Knowledge Capital, Endogenous Growth and Regional Disparities in Productivity: Multi-level Evidences from China.

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Abstract

This paper examines the role of knowledge capital in persistent regional productivity disparities in developing countries. The hypotheses are tested using regional and firm level longitudinal data from China. It is found that inequalities in knowledge creation and transfer, both inter-generational and international, played a significant role in increasing regional disparities in productivity. These inequalities are exacerbated by the accumulative nature of knowledge capital. All this leads to self-perpetuating cycles of success and failure, particularly compounded with asymmetric financial and human capital between different regions.

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1. Introduction

Horizontal inequalities (HI) are an important but neglected dimension of development. Groups' relative performance in economic, social and political dimensions is an important source of individual welfare and can cause serious political instability (Stewart, 2005). One of the important types of HI is regional inequalities, which can give rise to separatist movements. There has been a vast literature dedicated to the sources of regional income inequalities. Many find differences in technologies to be a significant determinant of differences in national or regional incomes (Parente and Prescott (2000), Easterly and Levine (2001) and Di Yo et al (2003)). Differences in physical and human capital can only partially explain the variation in output per worker across countries (Hall and Jones, 1999, Klenow and Rodriguez-Clare, 1997). Most of the variation in output per worker across countries arises from differences in the Solow residual or total factor productivity (TFP). Easterly and Levine (2000) suggest that around 50% of the average per-capita output growth and 90% of the cross-country variation in growth rates can be explained by differences in TFP. They conclude that it is Solow residual TFP rather than factor accumulation that accounts for most of the variation in income and growth across nations. Boldrin and Canova (2001) find that per capita GDP is much more correlated with TFP than with the capital-labor ratios based on a sample of 101 EU regions. Byrne, Fazio and Piacentino (2005) find that international cross-country variation in labor productivity depends more on TFP than on capital intensity. They argue that structural differences across countries will have an effect on long-run growth by affecting TFP. Therefore, estimation of TFP dynamics in the long run is important for understanding cross-sectional differences in income.

The endogenous growth literature (Romer, 1990) has highlighted the role and the externalities of "knowledge capital", in association with research and development (R&D) and learning, in the growth process. Given the evolutionary nature of our knowledge and understanding of the world, knowledge capital is accumulated and path dependent (Nelson, 1992). What is the role of this evolutionary knowledge capital in the of productivity dynamics across regions? Does it lead to persistent or even increasing regional disparities in productivity or the other way round? Though there has been considerable research investigating the sources of regional income inequalities and some research documenting the existence of regional disparities in productivity, research on the dynamics of such regional disparities, and the role of knowledge capital in shaping the dynamic patterns is rare.

This paper aims to fill this gap in the literature by developing a theoretical framework in which the accumulative nature of knowledge and the endogeneity between productivity and some knowledge capital channels tend to lead to self-perpetuating cycles of success and failure. It classifies the inequalities of knowledge capital into 4 categories: inequalities in knowledge creation (R&D and innovation), inequalities in internal and inter-generational knowledge transfer (education), inequalities in external knowledge transfer (trade & FDI), and agglomeration, economies of scale and accumulation of knowledge capital. We test our hypotheses using panel data at both regional and firm-level from China.

China provides a good case for the study of regional disparities given the vast size of the country in terms of geography, population and economy and the well documented regional disparities across China's regions (e.g. World Bank, 1997; Fu, 2004). China furthermore exhibits exponential growth of trade, foreign direct investment (FDI) and investment in research and development (R&D). Since the start of the reform era and the opening-up in 1978, China has witnessed rapid economic growth. In 2006, China's real GDP was 6.0962 trillion Yuan, about 17 times its 1978 value andthe average annual growth rate was about 10% over the 1978-2006 period. Researchers find that economic growth in China largely depends on TFP growth. While the increase in physical capital, employment and human capital accounted for 57%, the increase in TFP accounted for 43%, of economic growth in China over the period 1978-95 (Bhattasali, 2001, Zheng and Hu, 2005 and World Bank, 1997). This rapid growth however is unevenly distributed with increasing regional disparities over the post-reform period.

Most regional productivity and income studies use aggregate regional level data for their analysis. Given that each region forms an integrated economic system (Nelson, 1992) and that knowledge spillovers are often geographically bounded (Venables, 1996), it is well justified using regional data to model the economic behavior of regions. The officially published regional level also consists of comprehensive information of the whole regional economic system, not only the business sector, but also the public sectors. However, each region consists of a large number of lower level economic units, with firms being the most basic economic agents and decision making units that carry out various economic and social activities. Given the huge heteroscedasticities among the firms and the different industry structure of each region, studies using aggregate regional level data will suffer from an aggregation bias. Therefore, a multi-level analysis linking the micro with meso level economic factors and policies is much needed and will provide complementary insights on the research questions under study. In this study, we will make such a first attempt.

The structure of the paper is as follows. Section 2 of the paper presents the theoretical framework for our paper. Section 3 discusses the model, methodology and data. Section 4 presents the empirical results. In section 5 we conclude.

2. Theoretical framework

In this section, we will present a theoretical framework for the relation between knowledge capital inequalities and persistent regional disparities in productivity. In the endogenous growth literature (Romer, 1990), knowledge capital is recognized as a stimulus to economic growth. The “knowledge capital” is embedded in either human or physical capital, for example, innovation and education. It is found to be an important factor for innovation and growth at different levels and for international investment decisions (Loof and Heshmati, 2002; Laperche, 2007; Morrison and Siegel, 1998; Moomaw, Mullen and Williams: Carr, Markusen and Maskus, 2001). Inequalities of knowledge capital between countries / regions / groups / firms arise from inequalities in the creation of knowledge, for which innovation serves as the main generator; from inequalities in the access, transfer and assimilation of inter-generational knowledge through education; and from inequalities in the access, transfer and assimilation of international knowledge through international trade and foreign direct investment. Moreover, the endogenous growth theory and the augmented Solow model (Solow, 1988) suggests that R&D and human capital are endogenous to the growth process. The empirical literature on trade, FDI and growth though produces mixed evidence: recent empirical research suggested an increasingly endogenous relationship between trade/FDI and economic growth (Li and Liu, 2005). This endogenous characteristic of knowledge capital is likely to lead to self-perpetuating cycles of success and failure. The accumulative and path dependent feature of knowledge capital (Nelson, 1992) will serve to reinforce these self-perpetuating cycles and result in persistent regional productivity disparities.

(1) Innovation and knowledge creation

An important factor contributing directly to the growth of TFP is technological advancement. A country and region can advance technologically by indigenous innovation and/or imitation of technologies from abroad. Two factors are important in explaining technological innovation. The first is R&D and the second is education or human capital (Ascari and Di Cosmo, 2004). R&D activity impacts productivity growth directly by promoting knowledge accumulation, and indirectly by promoting technology transfer. R&D spillovers may come from inter-industry R&D linkages or from international technology transfer (Coe and Helpman, 1995). Innovation activities can be a key determinant of TFP growth by directly boosting knowledge accumulation, and by indirectly improving the ability of domestic firms to learn from spillovers of knowledge from abroad (Cohen and Levinthal, 1989). Moreover, there can be complementarities between technological spillovers and domestic R&D or human capital accumulation (e.g., Griffith et al., 2004; and Cameron et al., 2005). Using the stochastic frontier method, Sharma, et al. (2007) identifies that regional TFP growth mainly results from technological progress for 48 U.S. states over the period 1977-2000. Ascari and Di Cosmo (2004) find that the strong difference in regional TFP between Northern and Southern Italian regions can be attributed to the effect of research activity and social capital over the period from 1985-2000.

(2) Education and inter-generational knowledge transfer

The augmented Solow model (Solow, 1988) suggests that human capital is the most important factor in the growth process. Compared with physical capital, the endowment of human capital plays a crucial role in determining the future level of TFP for a given country and region (Senhadji, 2000; Ascari and Di Cosmo, 2004). Education serves as the most important tool for inter-generational knowledge transfer and human capital accumulation. Inequalities in investment in education and human capital are found to be one of the main sources of increasing regional income inequalities in China (Fu, 2007). In addition, training is also found to be a significant factor enhancing productivity and performance at the firm level (Acemoglue, 1997; Baldwin and Yates, 1999; Fu and Gong, 2008).

(3) Trade / FDI and international knowledge transfer

Trade and FDI are often regarded as the engine and catalyst of economic growth (Greenaway, 1996; Balasubramanayam et al., 1996). Trade and FDI may contribute to economic growth through several channels including increased productive inputs, market augmenting, as well as productivity enhancing effects through competition pressure and knowledge transfer and spillovers. Empirical evidence with regard to the relationship between FDI/trade and productivity growth is, however, mixed. Cross country studies by Coe and Helpmann (1995), Bayoumi et al., (1999) and Madsen (2007) find that domestic and foreign R&D is the most important determinant of TFP at country level. The impact of international R&D spillovers through trade and FDI on

TFP is not entirely deniable. Evidence at the industry and firm levels is again mixed. For developing countries, most studies failed to find positive productivity spillovers from FDI (e.g., Haddad and Harrison, 1993; Aitken and Harrison, 1999; Kathuria, 2000; and Jefferson and Hu, 2003) with a few exceptions (eg., Javorcik, 2004). Fu and Gong (2008) argue that FDI contributes to static industry capabilities by advanced technologies embedded in imported machineries, but not to dynamic technological capabilities of indigenous firms in developing countries. In the case of developed countries, evidence is also mixed although there is more evidence in favor of positive productivity spillovers, as shown by Girma et al. (2001), Harris and Robinson (2004), Liu et al (2000); Hubert and Pain (2001), Haskel et al (2002) and Kellar and Yeaple (2003). Problems in measurement, data and methodology are likely to be responsible for this mixed evidence[1] (Gorg and Greenaway, 2001, Javorcik, 2004). Studies at country, industry and regional levels may suffer from aggregate bias; one the other hand, research using firm level data may omit some macro- or meso-level economic and policy variables. Moreover, the type and quality of FDI also matter (Fu, 2004).

Two factors make the relationship between productivity and knowledge capital factors even closer. The first factor is the possible endogeneity between TFP and the knowledge capital factors; the second factor is the interactions among the knowledge factors. The endogenous growth theory suggests that R&D is endogenous to the growth process. Recent empirical research suggested an increasingly endogenous relationship between trade/FDI and economic growth (Li and Liu, 2005). This endogenous characteristic of knowledge capital is likely to lead to self-perpetuating cycles of success and failure. Focusing on the relationship between FDI and

[1] For surveys of the literature on spillovers from FDI see Holger Gorg and Eric Strobl (2001), Holger Gorg and David Greenaway (2001) and Robert E. Lipsey (2002).

productivity, although there is considerable theoretical justification in support of the positive contribution of FDI on productivity, empirical evidence is mixed. On the other hand, the causality from productivity to FDI is uncertain. The motivations of FDI can be different. They can be efficiency seeking, but can also be resource seeking, market seeking or strategic asset seeking (Dunning, 1958).

Secondly, differences in absorptive capacity of knowledge (human capital and R&D) may also affect the degrees of knowledge capital inequalities across horizontal groups (the regions). This may reinforce the existing regional inequalities as the higher absorptive capacity in better developed regions will enable greater assimilation of advanced knowledge and lead to greater technological advancement and higher TFP growth (Fu, 2008). Human capital and FDI are inter-dependent (Miller and Upadhyay, 2000 and Xu, 2000). Human capital is less productive where it does not have access to advanced technology (Pissarides, 1997). In low income countries human capital does not have a positive effect on TFP unless trade openness crosses a threshold level Miller and Upadhyay (2000).

3. Methodology and Data

(a) Estimation of TFP

The empirical test for this study is designed in 3 steps. First we estimate regional productivity using a trans-log production function. Second, dynamics of the regional productivity is analyzed to evaluate whether the disparities are persistent and whether there exists convergence or divergence. Finally, regression analyses are employed to investigate the sources of the increasing disparities in productivity across regions.

Following Ascari and Di Cosmo (2004), we estimate TFP at the level of provinces in China using a standard a Cobb Douglas production function as follows,

$$Y_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} \tag{1}$$

where Y_{it}, K_{it}, L_{it} represent the output, capital stock, and labor input at time t in region i respectively. α_K and α_L represent the coefficients of elasticity of capital and labor input at the provincial level, respectively. ε_{it} is a random error term. Similar to Ascari and di Pavia (2004) and Zhang (2005), we assume constant returns to scale with regard to the production technology. A_{it} indicates the TFP level of region i at time t, and is defined as:

$$A_{it} = \frac{Y_{it}}{K_{it}^{\alpha_K} L_{it}^{\alpha_L}} \tag{2}$$

Taking logarithms, allowing for greater flexibility in the production function, we use the translog function form following Diewert (1974) specified as,

$$\ln Y_{it} = \delta_i + \lambda_t + \alpha_K \ln K_{it} + \alpha_L \ln L_{it} + \frac{1}{2}\alpha_{KK} (\ln K_{it})^2 + \frac{1}{2}\alpha_{LL} (\ln L_{it})^2 + \alpha_{KL} \ln K_{it} \ln L_{it} + \varepsilon_{it} \tag{3}$$

Under the condition of constant return to scale, the translog function (3) can be simplified to the following form (Zhang, 2005).

$$\ln(Y_{it} / L_{it}) = \delta_i + \lambda_t + \alpha_K \ln(K_{it} / L_{it}) + \alpha_{KK} (\ln(K_{it} / L_{it}))^2 + \varepsilon_{it} \tag{4}$$

At the firm level, for each of the 30 two-digit industries panel, fixed effects translog production functions are estimated. For ease of presentation let K and L denote log of capital and labor respectively.

(b) Dynamics of regional TFP: convergence or divergence

Dynamics of regional TFP are analyzed using standard convergence estimates and the Markov transition matrix. Convergence is defined as a process whereby output differences between different economic regions decrease as the forecasting horizon increases (Evans, 1998). We estimate the standard β convergence for provincial TFPs. However, as noted by Quah (1993), β convergence cannot reveal the entire behavior of regional income distribution over time and cannot provide convincing insights into dynamic changes in income distributions during the process of convergence or disparity. Therefore, following Quah (1993), we also use the non-parametric Markov transition matrix to evaluate how the income distribution within countries and regions evolves over time and to explore regional economic convergence.

A Markov transition probability matrix for provincial TFP distribution is as follows:

$$M_{t_1,t_2} = \begin{bmatrix} m_{11} & \cdots & m_{1j} & \cdots & m_{1k} \\ \vdots & & & & \\ m_{ij} & \cdots & m_{ij} & \cdots & m_{ik} \\ \vdots & & \vdots & & \vdots \\ m_{k1} & \cdots & m_{kj} & \cdots & m_{kk} \end{bmatrix} \tag{5}$$

Where m_{ij} represents the transition probability of provinces moving from TFP class i at time t_1 to TFP class j at time t_2. k represents the largest classification number of provincial standardized TFP. This paper creates four intervals of annual provincial TFP between ranges of { $(-\infty,-0.58]$, $(-0.58,-0.30]$, $(-0.30,\ 0.0)$, $[0.0,\ +\infty)$ } denoted by classes 1, 2, 3 and 4. This ensures that every TFP class includes the same number of provinces in 1978. It also allows us to infer the number of provinces transitioning from one class to another and the direction of their mobility in the following year. After this classification, P_t is set as the TFP distribution vector in year t and empirical transition probability matrix maps the TFP distribution from period t_1 onto period t_2.

$$P_{t_2} = P_{t_1} M_{t_1, t_2} \tag{6}$$

The characteristics of the Markov transition matrix can provide rich insights into the evolution of the TFP distribution across provinces over time. If there is a trend for convergence in TFP across provinces in China then this will be reflected in concentration of the provinces in the middle classes. A larger value in the diagonal entries of the transition probability matrix implies greater persistence and means that those provinces are more difficult to upgrade or downgrade from one class onto another. The off-diagonal entries in the transition matrix record dynamic changes in TFP distribution, that is, a larger value for these entries indicates high mobility of TFP for the whole economy.

(c) Testing the impact of knowledge capital on regional TFP

We test the impact of knowledge capital on regional TFP using regression analysis. Following the theoretical framework set out earlier, the basic empirical model is specified as follows,

$$TFP_{it} = \alpha + \beta_1 KC_{it} + \beta_2 KTG_{it} + \beta_3 KTN_{it} + \gamma X_{it} + \varepsilon_{it} \tag{7}$$

Where *KC* is knowledge creation measured by innovation, *KTG* is inter-generational knowledge transfer measured by education, and *KTN* is inter-national knowledge transfer measured by FDI. *X* is a vector of control variables.

Innovation is measured by number of patent authorization per thousand population (*Inp*). Human capital is measured by the average level of education among population aged 6 and above to measure educational development at the level of regions (*Aedu*). This indicator is calculated as follows: average years of educational attainment of targeted population group = [undergraduate (educated population)*16+ college*14.5+ specialized secondary*12.5+ high schools*12+ junior middle school*9+ primary school*6]/total population of targeted population group.

Trade and foreign direct investment are the two main channels of technology transfer. Since FDI and trade are highly correlated in China, we only use one indicator to measure openness and international knowledge transfer. Following Coe and Helpmann (1995), we use the ratio of foreign direct investment to investment in fixed assets (*Rfdi*) to proxy technological knowledge transferred through imports and FDI.

The control variables include agglomeration effects and a geographical dummy which equals 1 for coastal regions and 0 for the rest. Following Fu and Balasubramanyam (2003), the effect of agglomeration and economies of scale is measured by the ratio of industrial value to the total number of industrial firms in China (*Escale*). Admittedly institutional arrangement may also have impact on productivity, for example marketization and infrastructure (Fleisher et al (2006), Demurger (2001). However, statistical test suggests that these two variables are highly and significantly correlated with the main variables we concern in this study[2]. Thus we can set the empirical equation on determinant of regional TFP disparity as follows.

[2] The correlation coefficients between innovation and these institutional and infrastructure variables are all over 0.60; and that between FDI and infrastructure and marketisation are around 0.45.

$$\log(TFP_{it}) = \alpha_{it} + \alpha_1 Inp_{it} + \alpha_2 Rfdi_{it} + \alpha_3 \log(Aedu_{it}) + \alpha_4 \log(Escale) + \alpha_5 Coast_{it} + \varepsilon_{it} \tag{8}$$

At the firm level, we have included firm age, a Herfindhal index of market concentration and exports as control variables. It is largely accepted in the literature that there is a positive relationship between firm performance and exporting (Kraay, 1999; Girma and Gong, 2007). By contrast, higher market concentration is generally believed to have a negative impact on firm performance. Due to data availability, there are some slight modifications in the measurement of the knowledge capital variables. FDI is measured by the share of foreign capital in firm's total capital, R&D is measured by R&D expenditure per person, and education is measured by training expenditure per person. Two-digit industry, region and year dummies are also employed in the regressions.

There are several methodological issues here. First, innovation and FDI are arguably determined simultaneously with the dependent variable. In other words, there might be a potential endogeneity problem, even after controlling for fixed effects. Wu-Hausman test is applied to test the endogeneity between innovation and FDI on one hand and TFP on the other. If significant endogeneity is detected, we employ the fixed effects generalised method of moments (GMM) regression technique (see, inter alia, Hansen, 1982 and Arellano and Bond, 1991). Lagged values of the potentially endogenous variables and other exogenous variables are used as instruments. In addition, population and the shares of stated-owned firms in the region are also used as extra instruments in the regional level regressions. Likewise, the shares of stated-owned firms in the industry and region and the growth of total industry sales are used as extra instruments in the firm level regressions. We formally test whether our instruments are relevant in that they exhibit sufficiently strong correlation with the potential endogenous variables. We also carefully test for the appropriateness of the instrumental variable candidates using Hansen J's test for overidentifying restrictions and the validity of the instruments with Sargan test. Reassuringly we find that our instruments are appropriate on all counts.

Second, by including a lagged dependent variable into the right hand side of the regression to capture the knowledge accumulation process, it raises the problem of convergence of the estimators because the lagged dependent variable is correlated with the disturbance term. For estimation of a dynamic panel data macroeconomic model in a small sample, the Corrected least squares dummy variables (LSDV) approach, though provides the best result, it cannot be easily implemented. GMM is a second-best solution especially when $T<10$ (Judson and Owen, 1999). We, therefore, employ the GMM method for the estimation.

Thirdly, the estimated coefficients can be spurious if the variables are non-stationary since we are exploring the time series and cross sectional information at the same time. Therefore, before proceeding to estimate with panel data, we carry out unit root tests to examine whether the variables are stationary. The widely used methods include LLC (Levin, Lin and Chu, 2002), IPS (Im, Pesaran and Shin, 2003) and MADF (Maddala and Wu, 1999). In this test, we use all the LLC, IPS and MADF tests to examine unit roots in the data giving the advantages and limitation of these methods. Results of these three tests reported in Table 1 are consistent confirming that the variables are stationary at first order difference and there is long run relationship between the selected variables.

(e) The data

Two panel datasets are used for the empirical test at regional and firm-level, respectively. The regional level data we use is a panel dataset for the period 1978 to 2004 for 28 provinces, autonomous regions and municipalities (hereafter called provinces). Tibet is not included in the sample because of lack of data. The data on variables for Chongqing and Hainan are included in that for Sichuan and Guangdong, respectively. All data is collected from *China Compendium of Statistics 1949-2004* and *Chinese Statistic Yearbook* (various years). Output is measured by regional GDP deflated by each province's CPI from 1978 to 2004. Where CPI data is not available for some provinces for the period 1978-83, it is replaced by retail price index (RPI) for those years. Capital stock in every province is estimated using the Perpetual Inventory Method. The parameters used to calculate the capital stock are the same as those used by Zhang (2005).

Table 2 compares the mean values of the knowledge capital indicators of the coastal and inland regions at the start and end of the sample period. Evidences show that there is significant gap in knowledge creation and transfer activities between the regional groups, especially in terms of R&D, international trade and foreign direct investment.

The firm level data draws on the Annual Report of Industrial Enterprise Statistics compiled by the State Statistical Bureau of China, covering all state-owned firms and other type of firms with annual turnover of over five million Renminbi (about \$0.6 million) for the period over 1999-2005. It is estimated that the firms contained in the dataset account for about 85-90% of total output in most industries[3]. The data set includes variables such as firm ownership structure, industry affiliation, geographic location, establishment year, employment, gross output, value added, fixed assets, exports, R&D and employee training expenditures[4]. Foreign-owned firms are divided into firms with investments from Hong Kong, Taiwan and Macro investors (so-called Ethnic firms) and firms with investments from other foreign sources (FIEs)[5]. The final data set consists of 1,228,104 observations from 407,389 firms[6].

4. Results – regional level evidence

(a) Provincial TFP and the dynamics

Figure 1 shows the estimated provincial TFP over the sample period[7]. Average TFP for the central region is below that for the eastern region, higher than that for the western region and is below that for the nation as a whole. The results suggest that provincial TFP in China varies substantially. Shanghai and Tianjin have high levels of TFP while Guizhou and Gansu have low levels of TFP relative to the other provinces. The average TFP level of Shanghai from 1978 to 2004 is 0.6317 and the average TFP level of Guizhou is 0.1594, which is about a quarter of the former.

[3] In a recent OECD project Holz (2005) examines the validity of this Chinese dataset and concludes that the data for the above-norm enterprises are likely to be of high quality.
[4] Nominal values are deflated using industry-specific ex-factory price indices obtained from China Statistical Yearbook 2006.
[5] Firms are classified as foreign-owned multinational once foreign participation exceeds 25 percent of ownership.
[6] Tibet is included and Chongqing and Hainan are listed as independent provinces in the firm level dataset.
[7] The regression coefficient of log(*K*/*L*) doesn't vary in essential from traditional C-D function or translog function, 0.2794 and 0.2638 respectively, and is statistically significant at the level of 1%. The estimation result also shows that from 1978 to 2004, the labor elasticity of output was far higher than the capital elasticity of output. However, if we introduce human capital variable *H* into the production function[7], the empirical result indicates that the regression coefficient of generalized capital (including human capital) is more than that of labor.

The results for the absolute β convergence of regional TFP in China are reported in table 2. For the whole sample period 1978-2004, the coefficient of the log value of the initial TFP is negative, although it is not significant even at the 10%-level. For the sample period 1978-1990, the coefficient of the log value of initial TFP is -0.018 and significantly different from zero at the 1%-level, which suggests TFP convergence; while for the period 1990-2004, the empirical result indicates that there exists TFP divergence among regions in China. The convergence of provincial TFP during the 1978-90 period is likely due to several reasons. First, during the "Third-line" Construction for more than 10 years before 1978, a large part of central-western China was provided with more fiscal subsidies and transfer payment than the coast region. In the meantime, during the initial period of reform and opening the western provinces such as Tibet and Xinjiang owned higher wage subsidy while government policy also encouraged people to work in western China. On the contrary, during this period, though China had carried out a series of preferential opening policies in coastal regions, there was no free trans-regional flow among coast provinces for production factors and resources which limited productivity growth. These facts above could have, to a certain degree, contributed to provincial TFP convergence in China during the period of 1978-1990.

After 1990, China's reform and opening has been impelled and deepened. FDI inflow into the coastal regions has gone up sharply and the total import and export has expanded rapidly, which not only drove economic growth, but also promoted technological advance in this region via technology spillovers. In addition, fiscal decentralization facilitated different regions to develop their economy more independently. Good economic conditions and comfortable fiscal revenues encouraged the coastal provinces to invest more R&D expenditure every year than the inland provinces. The R&D investment effectively accelerated productivity growth in coastal regions. In contrast with the period of 1978-1990, the average TFP growth rate in the coast region is far higher than that in the inland during the period of 1990-2004 based on table 3. This provides some possible explanations for the divergence of provincial TFP during this period, which waits to be tested statistically in later sections of this paper.

Tables 4 tabulate Markov transition matrixes M_{t_1,t_2} for the years 1978-90 and 1990-2004 respectively. Categories in rows (or columns) of these tables represent the classes where different provinces are located at the beginning (or the end). The number of provinces belonging to each category was 7 in 1978. However, the number of provinces in the two middle categories decreased from 14 to 9, and the number of provinces in the highest TFP class increased to 11 over the period from 1978 to 1990.

Similar characteristics can be observed from the Markov transition matrix during the period 1990-2004 in table 4. The number of provinces in the two middle groups further dropped from 9 to 4 while the number of provinces in group 1 and group 4 respectively rose to 10 and 14. Provinces in the highest and lowest TFP classes had a high level of persistence: 100% and 91% of TFP observations in group 1 and 4 remained in the same group in 2004. The two middle classes had high mobility and its direction is more noticeable. In group 2 the possibility of provinces remaining in the same group over the sample period is 25%. 50% of provinces in this group move into group 3 or 4, and 25% of provinces move into group 1. The entrance probability of group 2 is less than 30% and much lower than the exit probability (75%), which indicates that there is a strong trend of mobility. As far as group 3 is concerned, the exit probability is 100% while the entrance probability for this group is only 25%. Furthermore we can find that the exit probability from group 3 to the higher TFP group is 60% and the probability of a higher TFP provinces falling into this group is zero. On the contrary the exit probability from this group to the lower TFP group is about 40% and the probability of a lower TFP province rising into this group is 25%. All these results show that provinces in this group tend to move into group 4 more easily than into the lower TFP group. Figure 2 shows the spatial distribution for the provincial TFP standardized in 2004. In contrast to the spatial distribution in 1978, we can clearly observe group 4 with the highest TFP level which is mainly located in the "new eastern China".[8] Empirical results from the Markov transition matrix suggest that there is a significant polarization or division into twin peaks in TFP among Chinese provinces. Provinces located in the central and western regions tend to form a convergence club with lower TFP level while the "new eastern region" converges to a higher TFP club.

(b) Knowledge capital and TFP: evidence from regional-level panel

Because the divergence of regional TFP started to be significant since 1990, we focused on the 1990-2004 period for the regression analysis. The test results suggest that over the sampled period 1990-2004, the estimated Wu-Hausman statistics are 0.000 and 0.0579, respectively. This suggests that endogeneity is significant for the innovation variables, and FDI is weakly endogenous at the 10% significance level. Therefore, we employ GMM for the estimation. Table 5 reports the empirical test of

[8] The new eastern China denotes the northeast plus traditional eastern China(excluding Guangxi).

the impact of knowledge capital on regional TFP at regional level. Column 1 reports the GMM estimates of the TFP equation. All three knowledge factors, namely innovation, FDI and education, show the expected positive impact on TFP and are statistically significant. The estimated coefficient of the coastal dummy is also positive and significant, suggesting provinces in the coastal region enjoy faster TFP growth than the inland region. Column 2 reports the dynamic panel model estimates which includes the lagged dependent variable as an explanatory variable. The estimated coefficient of the lagged TFP is positive and significant at 1% significance level, suggesting previous TFP level is a significant determinant of current TFP level, and therefore supporting our proposition that knowledge capital is cumulative. However, education and the coastal dummy variables lost the statistical significance in the dynamic model, which is likely due to the high correlation between them and the lagged dependent variable.

Columns 3, 4 and 5 report the simultaneous equations of the determinants of innovation and FDI. The estimated coefficients of the TFP variables are positive and statistically significant. This confirms that more efficient regions innovate more to keep their competitive advantages; and that foreign firms invest in regions that are more productive. FDI and innovation do not show a significant relationship when they enter the regression both with current values. The Wu-Hausman test also indicates that there is no endogeneity between these two variables. There are two possible reasons. First, there are different motivations for FDI. FDI can be resource-seeking, market-seeking efficiency-seeking, or strategic-asset seeking. R&D outsourcing by MNEs has become an increasing trend, although it is not the major motivation of MNEs into China, especially during the 1990s period. Second, the contribution of

FDI to regional innovation performance may take some time (Fu, 2008). Therefore, a time lag is needed when we consider the contribution of FDI to regional innovation performance, especially when it is measured by patent numbers. Using the lagged innovation inputs as the independent variables, Columns 6 and 7 show that lagged FDI investment has a positive impact on regional innovation performance. The estimated coefficient turns to be statistically significant when the education variable is dropped from the regression[9]. The impact of lagged variable *Inp* on FDI is positive but not statistically significant, confirming that innovation is not the major decision factor for FDI in China during the sample period.

(c) Knowledge capital and TFP: evidence from firm-level panel

Tables 6 and 7 report the estimated results of both TFP level and TFP growth regressions using firm level dataset. Consistent with that from the regional level panel, Wu-Hausman tests indicate significant endogeneity between R&D and FDI on the one hand and TFP on the other hand. R&D, FDI and training all show significant positive effects on TFP, and TFP also exerts a significant positive effect on FDI and R&D intensities. The estimated coefficients of the coastal region dummy are positive and statistically significant at 1% level for all TFP, FDI and R&D (Table 6), and at the 5% level for TFP growth (Table 7). This firm level evidence reinforces earlier finding that firms in the coastal region enjoy greater resources and opportunities for knowledge creation and transfer than those in the inland region. They enjoy higher levels of productivity and are growing faster. This forms a self-perpetual cycle and leads to increasing gaps in productivity between the regional groups.

[9] The correlation coefficient between FDI and labour skills is 0.45, suggesting a high and significant correlation between the two variables and a possible multicolinearity problem when they enter the regression at the same time.

Younger firms enjoy higher TFP, but older firms invest more in R&D. Firms with higher export intensity have higher TFP levels, greater FDI and R&D intensities. Market concentration hinders TFP growth and FDI investment. But firms in industries with greater market concentration have higher R&D intensity. Interestingly, the relationship between R&D and FDI intensities are negative[10]. While the direction of the sign is consistent with that from the regional level, results at the firm level are statistically significant at 1% level. This is likely to be explained by two reasons. First, at firm level, firms with greater innovation activities and with higher investments in training are more competitive than others and thereby less likely to be acquired by foreign capital. Second, similar to what we discussed earlier, R&D capacity is not the major decision factor for FDI into China.

We also report the TFP growth equations for the coastal and inland regions separately in table 7. The estimated productivity elasticities of R&D, training and exporting variables are higher in the inland region than that in the coastal region, with exporting impacts almost doubled. However, the coefficients of both ethnic and foreign participants are smaller in the inland region. This evidence suggests that 1) the firms in the inland region enjoy less benefits from foreign investments than those in the coastal region. However, a firm which is more involved in export activities and invested more on R&D and training in the inland region is more likely to have faster TFP growth. 2) Increasing investment in R&D and training, encouraging more firms to participate in the international markets can promote greater TFP growth in the inland regions and thereby possible catch-up by the inland to the coastal regions.

[10] The sign of the estimated coefficients remain negative even taking one year lag of the independent variables.

5. Conclusions

This paper attempts to explore the role of knowledge capital in the dynamics of regional productivity disparities using multi-level evidence. Findings from both the regional and firm level confirm that unequal capabilities and opportunities in knowledge creation, transfer and assimilation have led to increasing disparities in regional productivity, despite some differences in other aspects between the results from the two levels. The relationship between innovation, FDI and education on the one hand and TFP on the other hand is endogenous and significant. It is reinforced by the accumulative nature of knowledge capital. All this leads to self-perpetuating cycles of fast versus slow growth of TFP.

There are two possible ways to reduce the regional inequalities in productivity. One is strong spillovers from the growth poles to the backward regions; the other is to enhance the access to knowledge sources and the capabilities in knowledge creation and assimilation. However, cross regional spillovers may be limited because knowledge spillovers are geographically localized (Jaffe, et. al., 1993; Audretsch and Feldman, 1996; Anselin, et al., 1997; and Almeida and Kogut, 1997). Moreover, the type and quality of FDI does matter. An emphasis on processing-trade-driven, labor-intensive, export-oriented FDI may attract human capital to migrate from poor to richer regions, but offers only limited growth linkages to the home region. Therefore, growth led by this type of FDI in rich regions may offer limited growth linkages and spillovers to the poor regions. It may exacerbate the inequalities between the regions by reallocation of human capital (Fu, 2004).

The feasible and effective way to reduce regional inequalities in productivity is to intervene in the motivation and process of knowledge creation and transfer. Therefore, there is a role for government policy. Findings from this research suggest 3 areas for policy intervention. First, financial support and tax exemption in support of innovative activities in the poor regions; second, special government policies to encourage suitable and quality FDI to the poor regions; and finally, investment in education and training. The larger productivity elasticities of R&D and training in inland regions compared to the coastal regions in China suggest that there is a greater demand and more efficient use of such knowledge creation and transfer resources in the less rather than the more productive regions. Policies that correct regional imbalances in these knowledge creation and transfer processes, that increase investment in R&D and training and encourage more firms to participate in international markets can promote greater growth in TFP in the backward regions and thereby possible catch-up by these regions.

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Table 1. Unit root test of panel data

Vaviables	ΔLog(TFP)	ΔInp	ΔRfdi	ΔLog(Aedu)	Δlog(Escale)	ΔRex	ΔRsoe
LLC Test	-9.43**	-19.52**	-13.09**	-21.06**	-20.04**	-18.32**	-17.30**
IPS Test	-6.92**	-16.60**	-11.61**	-20.64**	-18.47**	-15.83**	-13.35**
MADF Test	146.88**	391.07**	231.28**	404.75**	366.76**	314.98**	258.00**

Note：（1）The null hypotheses of test above are that there exists a unit root.

（2）Values in the table are statistics for related unit root test. ** and * are respectively significant at the 1% and 5%.

(3) Δ indicates the first difference of related variables.

Table 2. Comparison of knowledge capital indicators between coastal and inland regions

Knowledge capital	1990		2004	
	The coastal	The inland	The coastal	The inland
Edu	6.8896	5.9435	8.7050	7.9555
RD	0.7736	0.4688	14.2573	3.9935
Innovation	4.5366	1.1713	26.9762	4.1666
FDI（10th USD）	27692	3208	571965	72051
Trade （10th USD）	724048	67467	9152601	469767

Note：The coastal includes 11 provinces and the inland includes the other 17 provinces. *Edu* indicates the average level of education among population aged 6 and above. *RD* indicates "science-technology three-cost" expenditures (unit: ￥100 million). Innovation is measured by number of patent authorization per thousand population. *FDI* is foreign direct investment (unit: $ 10 thousand). *Trade* is the volume of exports and import. Values in the table are the provincial average level for the coastal and inland.

Table 3. Absolute β convergence of regional TFP in China

Dependent variable	$GTFP_{1978-1990}$	$GTFP_{1990-2004}$	$GTFP_{1978-2004}$
Constant	-0.0221*** (0.0047)	0.0409*** (0.0062)	0.0098*** (0.0036)
$Log(TFP_{1978})$	-0.0180*** (0.0028)		-0.0026 (0.0020)
$Log(TFP_{1990})$		0.0147*** (0.0043)	

Note**:** (1) TFPs in the table above are estimated using **translog function** including labor L and physical capital *K* as factor inputs and under the condition of constant return to scale.

(2) $Log(TFP_{1978})$ and $Log(TFP_{1990})$ indicate respectively the log values of TFP in 1978 and 1990.
(3) $GTFP_{T1-T2}$ represents the growth rate of TFP during the period T1-T2 and is computed by the formula $(Log(TFP_{T2})- Log(TFP_{T1}))/(T2-T1)$.
(4) Standard errors are in parentheses. *** indicates 1% significant levels.

Table 4 Markov Transition Matrix

1978 \ 1990	Class 1	Class 2	Class 3	Class 4	Total Obs
Class 1	0.714	0.143	0.143		7
Class 2	0.286	0.143	0.286	0.286	7
Class 3	0.143	0.143	0.143	0.571	7
Class 4		0.143	0.143	0.714	7
Total Obs	8	4	5	11	28
1990 \ 2004					
Class 1	1.000				8
Class 2	0.250	0.250	0.250	0.250	4
Class 3	0.200	0.200		0.600	5
Class 4		0.091		0.909	11
Total Obs	10	3	1	14	28

Table 5. Regional level evidence of the determinants of TFP

	Fixed effects GMM estimator					FE	
	model1	model2	model3	model4	model5	model6	model7
Variable	TFP	TFP	TFP	Inp	FDIS	Inp	Inp
TFP				4.380**	10.800***		
				0.045	0.010		
R&D	0.042**	0.003	0.002**		-0.195		
	0.026	0.245	0.028		0.562		
FDI	0.008**	0.001*	0.001*	-0.015			
	0.015	0.091	0.097	0.584			
Education	0.204**	-0.002	-0.002	1.900	1.940		
	0.012	0.826	0.794	0.293	0.422		
Eco of scale	0.656***	0.098***	0.098***	-3.350*	-9.930**		
	0.001	0.000	0.000	0.061	0.040		
Coast dummy	0.044**	-0.003	-0.003	0.243	2.800***		
	0.032	0.251	0.252	0.361	0.008		
TFP(-1)		1.050***	1.050***				
		0.000	0.000				
R&D(-1)			0.001			0.911***	0.975***
			0.733			0.000	0.000
FDI(-1)						0.009	0.016**
						0.214	0.031
Edu(-1)						0.103***	
						0.000	
SOE share(-1)						-0.002	-0.001
						0.123	0.555
Constant	-0.183	-0.009	-0.008	-4.310	-4.460	-0.558***	0.065
	0.175	0.442	0.517	0.159	0.285	0.003	0.247
N	420	420	420	420	420	420	420
RMSE						0.481	0.487
Chi^2						1879	1817
F	37.100	3155.000	3307.000	6.000	13.400		
Hansen J test	21.700	24.600	24.700	24.700	21.000		

Notes:

1. p-value in parentheses
2. * significant at 10%; ** significant at 5%; ***significant at 1%.
3. The correlation coefficient between l.FDIS and l.aedu is as high as 0.45.

Table 6. Firm level evidence of the determinants of TFP

	OLS	Fixed effects GMM estimator			
	TFP	TFP	TFP	FDI	R&D
TFP				0.0174***	0.0589***
				(0.00039)	(0.00065)
TFP(-1)			0.880***		
			(0.0012)		
Ln(R&D)	0.297***	0.304***	0.0582***	-0.0300***	
	(0.0034)	(0.0026)	(0.002)	(0.00095)	
Ethnical MNE	0.0913***	0.0486***	0.004		-0.0659***
	(0.006)	(0.0056)	(0.003)		(0.0025)
Foreign MNE	0.250***	0.289***	0.0558***		-0.0451***
	(0.0066)	(0.0061)	(0.003)		(0.0031)
Ln(training)	0.589***	0.607***	0.161***	-0.0194***	0.492***
	(0.0076)	(0.0075)	(0.004)	(0.0024)	(0.0072)
Ln(exports)	0.0412***	0.0394***	0.00160***	0.0307***	0.00432***
	(0.0004)	(0.0003)	(0.0002)	(0.00012)	(0.00017)
Ln(age)	-0.118***	-0.180***	-0.0762***	-0.0590***	0.0141***
	(0.0021)	(0.0017)	(0.001)	(0.00041)	(0.00064)
Market concentration	-0.229***	-0.159***	-0.0830***	-0.00261	0.106***
	(0.016)	(0.012)	(0.007)	(0.0026)	(0.0047)
Coastal dummy	0.534***	0.394***	0.0580**	0.0592***	0.117***
	(0.057)	(0.045)	(0.028)	(0.0046)	(0.0094)
Constant	-0.650***	-0.137***	0.0325	0.173***	-0.0857***
	(0.056)	(0.045)	(0.028)	(0.0045)	(0.0084)
region dummy	yes	yes	yes	yes	yes
industry dummy	yes	yes	yes	yes	yes
year dummy	yes	yes	yes	yes	yes
Observations	1228104	801756	801756	801756	801756
R-squared	0.14	0.16	0.74	0.3	0.13
Exogenous test		0	0	0	0
Hansen J test		0.659	0.586	0.407	0.806

Note: 1. Values in parentheses are robust standard errors.
2. *, ** and *** are respectively significant at 10%, 5% and 1%.

Table 7. Firm-level evidence for determinant of TFP growth

	OLS	Fixed effects GMM estimator		
COEFFICIENT			Coastal region	Inland region
LTFP (-1)	-0.125***	-0.120***	-0.117***	-0.109***
	(0.0012)	(0.0012)	(0.0014)	(0.0024)
Ln(R&D)	0.0562***	0.0582***	0.0520***	0.0714***
	(0.0014)	(0.0015)	(0.0017)	(0.0036)
Ethnical MNE	-0.0137***	0.0043	0.00349	0.0238
	(0.0023)	(0.0032)	(0.003)	(0.016)
Foreign MNE	0.0148***	0.0558***	0.0560***	0.0503***
	(0.0024)	(0.0033)	(0.0033)	(0.013)
Ln(training)	0.163***	0.161***	0.147***	0.181***
	(0.0038)	(0.0038)	(0.0041)	(0.0098)
Ln(exports)	0.00805***	0.00160***	0.00132***	0.00257***
	(0.00015)	(0.00018)	(0.00019)	(0.00046)
Ln(age)	-0.0804***	-0.0762***	-0.0692***	-0.0868***
	(0.00099)	(0.00098)	(0.0011)	(0.0019)
Market concentration	-0.0814***	-0.0830***	-0.120***	-0.214***
	(0.0069)	(0.0069)	(0.0082)	(0.011)
Coastal dummy	0.113***	0.0580**		
	(0.028)	(0.028)		
region dummy	yes	yes	No	No
industry dummy	yes	yes	yes	yes
year dummy	yes	yes	yes	yes
Constant	-0.0214	0.0325	0.157***	0.190***
	(-0.028)	(-0.028)	(-0.0052)	(-0.0078)
Observations	801756	801756	594529	207227
R-squared	0.16	0.15	0.15	0.15
Exogenous test		0	0	0
Hansen J test		0.573	0.612	0.541

Note: Values in parentheses are Robust standard errors. *, ** and *** are respectively significant at 10%, 5% and 1%.

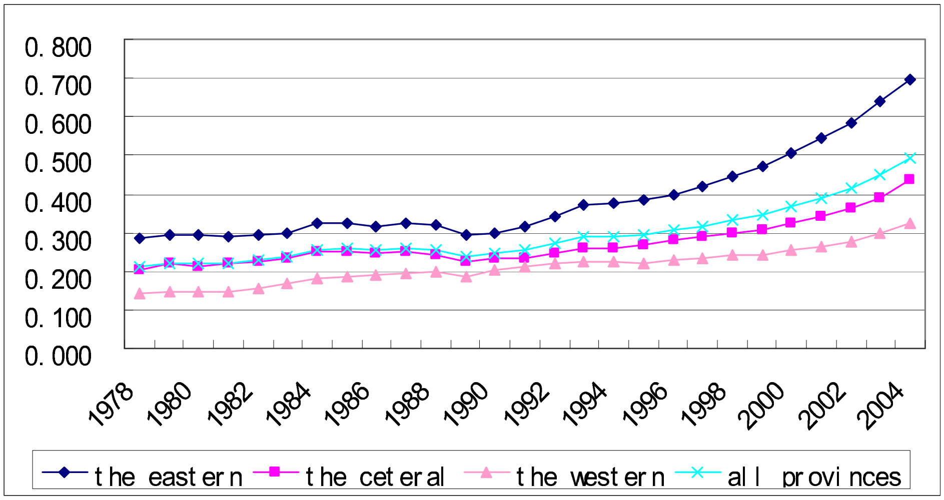
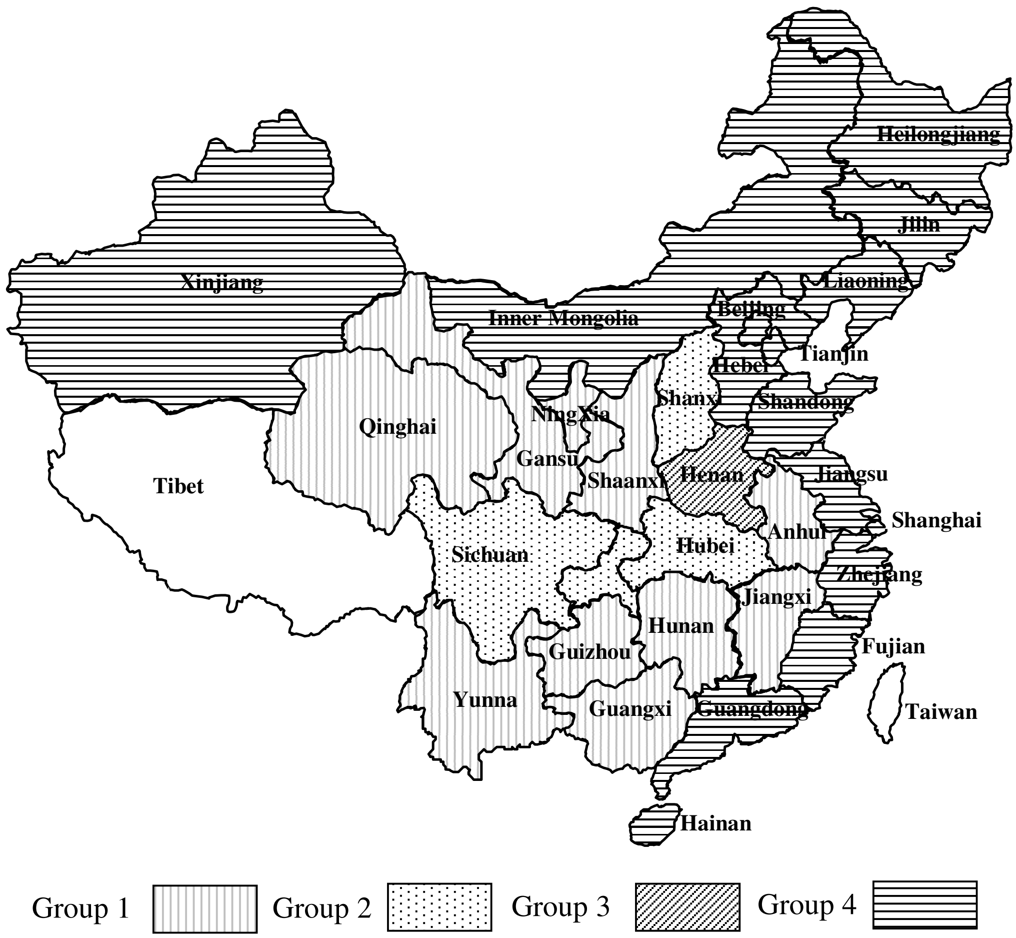


Figure 1. Average TFP levels for three regions and the whole country



Note: This map only describes the partial provinces in China where data was available. Group 1：Std. TFP≤-0.58，Group 2：-0.58<Std. TFP≤-0.30，Group 3：-0.30<Std. TFP≤0.0，Group 4：0.0≤Std. TFP

Figure 2 Spatial distribution for the provincial TFP standardized in 2004