^2	0.77	0.79	0.81	0.83								
Log likelihood	-23.498	-20.871	-18.795	-19.458-	-21.739	-19.401	-17.711	-17.162	-19.347	-20.665	-18.665	-17.359
2003												
high	0.130***				0.134***				0.123***			
secondary		0.040***				0.044***				0.039***		
primary			-0.037***				-0.038***				-0.036***	
s				1.005***				1.000***				0.988***

Adjusted R^2	0.74	0.73	0.77	0.79								
Log likelihood	-28.845	-27.532	-25.348	-25.657	-26.070	-25.834	-23.923	-23.148	-25.343	-26.578	-24.410	-23.239
2004												
high	0.103***				0.103***				0.096***			
secondary		0.024**				0.025**				0.020*		
primary			-0.026***				-0.027***				-0.023***	
s				0.764***				0.761***				0.714***
Adjusted R^2	0.77	0.68	0.72	0.76								
Log likelihood	-24.787	-28.905	-27.413	-25.034	-22.993	-27.292	-25.138	-23.450	-22.191	-27.169	-25.204	-23.398
2005												
high	0.119***				0.125***				0.113***			
secondary		0.021*				0.024*				0.017		
primary			-0.027**				-0.029***				-0.024**	
s				0.826***				0.851***				0.766***
Adjusted R^2	0.71	0.57	0.62	0.67								
Log likelihood	-29.607	-35.336	-33.245	-31.108	-27.370	-33.241	-31.113	-29.311	-26.429	-32.870	-31.063	-29.179
2006												
high	0.088***				0.088***				0.083***			
secondary		0.008				0.008				0.001		
primary			-0.023**				-0.023**				-0.019*	
s				0.761***				0.738***				0.694***
Adjusted R^2	0.76	0.60	0.65	0.71								
Log likelihood	-25.564	-32.489	-31.874	-28.056	-23.859	-31.391	-29.196	-26.643	-22.900	-30.786	-29.265	-26.606

Notes: In addition to the variables reported in the table, all the models control for logarithm of fixed asset investment and logarithm of the size of the workforce. Coefficient estimates are reported. ***, **, and * indicate the 1, 5, and 10 percent significance level, respectively. Due to limited space, standard error estimates are not reported, but available from the authors upon request.

Table 3: Diagnostic tests for spatial dependence in OLS regression, 1997-2006

Year	1997	1998	1999	2001	2002	2003	2004	2005	2006
Spatial error:									
Moran's I	1.935*	-0.128	0.543	1.247	2.107**	1.098	1.258	1.493	1.659*
Lagrange multiplier	1.228	0.445	0.008	0.290	1.516	0.192	0.329	0.578	0.954
Robust Lagrange multiplier	1.787	0.024	0.215	1.054	0.555	0.157	0.066	0.098	0.308
Spatial Lag:									
Lagrange multiplier	0.008	0.024	1.398	0.509	1.275	0.040	0.358	0.621	0.747
Robust Lagrange multiplier	0.567	0.499	1.605	1.272	0.313	0.005	0.094	0.140	0.101

Notes: Test statistics reported in the table are for the OLS model in which dependent variable is logarithm of patent application and explanatory variables include average years of schooling, logarithm of fixed asset investment, and logarithm of the size of workforce. ***, **, and * indicate the 1, 5, and 10 percent significance level, respectively.

Table 4: The Impact of Education and Innovation on Economic Growth

Dependent variable: GDP growth, measured by the annual change in Logarithm of GDP

	OLS Est.	OLS S.E.	2SLS Est.	2SLS S.E.	Spatial GMM SE
1998					
Log FCI	-0.00917	0.00705	-0.01068	0.00683	0.00720
Log Patent per capita	0.00161	0.01032	0.00653	0.01118	0.00778
Change of Log Employees	-0.22630	0.17424	-0.17922	0.17188	0.12310
1999					
Log FCI	-0.00558	0.00800	-0.00779	0.00770	0.00773
Log Patent per capita	0.00528	0.00765	0.01033	0.00807	0.00328
Change of Log Employees	0.44869	0.38095	0.47159	0.35876	0.20792
2001					
Log FCI	-0.01125	0.00516	-0.00950	0.00511	0.00721
Log Patent per capita	0.00841	0.00458	0.00511	0.00525	0.00731
Change of Log Employees	-0.19122	0.31586	-0.11413	0.30568	0.29314
2002					
Log FCI	-0.00387	0.00523	-0.00300	0.00539	0.00601
Log Patent per capita	-0.00093	0.00453	-0.00233	0.00558	0.00626
Change of Log Employees	0.09179	0.09859	0.10783	0.10114	0.07910
2003					
Log FCI	0.00515	0.00848	0.00156	0.00889	0.00748
Log Patent per capita	-0.00078	0.00691	0.00465	0.00876	0.00720
Change of Log Employees	0.31022	0.33771	0.18836	0.34469	0.29641
2004					
Log FCI	0.01627	0.00461	0.01386	0.00465	0.00404
Log Patent per capita	-0.00689	0.00391	-0.00263	0.00462	0.00295
Change of Log Employees	-0.63140	0.22903	-0.72101	0.22577	0.21535
2005					
Log FCI	-0.01693	0.02007	-0.03380	0.02103	0.01284
Log Patent per capita	0.03151	0.01599	0.06274	0.01991	0.01927
Change of Log Employees	0.27708	0.93486	-0.04066	0.93994	1.01136
2006					
Log FCI	0.00399	0.00511	0.00743	0.00616	0.00497
Log Patent per capita	-0.00594	0.00557	-0.01226	0.00871	0.00764
Change of Log Employees	0.00574	0.01245	0.01605	0.01638	0.01760

Notes: 2SLS estimation treats patent applications as endogenous and uses High (the percentage of workers with college or above education) as instrument. Spatial GMM S.E. is estimated following Conley (1999).

Appendix Table: Definition and Summary Statistics of Variables

	Variable definition	Mean	Standard Deviation	Min.	Max.
All Years					
GDP	Gross domestic product in 100 million RMB Yuan	4300.423	3528.126	168.020	13816.970
Patent	The number of Invention Patent Applications per 10,000 Population	5007.750	9501.473	314.447	44537.250
High	The percentage of workers with tertiary education in the labor force	6.727	4.714	0.434	24.792
Secondary	The percentage of workers with secondary education in the labor force	53.694	12.924	7.293	68.341
Primary	The percentage of workers with primary education in the labor force	39.651	15.884	8.579	92.293
S	Average years of schooling of the labor force	11.088	0.623	9.251	12.737
FCI	Fixed capital investment in 100 million RMB Yuan	1712.368	1325.588	114.228	4986.126
Employees	The number of employees in 10,000 people	1886.256	1304.005	115.461	4861.887
1997					
GDP	Gross domestic product in 100 million RMB Yuan	2482.471	1915.893	76.980	7315.510
Patent	The number of Invention Patent Applications per 10,000 Population	1318.172	2364.860	80.645	13524.190
High	The percentage of workers with tertiary education in the labor force	4.442	3.593	0.500	18.000
Secondary	The percentage of workers with secondary education in the labor force	48.958	13.724	3.100	72.000
Primary	The percentage of workers with primary education in the labor force	47.258	16.626	10.000	96.400
S	Average years of schooling of the labor force	10.839	0.627	9.128	12.420
FCI	Fixed capital investment in 100 million RMB Yuan	779.731	633.563	34.500	2291.050
Employees	The number of employees in 10,000 people	2053.765	1408.805	120.300	5017.000
2006					
GDP	Gross domestic product in 100 million RMB Yuan	7453.334	6422.115	291.010	26204.470
Patent	The number of Invention Patent Applications per 10,000 Population	11057.910	20218.590	747.331	89981.020
High	The percentage of workers with tertiary education in the labor force	8.191	7.088	0.488	35.696
Secondary	The percentage of workers with secondary education in the labor force	54.178	12.704	9.414	70.577
Primary	The percentage of workers with primary education in the labor force	37.630	16.271	8.287	90.098
S	Average years of schooling of the labor force	11.199	0.709	9.317	13.178
FCI	Fixed capital investment in 100 million RMB Yuan	3485.503	2712.135	231.142	11111.420
Employees	The number of employees in 10,000 people	377.844	231.365	18.915	954.439