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Michael Funke and Hao Yu

Economic growth across Chinese
provinces: In search of innovation-driven
gains



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Abstract

In this paper we analyse the impact of R&D on total factor productivity across Chinese provinces. We introduce innovations explicitly into a production function and evaluate their contribution to economic growth in 1993 - 2006. The empirical results highlight the importance and the interaction between local and external research. The evidence indicates that growth in China is not explained simply by factor input accumulation.

Keywords: China, R&D, R&D Spillovers, patents, regional economic growth, semiparametric estimators

JEL-Classification: C14, O47, R11, R12

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Tiivistelmä

Tämä tutkimus analysoi tutkimuksen ja tuotekehittelyn vaikutusta kokonaistuottavuuteen Kiinan alueilla. Tutkimme innovaatioiden vaikutusta talouskasvuun vuosina 1993–2006 asettamalla innovaatiot suoraan tuotantofunktioon. Tulokset paljastavat, miten tärkeää sekä paikallinen että muualla tehtävä tutkimus on talouskasvulle. Tutkimustulokset paljastavat, että pelkästään tuotannon-tekijöiden lisääminen ei selitä Kiinan talouskasvua.

Asiasanat: Kiina, tutkimus ja tuotekehittely, tutkimuksen ja tuotekehittelyn leviäminen, patentit, alueellinen talouskasvu, semiparametrinen estimointi

1 Introduction

Despite China's remarkable achievements and miraculous growth, a great deal of debate and attention has focussed on China's uneven regional developments. Urban and rural standards of living continue to be poles apart. Therefore, the country's leadership has recently been contemplating a smoother ride on its development path by setting forth a guideline prioritising "harmony". The sustained reforms and opening-up over the past two and half decades have resulted in prosperity for many Chinese citizens, but the cross-country income gaps are among the top concerns of the Chinese government. The government's uneasiness stems from the fact that China's history is littered with rebellions, uprisings, and revolutions sparked by economic inequalities. Against this historical experience, Chinese leaders have placed the concept of a "harmonious socialist society" for renewed political legitimacy and political cohesion of the country at the top of their list of things to do. It is envisaged that this harmonious society should enable all the people to share the social wealth brought by reform and development.

Productivity growth is probably the single most important indicator of an economy's health and driver of its real GDP in the long run. The more productive an economy, i.e. the more effectively it uses its capital and labour, the greater its prosperity and standard of living. Productivity can be measured in different ways. Labour productivity is a widely used and transparent measure, but it provides only a partial view of the relationship between inputs and outputs. Total factor productivity (TFP), which can be traced back to the seminal paper by Solow (1957), takes into consideration all inputs and is thus a better measure of technological change.¹ There is growing theoretical and empirical evidence that innovation is among the main sources of TFP growth. Product-related R&D activity creates new markets and process-related R&D activity reduces production costs. When an innovation is commercially successful, its effects spill over to other firms and across regional and national boundaries.²

The emergence of the R&D-based endogenous growth literature has re-emphasized the strategic role of technological advance in economic dynamics over time and space. The technological gap is frequently cited as an important factor in explaining income disparities between countries and regions. The recent rise of new growth theory has also led to an overlap between the macroeco-

¹ Labour productivity growth may reflect "extensive" growth - doing more with more inputs - while TFP tries to measure "intensive" growth - doing more with less inputs. If China's fast labour productivity growth is entirely the result of capital deepening, then questions about its sustainability would arise.

² A large body of literature has been devoted to these social benefits of R&D investment. See, for example, Coe and Helpman (1995) and Coe et al. (1997).

economic growth literature and the empirical literature on R&D. R&D-based growth models emphasize the idea that economic growth results from the increasing returns associated with new knowledge. These are models with two sectors: producers of final output and an R&D sector. The R&D sector develops ideas that lead to a monopoly situations. R&D firms are assumed to be able to make monopoly profits by selling ideas to production firms, but the free entry condition means that these profits are dissipated on R&D spending. The implications of this approach are that the higher investment in R&D, the higher the innovative capacity and the faster the economic growth.³

In the paper below we try to disentangle the importance of R&D for growth across Chinese provinces. We also investigate different capacities to innovate and to assimilate innovation. These differences may be important for explaining persistent differences in economic performance.

The remainder of the paper is divided into three parts. Section 2 provides a brief overview of the methodological issues of estimating production functions and the building blocks of existing estimators for resolving them. In section 3, we detail our estimation of the structural parameters of the production function and discuss the estimation results in the light of previous studies. Finally, conclusions and implications for Chinese policy making are presented in Section 4.

2 Growth accounting: Methodological issues

As stated above, the objective of this paper is to shed light on the determinants of regional economic growth in China. Production functions are used to examine the role of human capital, physical capital, R&D and R&D spillovers in China's innovations. For the purpose of exposition, we introduce our empirical approach by means of the simplest conceivable two-factor Cobb-Douglas production function

$$(1) \quad Y_{it} = A_{it} K_{it}^{\beta} L_{it}^{\gamma},$$

where Y_{it} is *GDP* of province i in period t , K_{it} and L_{it} and inputs of capital and labour, and A_{it} is the efficiency level of province i in period t .⁴ The subscripts i and t refer respectively to the province

³ Izushi (2008) examined the role of R&D underlying the Romer (1990) model and its subsequent modifications, and compared the models against productivity growth of European regions in the 1990s.

⁴ The estimation methods discussed extend immediately to more factors of production and/or other functional forms, provided that variable inputs have positive cross-partial derivatives with respect to productivity.

and the year. While Y_{it} , K_{it} and L_{it} are observable, A_{it} is not observable to the researcher. Taking the logarithm of both sides and appending an iid error term yields

$$(2) \quad y_{it} = \alpha + \beta k_{it} + \gamma_{it} + \varepsilon_{it},$$

where lower-case letters refer to natural logs and $\ln(A_{it}) = \alpha + \varepsilon_{it}$. α measures the mean efficiency across China and ε_{it} is the province- and time-specific deviation from that mean. $\ln(A_{it})$ can further be decomposed into an observable (or at least predictable) and an unobservable component according to

$$(3) \quad y_{it} = \alpha + \beta k_{it} + \gamma_{it} + \kappa_{it} + u_{it},$$

where κ_{it} represents province-level productivity and u_{it} is an iid component representing measurement errors and/or omitted variables. In other words, the difference between κ_{it} and u_{it} is that the former is a state variable and hence impacts regional economic performance. Estimated productivity can then be calculated as

$$(4) \quad \kappa_{it} = y_{it} - \hat{\beta}k_{it} - \hat{\gamma}_{it}$$

and TFP in levels can be obtained as the exponential of κ_{it} , i.e. $TFP_{it} = \exp(\kappa_{it})$. Three prominent econometric difficulties arise when TFP is estimated applying ordinary least squares (OLS) to equation (4). First, when using a balanced panel of Chinese provinces no allowance is made for endogenous location decisions, resulting in a selection bias. Second, since productivity and input choices of provinces are likely to be correlated, OLS introduces an endogeneity problem. Third, the product mix is likely to be related to TFP.

The location bias results from the fact that investment decisions of Chinese firms are related to productivity.⁵ To make a long story short, high productivity may trigger investment. If

⁵ Because of their geography and preferential policies, the more developed coastal regions have also been able to attract more foreign direct investment. It is very likely that this exposure to foreign direct investment had a positive impact on TFP. Aziz and Duenwald (2001), Zou and Zhou (2007) and Maasoumi and Wang (2008) have identified club convergence across Chinese provinces. While per capita GDP of poor provinces is catching up with those of the rich ones, the relative income distribution appears to be stratifying into several modes or clubs.

firms have prior knowledge about regional productivities levels κ_{it} prior to the investment decision, this will generate correlation between u_{it} and fixed capital. In sum, the problem of endogeneity of attrition or location will generate a negative correlation between u_{it} and κ_{it} , causing the capital coefficient in the production function to be biased downwards. The endogeneity problem arises because the inputs in the production function (2) are determined by the characteristics of the province, including its efficiency level. This endogeneity of inputs is defined as the correlation between the level of inputs chosen and unobserved productivity shocks.⁶ Finally, Bernard et al. (2005) noted that TFP estimates encounter the product mix problem: the provinces' output composition is likely to be correlated to their productivity.⁷

To remedy these problems, instrumental variables (IV) or fixed effects may be used. IV estimation tries to achieve consistency of coefficient estimates by instrumenting the independent variables that cause the endogeneity problem with regressors that are correlated with these inputs, but uncorrelated with unobserved TFP. In practice, IV estimators have not been particularly useful. One of the obvious shortcomings is the lack of instruments. Furthermore, IV estimation techniques do not provide any solution to the endogeneity-of-location problem.

By assuming that κ_{it} is province-specific but time-invariant, it is possible to estimate (2) using a fixed effects estimator. Moreover, when the endogeneity of location is determined by the time-invariant fixed effects, the fixed effects estimator should also sort out the attrition problem. In spite of the attractive properties of the fixed effects estimator, however, it often leads to unreasonably low estimates of the capital coefficient β . To sum up, traditional estimation methods are vitiated by endogeneity and attrition problems and estimation biases.⁸

Below, we briefly introduce the more suitable semiparametric (control function) estimator suggested by Olley and Pakes (1996), with special attention to its advantages and drawbacks. Olley and Pakes (1996) were the first to introduce an estimation algorithm that controls for both the endogeneity and the attrition bias and yields reliable production function estimates. The idea of the

⁶ In the presence of many issues of inputs and simultaneity it is usually impossible to determine the direction of bias in the estimated β coefficient in equation (2). Levinsohn and Petrin (2003) illustrated, for a two-input production function where labour is the only freely variable input and capital is quasi-fixed, that the estimated β coefficient will be biased downward if a positive correlation exists between labour and capital. The coefficients of the variable inputs will be biased upwards.

⁷ In a complementary strand of literature, Rodrik (1996) recently emphasized the importance of the product mix. China's exports are as sophisticated as those of a country three times richer. The goods it sells to America overlap to a surprising extent with the merchandise America buys from members of the OECD, argues Schott (2006).

⁸ Olley and Pakes (1996) applied fixed effects to various samples and found that the time-invariant nature of κ_{it} underlying the model is invalid. This also obtains for Chinese provinces experiencing rapid growth and structural change.

estimator is to invert demand for capital to infer unobserved productivity shocks and then use the estimated productivity shock as a regressor in the production function.⁹ The additional attrition problem is addressed by using attrition probabilities.¹⁰

To be specific, the amount of domestic and foreign investment in region i is assumed to depend on capital and productivity according to

$$(5) \quad i_{it} = f_t(k_{it}, \kappa_{it}).$$

Provided investment is strictly increasing in productivity and conditional on capital, it is straightforward to invert factor demands:

$$(6) \quad \kappa_{it} = g_t(k_{it}, i_{it}),$$

where $g_t(\cdot) = f_t^{-1}(\cdot)$. Inserting (6) into (2), yields

$$(7) \quad y_{it} = \alpha + \beta k_{it} + \gamma_{it} + g_t(k_{it}, i_{it}) + u_{it}.$$

Define the function

$$(8) \quad \phi(k_{it}, i_{it}) = \alpha + \beta k_{it} + g_t(k_{it}, i_{it}).$$

Estimation then proceeds in three steps. In the first stage of the semiparametric algorithm, the following equation is estimated using OLS

$$(9) \quad y_{it} = \alpha + \gamma_{it} + \phi(k_{it}, i_{it}) + u_{it},$$

⁹ Other inversion (control function) estimators have been suggested by Levinsohn and Petrin (2003), Pavcnik (2002) and Doraszelski and Jaumandreu (2008). To address the endogeneity bias, the GMM system estimator is also a suitable estimation method provided lagged values and lagged differences are good instruments [see Blundell and Bond (2000)]. The degree to which these instruments are a good choice is subject to some discussion in the literature. Below we focus upon techniques which are more structural in nature.

¹⁰ Below we give a brief overview with emphasis on the mechanics of the estimator. More elaborated expositions can be found in Olley and Pakes (1996) and Akerberg et al. (2007).

where $\phi(\cdot)$ is approximated by a higher-order polynomial in i_{it} and k_{it} . Before moving further, let us recall that estimation of (9) leads to a consistent estimate of γ . However, estimation of (9) does not identify β , so some further effort is required to disentangle the effects of capital on investment from the effect on output.

In order to recover the coefficient of the capital variable, information on regional dynamics is exploited. We assume that productivity evolves over time as an exogenous first-order Markov process:

$$(10) \quad \kappa_{it+1} = E(\kappa_{it+1} | \kappa_{it}) + \xi_{it+1},$$

where the stochastic nature of productivity improvement is captured by ξ_{it+1} which is treated as an *iid* shock with zero mean and variance σ_{ξ}^2 .¹¹ Regions will remain as attractive investment locations ($\chi_{it+1} = 1$) as long as productivity exceeds a lower bound, i.e. $\chi_{it+1} = 1$ for $\kappa_{it+1} \geq \tilde{\kappa}_{it+1}$, where χ_{it+1} is a survival indicator. Considering the expectation of $E[y_{it+1} - \mathcal{N}_{it+1}]$ yields

$$(11) \quad \begin{aligned} E[y_{it+1} - \mathcal{N}_{it+1} | k_{it+1}, \chi_{it+1} = 1] &= \alpha + \beta k_{it+1} + E[\kappa_{it+1} | k_{it}, \chi_{it+1} = 1] \\ y_{it+1} - \mathcal{N}_{it+1} &= \alpha + \beta k_{it+1} + E[\kappa_{it+1} | k_{it}, \chi_{it+1}] + \xi_{it+1} + u_{it+1} \\ y_{it+1} - \mathcal{N}_{it+1} &= \alpha + \beta k_{it+1} + g(p_{it}, \phi_{it} - \beta k_{it}) + \xi_{it+1} + u_{it+1} \end{aligned}$$

where $E[\kappa_{it+1} | k_{it}, \chi_{it+1}] = g(p_{it}, \phi_{it} - \beta k_{it})$ follows from the law of motion for productivity shocks and p_{it} is the probability of attrition of region i in period $t+1$, i.e. $p_{it} = \text{prob}\{\chi_{it+1} = 1\}$. In our implementation, we estimate the probability of attrition in the second stage by fitting a probit model of χ_{it} on i_{it-1} and k_{it-1} and their squares and cross products. Denote the predicted probabilities from the probit model as \hat{p}_{it} .

In the third stage, this finally leads to the following equation by nonlinear least squares, which enables identification of the coefficient of capital, β :

¹¹ In equation (10), productivity is modelled as an exogenous Markov-process. Recently, Doraszelski and Jaumandreu (2008) endogenised productivity by allowing it to depend on R&D. The Markov transition matrix methodology was adopted by Curran et al. (2007) and Sakamoto and Islam (2008) to study real GDP per capita convergence across Chinese counties and provinces and to capture the dynamics embodied in the Chinese data.

$$(12) \quad y_{it+1} - \hat{y}_{it+1} = \alpha + \beta k_{it+1} + g(\hat{p}_{it}, \hat{\phi}_{it} - \beta k_{it}) + \xi_{it+1} + u_{it+1},$$

where the unknown function $g(\cdot)$ is approximated by a second-order polynomial.¹² Because the estimation routine involves three steps, deriving analytical standard errors is nontrivial. Therefore bootstrapped standard errors are used and the variation in the bootstrapped samples provides an estimate of the standard errors of the original point estimates.

3 Empirics: Economic growth across Chinese provinces

Empirical research on economic growth is faced with considerable uncertainty given a set of multiple, overlapping theories emphasizing different growth channels. Brock and Durlauf (2001) referred to this as “openendedness” of economic theories, in the sense that the truth of one theory does not imply the falsity of another. Furthermore, within each channel there may be alternative measures representing the same theory. Against this background, we introduce our specification of the production function and our dataset.

The data are a balanced panel for 30 Chinese provinces for the period 1993 to 2006.¹³ GDP data were obtained from the *Statistical Yearbook of China*.

Measuring provincial capital stocks is a challenging task. Of particular relevance are the assumptions concerning depreciation rates, initial capital stock and the appropriate deflators. We compiled the capital stock data using the perpetual inventory method recently suggested by He et al. (2007).

Needless to say, human capital stock data for China are hard to come by. Therefore, various previous papers have not paid attention to the differences between unadjusted labour input and human capital. Neither have they addressed the differences between the accumulation and the stock of human capital. In our approach below we use a proxy for the stock of human capital, since we believe that the stock of human capital generates technological innovations and facilitates learning

¹² The estimates are based on Newton’s method. We have also used grid search for confirming that the procedure finds the global minimum of the objective function.

¹³ China currently has 23 provinces, four Centrally Administered Municipalities, and five autonomous regions. Since these entities are administratively equal, we will use the term “province” throughout the paper. Chongqing became a new municipality only in 1997. In our database we therefore combined Chongqing and Sichuan.

and technology diffusion.¹⁴ We first calculate the number of workers at different education levels using microcensus data. The Chinese microcensus provides the official representative statistics for the population and the labour market (*National Sample Survey of Population Changes*), covering each year 1% of all households in China. The survey allows one to calculate for each province i ($i = 1, \dots, 30$) the shares of workers having finished primary school (S_1), junior secondary school (S_2), senior secondary school (S_3), special school (S_4) and higher education (S_5). Primary schooling is assumed to last 6 years, junior secondary school 9 years, senior secondary school 12 years, special school 11-12 years and higher education 16 years. The average length of schooling of the provincial workforce in period t can then be calculated according to

$$(13) \quad l_{it} = \frac{(6S_{1,it} + 9S_{2,it} + 12S_{3,it} + 11.5S_{4,it} + 16S_{5,it})}{\text{Population}_{it}}.$$

Multiplying l_{it} with the provincial labour force then enables calculation of the stock of human capital as

$$(14) \quad H_{it} = l_{it} \text{Labour Force}_{it}.$$

It is well known that it is difficult to disentangle technological improvement from production inputs. Therefore, it is hardly surprising that contributions within this strand of research differ widely as to how R&D activities are inferred. In our study, patent applications are used as a proxy for technological innovations. Patent applications are easily accessible data and have been widely used as indicators of innovation and diffusion.¹⁵ Another reason is that most studies find a very strong relationship between R&D and patent applications at the cross-sectional level: the median R^2 is around 0.9.¹⁶ Because patent applications are disclosed only 18 months after filing, 2006 is the latest year for which data are available.

¹⁴ Similar methodologies have been used by Wang and Yao (2003) and Islam et al. (2006). Although on-the-job training and firm-specific human capital investments contribute to the improvement of the human capital stock, they were excluded due to missing data and measurement problems.

¹⁵ One might be inclined to think that the number of patent filings is only a sketchy indicator of a country's ability to generate ideas. This is because the usefulness of patents can vary widely, nor are all invention patents commercially successful. A good reference on the caveats of using patent data as a measure of innovation is Griliches (1990).

¹⁶ See e.g. Griliches (1990) and Hausman et al. (1986) for the international evidence. Sun (2000) analysed the innovation landscape across Chinese provinces. The analysis supports the view that state-supported R&D activities are the major source of invention patent applications. Agglomeration does not seem to be a significant factor for patents in China, in contrast to findings of other studies.

China's patent system is evolving fast, and enforcement, though lagging, is improving. China's Patent Law went into effect on 1 April 1985. Generally, the technology to be patented must pass four tests: that it is novel, useful, non-obvious and man-made. The law grants three types of patents: invention, utility model and design patents. Applications for invention patents are more rigorously scrutinized for novelty and non-obviousness before the patents are granted. Invention patents receive 20 years of protection, up to the global standard. On the contrary, the utility and design patents generally cover more incremental innovations and are not subject to examination for novelty and inventive step. In the empirical work below we use invention patent applications because we consider them to represent high quality ideas.

The first amendment of the Chinese Patent Law entered into effect on 1 January 1993. The duration of invention patent protection was extended from 15 to 20 years. The Law was then revised again in August 2000. The amended law simplified the procedures of patent application and examination.¹⁷

Chinese patent applications increased at an annual rate of 3.5 per cent in 1993 – 1999; from 2000 to 2006, the annual increase was 29.7 per cent.¹⁸

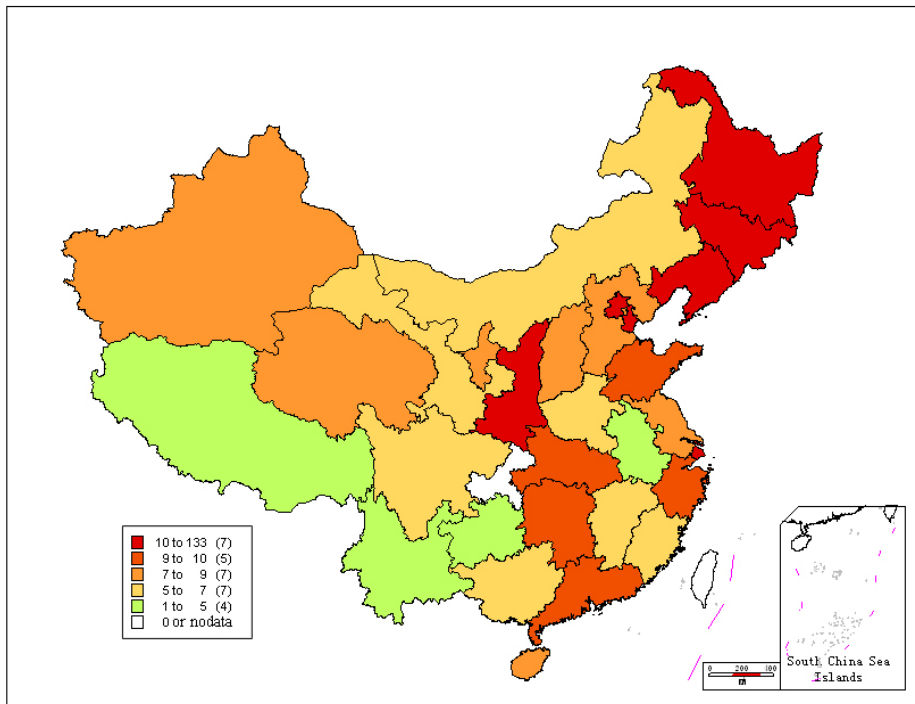
Using the invention patent application data, we compiled the provincial patent stock data using the perpetual inventory method. Before turning to the estimation results, it is interesting to look at the R&D intensity across provinces.¹⁹ Figures 1 and 2 show the distribution of invention patent stocks by province. The evidence is quite striking and reveals that R&D intensity varies substantially between subsets of provinces. The figures provide a landscape and league table of China's most intellectually creative regions. In 2006, the geographical distribution of patents exhibits a clear pattern: the coastal and central provinces, such as Guangdong, Beijing, Shanghai, Jiangsu, Zhejiang, Shandong, Tianjin, Liaoning, Hunan, and Sichuan, are all among the top 10 innovative regions. These top 10 regions account for 80 per cent of the total invention patent stocks in 2006.

¹⁷ One caveat is worth mentioning. Focussing on patents as an indicator of innovativeness overlooks an important fact. What matters for economic innovation is turning scientific discoveries into new products and smart processes. In other words, a venturesome array of products and venturesome consumption patterns matter. One may argue that Chinese firms have a large pool of domestic customers that do not have the same high expectations as Western customers typically have. Chinese firms can therefore practise on their domestic customers while they improve quality to the point where they can begin to export.

¹⁸ This trend is important because countries that create intellectual property eventually enforce it as well.

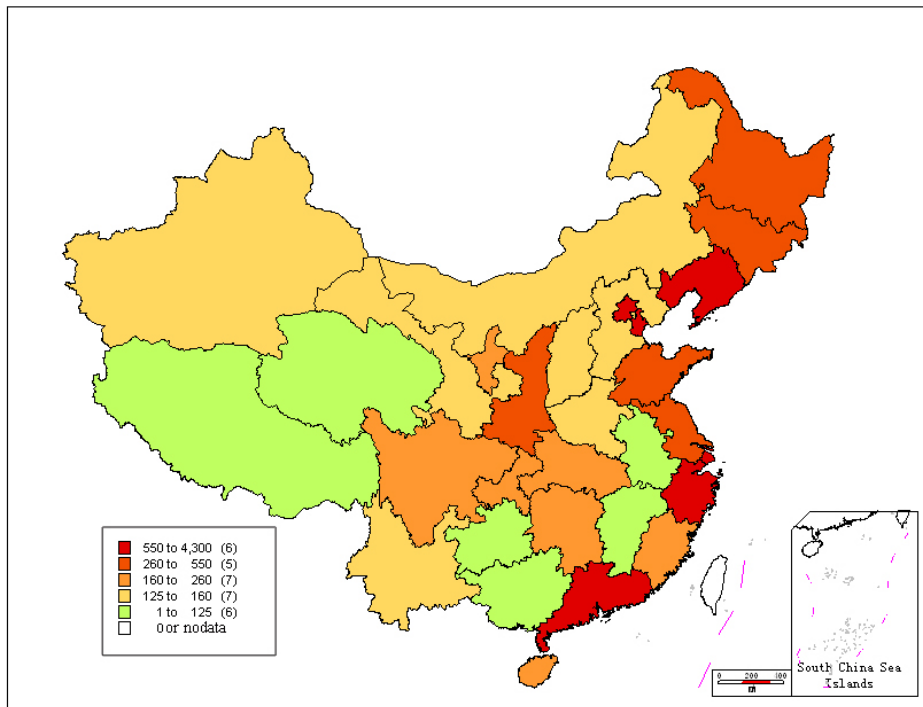
¹⁹ Chinese patents include filings from domestic and foreign firms. Unfortunately, it is impossible to winnow domestic from foreign patents neatly because filings from joint ventures are always classified as having a Chinese origin. This implies that some international R&D spillovers arising from China's "open door policy" are reclassified as intranational spillovers and hence included in the analysis. Cheung and Lin (2004) found supporting evidence that spillovers from FDI have sparked patent applications. Likewise, Hu and Jefferson (2009) found that China's surge in patent activity is due to the amendments to property right laws and the expansion of FDI.

Figure 1 Inter-regional differences in invention patent stocks, 1993



Notes: The Chinese patent data are available online at <http://www.sipo.gov.cn/sipo2008/>

Figure 2 Inter-regional differences in invention patent stocks, 2006



Notes: The Chinese patent data are available online at <http://www.sipo.gov.cn/sipo2008/>

One element that is missing is the possibility that regions benefit from spatial spillovers. The idea is that provinces can benefit from external knowledge. This requires a proxy for the ability of regions to learn or assimilate knowledge from others. The knowledge spillovers approach has been adopted by economists using different quantitative methods. To guide our thinking, we follow Funke and Niebuhr (2005) and Kuo and Yang (2008) and define a patent externality variable as

$$(15) \quad PS_i = \ln \left[\sum_{\substack{j=1 \\ j \neq i}}^{30} P_j w_{ij} \right],$$

where P_j represents the stock of patents in province j , w_{ij} represents the spatial weight and PS_j is the patents spillovers variable. Knowledge external to a province is obtained as a combination of the stock of patents obtained by other provinces and weighted by a measure of proximity within the geographic space.²⁰ We assume that the spatial weights w_{ij} decline with geographic distance and follow a negative exponential function with distance decay parameter β_E defined as

$$(16) \quad w_{ij} = e^{-\beta_E d_{ij}},$$

where d_{ij} is the rail travel time between the provincial capital cities i and j .²¹ As β_E increases, the frictional effect of distance rises and interaction declines.²² Lastly, the parameter β_E is defined as

²⁰ The decisive factor in the knowledge transmission process is the difference between codifiable and tacit knowledge. This distinction helps one to understand why modern information technologies do not erase the importance of proximity. It is indeed difficult to visualise any barriers to the diffusion of codifiable information. But tacit knowledge is clearly different. Tacit knowledge is embedded in the minds of people and the routines of firms and so does not move easily from place to place. Even codified innovations like those covered in patents do not flow freely from place to place. Frequently, in order to make full advantage of the insights provided in a patented (codified) innovation, one needs to have the complementary tacit knowledge to apply it. Below we investigate this idea in more detail.

²¹ We choose rail travel time, rather than straight line distance, as it gives a more realistic representation of the cost of interaction and contacts across space. The use of kilometres would not allow us to take into account different types of train connections which significantly affect real world interactions.

²² Adams and Jaffe (2002) have emphasized that the flows of interregional knowledge spillovers are likely to wane with distance, as the potential for face-to-face and other forms of interaction decay. At the EU level, Greunz (2003) found a bounded effect on local patenting activity of innovative efforts pursued in the neighbourhood of up to 360 kilometres. In the same vein, Bottazzi and Peri (2003) found regional spillover effects with a positive impact of neighbouring regions' R&D efforts within a 200-300 kilometre limit. This implies that knowledge spillovers are mainly an intra-national phenomenon.

$$(17) \quad \beta_E = \frac{-\ln(1 - \gamma_E)}{D_{Min}},$$

where D_{Min} is the average distance between the capital cities of adjacent provinces and $0 \leq \gamma_E \leq 1$ is a transformed distance decay parameter. As is customary in the literature, we chose $\gamma_E = 0.8$. The amount of knowledge flowing from outside the province is thus proxied by the magnitude of all other provinces' R&D activity weighted by the inverse of the bilateral travel time.

In order to provide a sense of the data, the calculated neighbouring provinces' patent stocks are given in Figures 3 and 4. The data shed light on the role of technological diffusion, geographic distance and external accessible patents in the Chinese innovation process.

Figure 3 Neighbouring regions' patent stocks, 1993

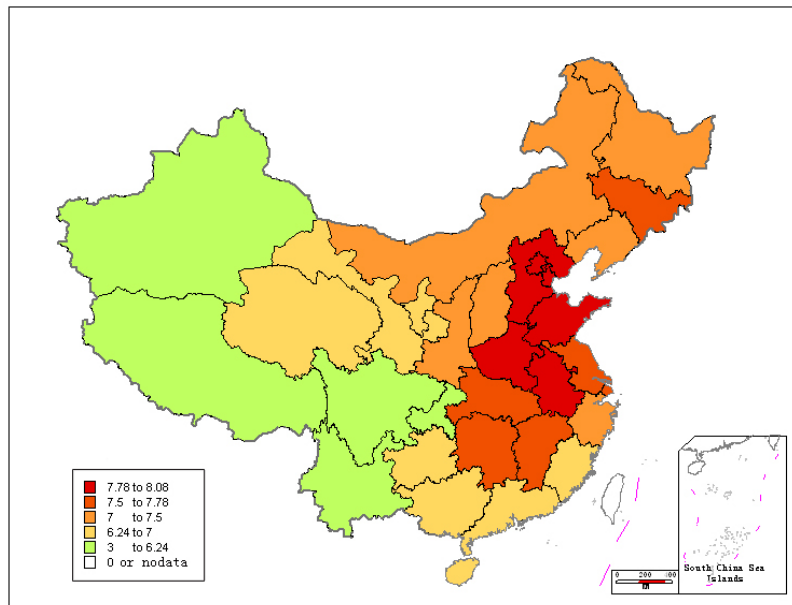
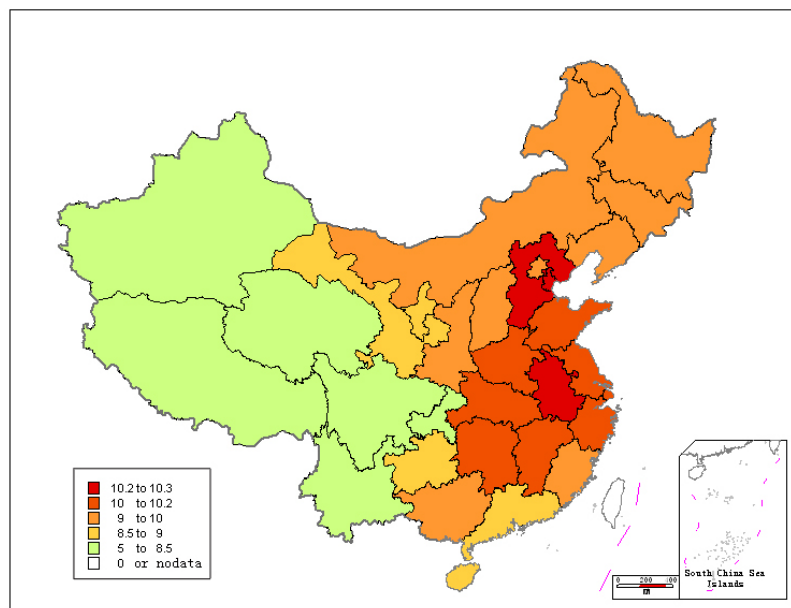


Figure 4 Neighbouring regions' patent stocks, 2006



The above ideas are embedded in the production function:

$$(18) \quad y_{it} = \alpha h_{it} + \beta k_{it} + \gamma p_{it} + \delta ps_{it} + \theta coast_i + \rho (coast_i \times ps_{it}) + \lambda_t + \varepsilon_{it},$$

where y_{it} is logged GDP (constant prices), k_{it} is the logged capital stock, h_{it} is the logged stock of human capital, p_{it} is the logged provincial stock of patents, ps_{it} is the logged stock of knowledge spillovers, $coast$ is a dummy variable representing the economically most developed coastal belt, the λ_t are time dummies and ε_{it} is an iid error term.²³ The time dummies may control for macroeconomic shocks and potential endogeneity arising from transitory shocks while the “coastal effect” may pick up some omitted variables.²⁴ Previous work on regional growth across Chinese provinces has typically found a dummy variable for the coastal provinces to be positive and statistically significant. Table 1 looks at the contribution of each factor to GDP.

²³ The coastal belt consists of the province/municipalities Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan.

²⁴ Note that the stock of human capital is rather sluggish and remains fairly constant over time. This implies that fixed effects cannot be estimated because coefficients will be weakly identified. Put differently, there is not enough variation in the data for a separate identification of all coefficients.

Table 1 Olley-Pakes estimates

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
h_{it}	0.291 (20.1)	0.286 (19.6)	0.282 (18.6)	0.278 (18.4)	0.328 (19.2)	0.321 (18.5)	0.328 (19.0)	0.321 (18.5)
k_{it}	0.339 (1.9)	0.399 (2.2)	0.306 (2.1)	0.300 (2.4)	0.216 (1.2)	0.296 (1.9)	0.204 (2.1)	0.172 (1.7)
p_{it}	0.235 (2.5)	0.308 (3.7)	0.278 (3.5)	0.358 (4.6)	0.243 (2.9)	0.340 (4.2)	0.251 (4.1)	0.297 (4.7)
sp_{it}	-	-	0.066 (1.9)	0.020 (0.6)	0.049 (1.4)	0.020 (0.6)	0.025 (0.9)	0.010 (0.3)
$coast$	-	-	-	-	0.106 (5.1)	0.096 (4.6)	0.122 (0.9)	0.045 (0.3)
$coast \times sp_{it}$	-	-	-	-	-	-	0.094 (3.3)	0.085 (3.1)
λ_t	No	Yes (prob = 0.01)	No	Yes (prob = 0.01)	No	Yes (prob = 0.25)	No	Yes (prob = 0.24)

Notes: Olley-Pakes panel data estimation; sample period: 1993-2006; bootstrapped t -values are given in parentheses; the constant terms from the 1st stage of the procedure are not reported. The prob value of the joint significance of the time dummies is given in the last row.

Several results are worth noting. First, in columns 1 and 2 we start from the base specification without R&D spillovers. All estimated coefficients are significant and the resulting returns to scale are broadly in line with common sense. Thus, our results verify the role of patents as a source of growth in China.²⁵ This implies that growth in China in 1993 - 2006, contrary to the seminal work by Chow (1993) for the upstream period 1958 - 1980, was not solely brought about by capital accumulation. The results also shed doubt on Krugman's (1994) former assertion that growth in Asia is simply explained by input accumulation.²⁶

Second, in columns 3 and 4 we have added the stocks of external accessible patents. The significant spillover variable in column 3 suggests that, to some extent, external R&D may even compensate for weak contributions of the R&D activities pursued locally. The flip side is that individual provinces may be held back, not just by their own endowment but by the endowments of their neighbouring provinces. If true, economic development would best be coordinated to be fully effective. As expected, the impacts of inter-provincial R&D spillovers are smaller than those of the own-R&D effect. The estimated magnitude of the stock of patents is 0.066, indicating that a 1 per

²⁵ This province-level evidence is consistent with the firm-level evidence in Hu and Jefferson (2004) indicating substantial and significant returns to R&D.

²⁶ The claim that "the newly industrializing countries of Asia, like the Soviet Union of the 1950s, have achieved rapid growth in large part through an astonishing mobilization of resources ... Once one accounts for the role of rapidly growing inputs in these countries' growth, one finds little left to explain" [Krugman (1994), p. 70] has stimulated a heated debate. This is a somewhat extreme position, and Young's (1995) careful growth accounting work indicates that, except for Singapore, there is evidence of TFP growth in the three Asian tigers: Hong Kong, South Korea and Taiwan.

cent increase in the stock of neighbouring patents would boost regional GDP by about 0.066 per cent, controlling for other variables. Column 4, however, indicates that the spillover variable turns out insignificant once the time dummies are added. The implication is that the uniform spillover variable has to be considered fragile.

Third, in column 5 and 6 we augment the specification with the coastal dummy as a further robustness check. The empirical results in Table 1 show that the dummy variable turns out to be significant, indicating a “missing element” in explaining regional growth across mainland China. Alternatively, one might say that there is something unique explaining the coastal growth process. The results in columns (5) and (6) indicate that coastal regions were on average 10 per cent more efficient than what would be predicted given their other characteristics.

Finally, we looked at the interaction of the coastal dummy variable with the R&D spillover variable. The results are documented in column 7 and 8. As can be seen, the results show that an increase in neighbouring R&D significantly boosts growth in the coastal areas while the own-patent stocks are still highly significant. Thus, other things being equal, a coastal province within an innovative neighbourhood is more advanced than one in the vicinity of less innovative provinces. When the interactive term is included, the coastal dummy variable and the overall R&D spillover variable become insignificant. This implies that the intranational R&D spillover effects matter only for the more developed eastern provinces. The results also shed new light on the omitted causes of economic growth captured by the traditional eastern belt dummy.²⁷

4 Summary remarks and conclusions

If China is to sustain growth in the years ahead, it must become a more innovation-based economy. Firms need to introduce or improve products or production processes over time, first to satisfy market needs and second to cope with increased competition from diffusion phenomena.²⁸ We have therefore carefully utilized semiparametric estimation techniques and measurement to determine the impacts of innovation and diffusion on economic growth in China.

²⁷ The new perspective implies that there is no need for a special “coastal theory”, at least with regard to unequal growth across Chinese provinces. In other words, the suggested channel may be able to identify the cause of the “coastal enigma”.

²⁸ Japan, Taiwan and South Korea, which also started off by competing mainly on cheap labour, ended up challenging the West’s biggest technology companies. All three countries now own a plethora of patents.

Our econometric approach enabled us to analyse different regional capacities to innovate and to assimilate innovation. Several implications can be extracted from the results of the empirical analysis. Local patents show a positive and significant relationship with provincial GDP. This implies that innovation was an important engine of growth in China over the sample period. Furthermore, external patents and neighbourhood effects turn out to be significant solely in the economically more active coastal provinces. This distinction is important for understanding the nature of the innovative landscape across China and may help us to develop regionally differentiated development policies.²⁹

In the future one can imagine the development of even more elaborated methods and models. Nevertheless, we feel that already much is learned by applying state of the art models to the data, and seeing how well they describe reality. We hope this is what we have accomplished here.

²⁹ According to the recent “*Global Innovation Index*” of the Economist Intelligence Unit, China was one of the biggest gainers. China has moved from 59th to 54th in the ranking, a gain that was expected to take five years instead of two. The index, which measures innovation performance in 82 countries, is based on the number of patents granted by patent offices in the United States, European Union and Japan. It also includes factors that help and hinder the ability to innovate, such as the amount of research and development undertaken and the technical skills of the country's workforce (see http://graphics.eiu.com/PDF/Cisco_Innovation_Complete.pdf).

References

- Akerberg, D., Benkard, C.L., Berry, S. and A. Pakes (2007) "Econometric Tools for Analyzing Market Outcomes", in: Heckman, J.J. and Leamer, E.E. (eds) *Handbook of Econometrics*, Vol. 6A, Amsterdam (Elsevier), 4171-4276.
- Adams, J.D. and A.B. Jaffe (2002) "Bounding the Effects of R&D: An Investigation Using Matched Firm and Establishment Data", *Rand Journal of Economics* 27, 700-721.
- Audretsch, D.B. and M.P. Feldman (1996) "R&D Spillovers and the Geography of Innovation and Production", *American Economic Review* 86, 630-640.
- Aziz, J. and C. Duenwald (2001) "China's Provincial Growth Dynamics", *IMF Working Paper No. WP/01/3*, Washington.
- Bernard, A.B., Redding, S. and P.K. Schott (2005) "Products and Productivity", *NBER Working Paper* 11575, Cambridge.
- Blundell, R. and S. Bond (2000) "GMM Estimation with Persistent Panel Data: An Application to Production Functions", *Econometric Reviews* 19, 321-340.
- Bottazzi, L. and G. Peri (2003) "Innovation and Spillovers in Regions: Evidence from European Patent Data", *European Economic Review* 47, 687-710.
- Brock, W.A. and S.N. Durlauf (2001) "Growth Empirics and Reality", *World Bank Economic Review* 15, 229-272.
- Cheung, K.Y. and P. Lin (2004) "Spillover Effects of FDI on Innovation in China: Evidence from the Provincial Data", *China Economic Review* 15, 25-44.
- Chow, G. (1993) "Capital Formation and Economic Growth", *Quarterly Journal of Economics* 108, 809-842.
- Coe, D. and E. Helpman (1995) "International R&D Spillovers", *European Economic Review* 39, 859-887.
- Coe, D.T., Helpman, E. and A. Hoffmaister (1997) "North-South R&D Spillovers", *The Economic Journal* 107, 134-149.
- Curran, D., Funke, M. and J. Wang (2007) "Economic Growth Across Space and Time: Subprovincial Evidence from Mainland China", *Bank of Finland, BOFIT Discussion Paper No. 21/2007*, Helsinki..
- Doraszelski, U. and J. Jaumandreu (2008) "R&D and Productivity: Estimating Production Functions When Productivity is Endogenous", *CEPR Discussion Paper No. 6636*, London.
- Funke, M. and A. Niebuhr (2005) "Regional Geographic Research and Development Spillovers and Economic Growth", *Regional Studies* 39, 143-153.
- Greuz, L. (2003) "Geographically and Technologically Mediated Knowledge Spillovers Between European Regions", *Annals of Regional Science* 37, 657-680.
- Griliches, Z. (1990) "Patent Statistics as Economic Indicators: A Survey", *Journal of Economic Literature* 28, 1661-1707.

-
- Hausman, J., Griliches, Z, and B.B. Hall (1986) “Econometric Models for Count Data with an Application to the Patent-R&D Relationship”, *Econometrica* 52, 909-938.
- He, D., Zhang, W. and J. Shek (2007) “How Efficient Has Been China’s Investment? Empirical Evidence from National and Provincial Data”, *Pacific Economic Review* 12, 597-617.
- Hu, A. and Jefferson, G.H. (2004) “Returns to Research and Development in Chinese Industry: Evidence from State-Owned Enterprises in Beijing”, *China Economic Review* 15, 86-107.
- Hu, A. and Jefferson, G.H. (2009) “A Great Wall of Patents: What is Behind China’s Recent Patent Explosion?”, *Journal of Development Economics* (forthcoming).
- Islam, N., Dai, E., Sakamoto, H. (2006) “Role of TFP in China’s Growth”, *Asian Economic Journal* 20, 127-159.
- Izushi, H. (2008) “What Does Endogenous Growth Theory Tell about Regional Economies? Empirics of R&D Worker-based Productivity Growth”, *Regional Studies* 42, 946-960.
- Krugman, P. (1994) “The Myth of Asia’s Miracle”, *Foreign Affairs* 73, Number 6 (November/December), 62-78.
- Kuo, C.-C. and Yang, C.-H. (2008) “Knowledge Capital and Spillovers on Regional Economic Growth: Evidence from China”, *China Economic Review* 19, 594-604.
- Levinsohn, J. and A. Petrin (2003) “Estimating Production Functions Using Inputs to Control for Unobservables”, *Review of Economic Studies* 70, 317-341.
- Maasoumi, E. and Le Wang (2008) “Economic Reform, Growth and Convergence in China”, *The Econometrics Journal* 11, 128-154.
- Olley, S.G. and A. Pakes (1996) “The Dynamics of Productivity in the Telecommunications Equipment Industry”, *Econometrica* 64, 1263-1297.
- Pavcnik, N. (2002) “Trade Liberalization, Exit, and Productivity Improvement: Evidence from Chilean Plants”, *Review of Economic Studies* 69, 245-276.
- Rodrik, D. (2006) “What’s So Special About China’s Exports?”, *China & World Economy* 14, 1-19.
- Romer, P.M. (1990) “Endogenous Technological Change”, *Journal of Political Economy* 98, S71-S102.
- Sakamoto, H. and N. Islam (2008) “Convergence Across Chinese Provinces: An Analysis Using Markov Transition Matrix”, *China Economic Review* 19, 66-79.
- Schott, P.K. (2006) “The Relative Sophistication of Chinese Exports”, *NBER Working Paper No. 12173*, Cambridge (Mass.).
- Solow, R.M. (1957) “Technical Change and the Aggregate Production Function”, *The Review of Economics and Statistics* 39, 312-320.
- Sun, Y. (2000) “Spatial Distribution of Patents in China”, *Regional Studies* 34, 441-454.
- Wang, Y. and Yao, Y. (2003) “Sources of China’s Economic Growth 1952-1999: Incorporating Human Capital Accumulation”, *China Economic Review* 14, 32-52.
- Young, A. (1995) “The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience”, *Quarterly Journal of Economics* 110, 641-680.

Zou, W. and H. Zhou (2007) “Classification of Growth Clubs and Convergence: Evidence from Panel Data in China, 1981–2004”, *China & World Economy* 15, Number 5, 91-106.

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