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Soaring dragons, roaring tigers, growling bears

Determinants of regional growth and convergence in China, India and Russia[1]

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Abstract

We perform a comparative analysis of regional growth and convergence in China, Russia and India over the period 1993–2003 by means of non-parametric methods and kernel density estimates. Our results indicate that wealthy regions were largely responsible for the rapid growth in all three countries. For China and India, capital dissipation was identified as the major determinant of regional growth. In Russia, capital deepening impeded positive changes in labour productivity, leaving technological change as the only source of regional growth. Furthermore, we find that the increasing regional income inequality in all three countries was driven by technological change which more than offset the convergence resulting from capital deepening in China and India.

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1. Introduction

Over the past decade, China, Russia and India have become synonyms for fast-growing emerging economies, accounting together for about one-half of global growth and more than a quarter of world output in purchasing power terms. In the 1980s the transition in all three countries was marked by government efforts to overcome the inefficiencies and stagnation of their centrally administered systems through economic reforms. Their growth suffered simultaneously in the early 1990s as a result of the crackdown on the Tiananmen Square protests in the case of China, and the collapse of the Soviet Union in the case of Russia and India which was a major trading partner. Governments in all three countries responded by adopting a broad range of reforms aimed at speeding up the transition to a market-based economy through economic liberalization.

Yet the reforms of the early 1990s had strikingly different implications for China, Russia and India. While Russia's GDP was halved over the 1990s, China's GDP more than doubled over the same period. Even as India achieved an average growth rate of around 5 percent over the 1990s, China's growth was almost twice as high (Dethier, 2000). Furthermore, China developed vibrant export-oriented industries and emerged as a major global producer of manufactured goods by relying on unprecedented flows of foreign capital coupled with a large pool of domestic savings and cheap labour. By contrast, it was the service sector that became the driving force behind India's growth, accounting for more than one-half of its GDP and transforming the country into a prime destination for outsourcing of customer services and technical support in the world (Bosworth and Collins, 2007). Russia relied heavily on the natural resource sectors for its economic recovery and growth turning into a leading global supplier of oil, natural gas and other raw materials (Jha, 2003).

It goes without saying that faster economic growth implies enormous potential welfare gains. In the quest to find the sources for sustainable and balanced growth, however, it is important to investigate whether regional growth rates and growth paths converge, that is, whether income levels of poor regions tend to catch up with or converge towards the income levels of rich regions. For this reason, the focus of the recent empirical literature has turned from a distinctly international perspective back to a country-specific one, and therefore has spurred the exploration of empirical patterns of regional growth, especially within large economies. Two major growth theories suggest that different factors drive economic growth. While exogenous growth theory (built on work by Solow, 1956) posits technological change as the engine of economic growth, endogenous growth theory (built on more recent research by Lucas, 1988; Romer, 1986) argues that persistent growth is mainly driven by physical and human capital factors. Additionally, exogenous (endogenous) growth theory emphasizes that differences in capital deepening (technological progress) are the driving force behind growth convergence.

The main objective of this paper is to identify the factors responsible for the growth performance of China, Russia and India over the period 1993–2003. If, as forecasted, these economies are to become economic powerhouses and engines of world growth, they would have to maintain their current growth pattern over the following decades. Exploring the determinants of growth and their potential for sustainability in the long run can provide important insights into this issue. Furthermore, we chose to conduct the growth analysis at the regional level which allows us to address the increasing regional income inequality that has been a common feature of all three economies since the 1990s.

This paper differs from previous works in three major aspects. First, it represents, to our knowledge, the first comparative study of regional growth and convergence in China, Russia and India over the 1990s and early 2000s using a unified methodological framework. A number of studies have conducted a comparative analysis of the three economies, but have focused mostly on economic reforms (Chai and Roy, 2007; Das, 2006; Jha, 2003), decentralization (Blanchard and Schleifer, 2001; Dethier, 2000), international trade and finance (Broadman, 2007; Winters and Yusuf, 2007) or sectoral performance (Gregory *et al.*, 2007; Xu, 2004). Recent works that deal explicitly with regional growth issues in China (Henderson *et al.*, 2007; Miyamoto and Liu, 2005), Russia (Berkowitz and DeJong, 2002; Brock, 2005) and India (Krishna, 2004; Sachs *et al.*, 2002) use different methodologies and sample periods making comparisons across the three countries difficult. The few comparative studies on growth in China, Russia and India employ national-level data and limit their analysis to two of the three economies (for example, Bosworth and Collins, 2007).

A second feature of this paper is that it uses a non-parametric production-frontier approach to determine the sources of regional growth in China, Russia and India. The advantage of this type of approach over conventional growth accounting is that it requires neither a specification of a functional form for the technology nor the standard assumption that technological change is neutral. In addition, it also eliminates the need to make assumptions about market structure or the absence of market imperfections, which is particularly relevant for transition economies such as China, Russia and India, where markets have been extensively regulated by the state. Furthermore, the non-parametric approach allows us to decompose the growth of regional labour productivity into four components attributable to technical efficiency, technological change and physical and human capital accumulation. Only a handful of studies have employed non-parametric methods to examine regional growth performance in China (Henderson *et al.*, 2007; Unel and Zebregs, 2006), Russia (Obersteiner, 2000) and India (Kumar, 2004; Mukherjee and Ray, 2005); however, comparisons across the three countries based on their results are problematic due to variations in the sample period and in the extent of growth decomposition.

Lastly, we perform a distribution analysis to examine the issue of income divergence across regions within China, Russia and India. The majority of studies dealing with regional income inequality in the three countries estimate regressions to test for the existence of β- or σ-convergence. However, this parametric approach omits relevant information about the convergence process as it focuses only on the first two moments of the distribution of output per worker. Moreover, the conditional mean and variance are rather misleading in the face of non-linear or multimodal distributions which are commonly observed for output per worker (Quah, 1993, 1997). Instead, we apply a non-parametric kernel method to analyse the entire distribution of regional output per worker as well its evolution over time. In contrast to the few previous studies that have taken a similar approach to convergence in China (Aziz and Duenwald, 2001), Russia (Carluer, 2005; Herzfeld, 2006) and India (Bandyopadhyay, 2006), we link the distribution analysis to the growth decomposition by exploring the relative contribution of each of the four growth components to changes in the shape of the distribution which allows us to identify the factors responsible for the growing regional income inequality in the three countries.

Our results indicate that the production frontiers of China, Russia and India were defined by wealthy regions which achieved high levels of efficiency and drove the rapid growth at the national level. The lack of proportional development at all levels of output per worker demonstrated the fallacy of assuming non-neutral technological change and underscored the advantage of the non-parametric approach. Physical capital accumulation was found to be the largest contributor to regional growth in China and India. In Russia, technological change was the only source of growth as capital investment dropped dramatically and efficiency deteriorated during the period of market transition. Furthermore, rich regions in all three countries relied to a larger extent on technological change for their growth than poor ones. The analysis of the income distributions for China, Russia and India offered further proof of the advantage of non-parametric methods over the standard regression approach as it revealed the existence of multiple modes. Our findings suggest that the income divergence across regions in all three countries was mainly due to rapid technological advances in the rich regions that were not matched by poor regions. Some regional economies at the lower levels of output per worker managed to grow faster and achieve a certain level of catch up due, among other things, to higher rates of capital accumulation; however, this convergence was not enough to reverse the growing income inequality caused by technological change.

The remainder of the paper is organized as follows: the second and third sections describe the methodology and the data, respectively. Section 4 presents the results of the analysis and Section 5 the conclusions of the paper.

2. Methodology

2.1 Data envelopment analysis

We follow the methodology of Henderson and Russell (2005) to construct country-specific production frontiers and retrieve efficiency scores. More specifically, we use a non-parametric approach to efficiency measurement, data envelopment analysis (DEA), which rests on assumptions of free disposability to envelope the data in the smallest convex cone, the upper boundary of which is the 'best-practice' frontier. The distance from an observation to such a cone then presents a measure of technical efficiency. The DEA is a data-driven approach in the sense that it allows data to tell where the frontier lies without prior specification of the functional form of the technology (see Kneip *et al.*, 1998 for a proof of consistency for the DEA estimator, as well as Kneip *et al.*, 2008 for its limiting distribution). DEA as a mathematical programming method suffers from two major drawbacks because it does not treat measurement and sampling errors. Recent research has tackled these drawbacks and new ways to report the statistical significance of efficiency indices have been developed (Simar and Wilson, 2008). Rather than investigate the significance of efficiency scores themselves, we employ non-parametric tests to assess the significance of shifts in the distribution of productivity change and its components. Moreover, Henderson and Zelenyuk (2007) have found that as a result of employing advanced methods of efficiency measurement in cross-country settings the magnitude of efficiency scores changes but the ranks are mostly preserved and major conclusions are not affected.

Our technology contains four macroeconomic variables: aggregate output and three aggregate inputs – labour, physical capital and human capital. Let $\langle Y_{it}, K_{it}, L_{it}, H_{it}\rangle$, $t = 1,2,\ldots,T$, $i = 1,2,\ldots,N$, represent T observations on these four variables for each of the N regions. We adopt a standard approach in the macroeconomic literature and assume that human capital enters the model as a multiplicative augmentation of the labour input, so that our NT observations are $\langle Y_{it}, K_{it}, \hat{L}_{it}\rangle$, $t = 1,2,\ldots,T$, $i = 1,2,\ldots,N$, where $\hat{L}_{it} = L_{it}H_{it}$ is the amount of labour input measured in efficiency units in region i at time t. DEA does not require a prior specification of the functional form of the production frontier. The constant returns to scale technology in period t is constructed by using all the data up to that point in time as

$$\mathscr{T}_t = \left\{ \langle Y, \hat{L}, K\rangle \in \Re^3_+ \,\middle|\, Y \le \sum_{\tau \le t} \sum_i z_{i\tau} Y_{i\tau}, \hat{L} \ge \sum_{\tau \le t} \sum_i z_{i\tau} \hat{L}_{i\tau}, K \ge \sum_{\tau \le t} \sum_i z_{i\tau} K_{i\tau}, z_{i\tau} \ge 0 \; \forall i, \tau \right\}, \tag{1}$$

where $z_{i\tau}$ are the activity levels. By using all the previous years data, we preclude implosion of the frontier over time. It is difficult to believe that the technological frontier could implode. Thus, following an approach first suggested by Diewert

(1980), we chose to adopt a construction of the technology that precludes such technological degradation.

The Farrell (1957) (output-based) efficiency score for region i at time t is defined by

$$E(Y_{it}, \hat{L}_{it}, K_{it}) = \min\{\lambda | \langle Y_{it}/\lambda, \hat{L}_{it}, K_{it}\rangle \in \mathcal{T}_t\}. \tag{2}$$

This score is the inverse of the maximal proportional amount that output Y_{it} can be expanded while remaining technologically feasible, given the technology and input quantities. It is less than or equal to unity and takes the value of unity if and only if the *it* observation is on the period-t production frontier. In our special case of a scalar output, the output-based efficiency score is simply the ratio of actual to potential output evaluated at the actual input quantities.

2.2 Quadripartite decomposition

We again follow the approach of Henderson and Russell (2005) to decompose productivity growth into components attributable to: (1) changes in efficiency (technological catch-up), (2) technological change, (3) capital deepening (increases in the capital–labour ratio), and (4) human capital accumulation. Under constant returns to scale we can construct the production frontiers in $\hat{y} \times \hat{k}$ space, where $\hat{y} = Y/\hat{L}$ and $\hat{k} = K/\hat{L}$ are the ratios of output and capital, respectively, to effective labour. Letting b and c stand for the base period and current period, respectively, the potential outputs per efficiency unit of labour in the two periods are defined by $\bar{y}_b(\hat{k}_b) = \hat{y}_b/e_b$ and $\bar{y}_c(\hat{k}_c) = \hat{y}_c/e_c$, where e_b and e_c are the values of the efficiency scores in the respective periods as calculated in Equation (2). Hence,

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c}{e_b}\frac{\bar{y}_c(\hat{k}_c)}{\bar{y}_b(\hat{k}_b)}. \tag{3}$$

Let $\tilde{k}_c = K_c/(L_c H_b)$ denote the ratio of capital to labour measured in efficiency units under the counterfactual assumption that human capital had not changed from its base period and $\tilde{k}_b = K_b/(L_b H_c)$ the ratio of capital to labour measured in efficiency units under the counterfactual assumption that human capital was equal to its current-period level. Then $\bar{y}_b(\tilde{k}_c)$ and $\bar{y}_c(\tilde{k}_b)$ are the potential outputs per efficiency unit of labour at $\tilde{k}_c$ and $\tilde{k}_b$ using the base-period and current-period technologies respectively. By multiplying the numerator and denominator of Equation (3) alternatively by $\bar{y}_b(\hat{k}_c)\bar{y}_b(\tilde{k}_c)$ and $\bar{y}_c(\hat{k}_b)\bar{y}_c(\tilde{k}_b)$, we obtain two alternative decompositions of the growth of $\hat{y}$

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c}{e_b}\frac{\bar{y}_c(\hat{k}_c)}{\bar{y}_b(\hat{k}_c)}\frac{\bar{y}_b(\tilde{k}_c)}{\bar{y}_b(\hat{k}_b)}\frac{\bar{y}_b(\hat{k}_c)}{\bar{y}_b(\tilde{k}_c)}. \tag{4}$$

and

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c}{e_b} \frac{\bar{y}_c(\hat{k}_b)}{\bar{y}_b(\hat{k}_b)} \frac{\bar{y}_c(\tilde{k}_c)}{\bar{y}_c(\hat{k}_b)} \frac{\bar{y}_c(\hat{k}_b)}{\bar{y}_c(\tilde{k}_b)}. \tag{5}$$

The growth of productivity, $y_t = Y_t/L_t$, can be decomposed into the growth of output per efficiency unit of labour and the growth of human capital, as follows:

$$\frac{y_c}{y_b} = \frac{H_c}{H_b} \frac{\hat{y}_c}{\hat{y}_b}. \tag{6}$$

Combining Equations (4) and (5) with Equation (6), we obtain

$$\begin{aligned} \frac{y_c}{y_b} &= \frac{e_c}{e_b} \frac{\bar{y}_c(\hat{k}_c)}{\bar{y}_b(\hat{k}_c)} \frac{\bar{y}_b(\tilde{k}_c)}{\bar{y}_b(\hat{k}_b)} \left[\frac{\bar{y}_b(\hat{k}_c)}{\bar{y}_b(\tilde{k}_c)} \frac{H_c}{H_b} \right] \\ &\equiv \mathrm{EFF} \times \mathrm{TECH}^c \times \mathrm{KACC}^b \times \mathrm{HACC}^b, \end{aligned} \tag{7}$$

and

$$\begin{aligned} \frac{y_c}{y_b} &= \frac{e_c}{e_b} \frac{\bar{y}_c(\hat{k}_b)}{\bar{y}_b(\hat{k}_b)} \frac{\bar{y}_c(\hat{k}_c)}{\bar{y}_c(\tilde{k}_b)} \left[\frac{\bar{y}_c(\tilde{k}_b)}{\bar{y}_c(\hat{k}_b)} \frac{H_c}{H_b} \right] \\ &\equiv \mathrm{EFF} \times \mathrm{TECH}^b \times \mathrm{KACC}^c \times \mathrm{HACC}^c. \end{aligned} \tag{8}$$

Equations (7) and (9) decompose the growth of labour productivity in the two periods into changes in efficiency, technology, the capital–labour ratio and human capital accumulation. The decomposition in Equation (4) measures technological change by the shift in the frontier in the output direction at the current-period capital to effective labour ratio, whereas the decomposition in Equation (5) measures technological change by the shift in the frontier in the output direction at the base-period capital to effective labour ratio. Similarly, Equation (7) measures the effect of physical and human capital accumulation along the base-period frontier, whereas Equation (9) measures the effect of physical and human capital accumulation along the current-period frontier.

These two decompositions do not yield the same results unless the technology is Hicks neutral. In other words, the decomposition is path dependent. This ambiguity is resolved by adopting the 'Fisher Ideal' decomposition, based on geometric averages of the two measures of the effects of technological change, capital deepening and human capital accumulation and obtained mechanically by multiplying the numerator and denominator of Equation (3) by $(\bar{y}_b(\hat{k}_c)\bar{y}_b(\tilde{k}_c))^{1/2}(\bar{y}_c(\hat{k}_b)\bar{y}_c(\tilde{k}_b))^{1/2}$:

$$\frac{y_c}{y_b} = \text{EFF} \times (\text{TECH}^b \times \text{TECH}^c)^{1/2} \times (\text{KACC}^b \times \text{KACC}^c)^{1/2} \times (\text{HACC}^b \times \text{HACC}^c)^{1/2}$$
$$\equiv \text{EFF} \times \text{TECH} \times \text{KACC} \times \text{HACC}. \quad (9)$$

2.3 *Distribution analysis*

Our distribution analysis exploits the quadripartite decomposition of the productivity growth and examines the impact of each of the four components on the transformation of the productivity distribution over time. By following the idea of Henderson and Russell (2005) we rewrite the decomposition in Equation (9) so that the labour productivity distribution in the current period can be constructed by consecutively multiplying the labour productivity in the base period by each of the four components:

$$y_c = (\text{EFF} \times \text{TECH} \times \text{KACC} \times \text{HACC}) \times y_b. \quad (10)$$

To study the effect of a given component, we isolate its impact by constructing a counterfactual distribution introducing only this component. Accordingly, the compound effect of two components is isolated by creating a counterfactual distribution introducing these two components, etc. For example, we investigate the unique effect of capital deepening on the labour productivity distribution in the base period assuming no efficiency, technological change or human capital accumulation by looking at the distribution of the variable

$$y^K = \text{KACC} \times y_b. \quad (11)$$

By the same token, assuming no further technological change or human capital accumulation, we examine the compound effect of capital deepening and efficiency change on the labour productivity distribution in the base period by constructing the counterfactual distribution of the variable

$$y^{KE} = (\text{KACC} \times \text{EFF} \times y_b) = \text{EFF} \times y^K. \quad (12)$$

Assuming no further technological change, we are able to isolate the effect of capital deepening, efficiency change and human capital accumulation by focusing on the counterfactual distribution of the variable

$$y^{KEH} = (\text{KACC} \times \text{EFF} \times \text{HACC} \times y_b) = \text{HACC} \times y^{KE}. \quad (13)$$

It is evident that multiplying the distribution of y^{KEH} by the effect of technological change yields the labour productivity distribution in the current period allowing us to assess the effect of all four components. The choice of the sequence in which components are introduced in Equations (13)–(15) is arbitrary and depends on the focus of the analysis on the effect(s) of particular component(s).

3. Data

Our dataset covers all 31 Chinese provinces and 27 of the 35 Indian states and territories over the period 1993–2003.[2] The analysis of Russia was based on data from 78 of the 89 regions over the period 1994–2003.[3] Data on output, labour, capital and human capital for each region were drawn from official publications. For China, the major source was the *Comprehensive Statistical Data and Materials on 55 Years of New China* (National Bureau of Statistics, 2005). For Russia, the data were compiled from various issues of *Russia's Regions: Socio-Economic Indicators* (Federal State Statistics Service, various years). Data on Indian regions were supplied by the Central Statistical Organization (CSO) at the Indian Ministry of Statistics and Programme Implementation.

3.1 Output and labour

Chinese statistics report the nominal value and the real growth rate of regional GDP which were used to calculate the real GDP with 1993 as base year.[4] In the absence of data on the number of hours worked, we measure labour as the total number of employed persons.

Data on the GDP of Russian regions are only available since 1994.[5] Real GDP measured in 1993 constant prices was obtained by deflating the nominal value with

[2] The states of Jammu Kashmir and Mizoram along with three union territories (Dadra and Nagar Haveli, Daman and Diu, and Lakshadweep) were excluded due to lack of data. Chattisgarh, Jharkhand and Uttarakhand were treated as parts of the states from which they were carved out in 2000 (Madhya Pradesh, Bihar and Uttar Pradesh, respectively).

[3] Two republics (Chechnya and Ingushetia) were excluded due to lack of data. Furthermore, in accordance with the official reporting standards, nine autonomous regions were treated as subdivisions of other provinces, and were not listed separately.

[4] The quality and reliability of official GDP data, especially at the provincial level, have been a major concern in the empirical literature on China's growth. Data falsification by local cadres along with institutional and structural problems facing statistical authorities in China have been blamed for exaggerating real output growth in the 1990s (Cai, 2000; Rawski and Xiao, 2001). However, the results of an economic census conducted in 2004 indicate that provincial GDP figures over the 1993–2004 period were highly accurate in contrast to national GDP data which needed to be revised (Holz, 2006a).

[5] In contrast to Chinese statistics where over-reporting seems to be the problem, Russian data on aggregate output are likely to suffer from underreporting of economic activity due to the growing share of the informal economy during the 1990s. Although statistical authorities have made corrections to account for the informal economy, these seem to be largely arbitrary (Dolinskaya, 2001).

the region-specific consumer price index. Labour is measured as the number of employed persons.

India's CSO compiles data on real regional GDP and re-bases the series as new benchmark years are adopted. We use the most recent series of real regional output data comprising the period 1993–2003 with base year 1993.[6] Data on regional employment in India come from the population censuses in 1991 and 2001 which report the number of main and marginal workers. The former include individuals who worked for 6 months or longer in a given year, the latter those who worked for shorter periods. The labour variable is measured as the sum of the two categories.

3.2 Capital stock

The perpetual inventory method is used to estimate the capital stock of the regions in all three countries. With the exception of Russia, the initial value of the capital stock for each region was derived using a methodology developed by Nehru and Dhareshwar (1993). Accordingly, the initial value of the capital stock for region i was constructed as

$$K_i = \frac{I_i}{(\delta + g_i)}, \tag{14}$$

where I denotes the real value of initial fixed investment, δ is the national depreciation rate and g is the average growth rate of real fixed investment.

For China, the nominal value of regional investment in fixed assets is converted into the real value with base year 1993 by deflating it with a region-specific fixed investment price index.[7] For the initial value of the capital stock in 1993 (see Equation 14) we use the province-specific average growth rate of real fixed investment over the period 1978–1990 and a depreciation rate of 4.5 percent.[8]

Russia's Federal State Statistics Service compiles annual data on the value of fixed capital stock at the regional level which eliminates the need for Equation (14). However, these values are likely to overstate the actual size of the capital stock because they include equipment and machinery that have become outmoded and obsolete during the market transition in the 1990s. To solve this problem,

[6] Annual data in India are reported for fiscal rather than calendar years. The fiscal year begins on April 1 and ends on March 31 of the following year. For simplicity, we use single years to denote fiscal years in the case of India. For instance, for the fiscal year 2001/2002 we simply write 2001.

[7] The majority of studies on China's growth have used the perpetual inventory method to obtain capital stock series at the national and regional levels (Chow and Li, 2002; Wu, 2004). Recently, Holz (2006b) proposed an alternative method of estimation which is critically reviewed by Chow (2006).

[8] Holz (2006b) estimates the annual economy-wide depreciation rate of China over the period 1990–2003 and also reports the officially published depreciation rates of five provinces in 2000. Both national and regional figures fluctuate between 4 and 5 percent which is the reason we adopted the average of the two numbers.

Dolinskaya (2001) used capacity utilization rates in the industrial sector to amend the capital stock figures at the national level. Lack of data prevented us from replicating this exercise at the regional level. Instead, we employed the 1992 value of regional fixed capital stock only as the initial level of capital but applied the perpetual inventory method to calculate the remaining values for the sample period. Data on the nominal value and the real growth rate of fixed investment were used to derive the real value with base year 1993.[9]

While Indian statistics report gross fixed capital formation at the national level, regional data on aggregate investment are not available. Previous studies on regional growth in India have attempted to design proxies by using, for instance, the stock of credit extended by commercial banks in lieu of private investment and the capital expenditure of regional governments as a substitute for public investment (Bhide and Shand, 2003; Purfield, 2006). However, among other problems, these proxies rely on the assumption that credit is utilized for investment purposes and that regional governments do not depend on borrowing or off-budgetary outlays to finance infrastructure projects.

By contrast, we use a set of investment estimates provided recently by the CSO (Lakhchaura, 2004). This set contains data on gross fixed capital formation for 32 states and territories and has two major advantages. The data are compiled from a wide variety of sources and cover public and private fixed investment in all major sectors of the regional economy, including agriculture. Moreover, supraregional investment in railways, communications, banking and central government administration is dissected by region and taken into account as well. For the purposes of our study, the data were converted to real gross fixed investment with base year 1993 by deflating it with a GDP deflator derived from the nominal and real values of regional GDP. When calculating the initial level of the capital stock in Equation (14), we used the growth rate of real gross fixed investment over the period 1993–2003. In line with estimates by CSO for the period 1993–2001, we adopted a depreciation rate of 7 percent.

3.3 Human capital

We followed the approach by Bils and Klenow (2000) to construct a human capital index (H) for each region using the average years of schooling (ϵ). Labour in efficiency units in region i in year t was defined by

$$\hat{L}_{it} = H_{it}L_{it} = h(\epsilon_{it})L_{it} = \mathrm{e}^{f(\epsilon_{it})}L_{it}, \tag{15}$$

where

[9] Hall and Basdevant (2002) estimated that the annual depreciation rate was around 10 percent in 1994 but declined steadily to 4.5 percent in 1998. Based on their findings, we adopted a depreciation rate of 6 percent which corresponds to the average rate over the 1990s.

$$f(\epsilon_{it}) = \frac{\theta}{1-\psi}\epsilon_{it}^{1-\psi}. \tag{16}$$

The parameter ψ measures the curvature of the Mincer (1974) earnings function, whereby a larger value is associated with a higher rate of diminishing returns to schooling. Bils and Klenow (2000) estimate that $\psi = 0.58$ using data from Psacharopoulos (1994) for a sample of 56 countries (including China).[10] As the rate of return to education is

$$\frac{\mathrm{d}\ln h(\epsilon_{it})}{\mathrm{d}\epsilon_{it}} = f'(\epsilon_{it}) = \frac{\theta}{\epsilon_{it}^{\psi}}, \tag{17}$$

the parameter $\boldsymbol{\theta} = 0.32$ so that the average of $\theta/\epsilon_{it}^{\psi}$ equals the average rate of return to education from the Psacharopoulos (1994) sample.[11]

Regional data on average years of schooling necessary for the construction of the human capital index are not available for any of the three countries. Ideally, these would be calculated by adding up the years of schooling enjoyed by all employed persons in a given year, and then dividing them by the total number of employed persons. Due to data limitations, this formula was employed only for Russian regions. In the case of China and India, we computed the average years of schooling for the working-age population instead.[12]

Wang and Yao (2003) derived a time series of China's human capital stock in terms of average years of schooling; however, their method is difficult to replicate at the regional level due to the lack of data on the initial level of human capital. We estimated the average years of schooling for China using data from the two most recent national censuses conducted in 1990 and 2000. Census data contains the educational attainment of individuals in the age group 15–64 by region. The average years of schooling were estimated by

[10] We also tested the sensitivity of our results to different values of ψ, including 0.28 and 0. The value of 0.28 is 2 SDs below the estimate of 0.58 by Bils and Klenow (2000). And if ψ is zero, then there are no diminishing returns to education. The tests show that besides some minor changes in the magnitude of the four growth components, the relative contributions of each component to growth as well as to the shifts of the distribution remain largely unchanged. We conclude that the major conclusions of the paper are thus robust with respect to varying levels of ψ.

[11] This is an oversimplification of the Bils and Klenow (2000) model. Their construction of current human capital also incorporates (positive) externalities from past capital accumulation of human capital (as first proposed in Borjas, 1992).

[12] As the educational attainment of employed individuals is likely to be higher than that of the working-age population, this could overstate the human capital stock of Russian regions. However, the results in the next section suggest that this is unlikely due to the minor contributions of human capital accumulation to growth.

$$\epsilon_{it} = \frac{(s_1 N_{1it} + s_2 N_{2it} + s_3 N_{3it} + s_4 N_{4it})}{N_{it}}, \tag{18}$$

where N_{jit} is the number of individuals aged 15–64 in year t, with j being the highest level of education attained, $j = 1$ for primary, 2 for junior secondary, 3 for senior secondary and 4 for tertiary level. N_{it} denotes the population in the age group 15–64 in year t in region i. The schooling cycles (s_j) were assumed to be 6 years for primary, 9 years for junior secondary, 12 years for senior secondary and 15.5 years for tertiary education.[13]

Previous studies on human capital in Russia drew on data from the Russian Longitudinal Monitoring Survey to obtain average years of schooling (Cheidvasser and Benitez-Silva, 2007; Gorodnichenko and Sabirianova Peter, 2005). Unfortunately, this household survey divides Russia into eight supraregions and is therefore not suitable for our purposes. We exploited educational data provided by the Federal State Statistics Service (http://stat.edu.ru) which contain information on the number of employed individuals by education and region for each year of the sample period 1994–2003. Average years of schooling were calculated using the formula in Equation (18) except that now N stood for the number of employed, and j, the highest level of education attained, took the value of 1 for primary, 2 for secondary, 3 for vocational and 4 for tertiary level. The schooling cycles (s_j) were assumed to be 4 years for primary, 11 years for secondary, 13 years for vocational and 16 years for tertiary education.

Recent studies involving human capital estimates for India have used either census (Playforth and Schuendeln, 2007) or household survey data (Bosworth *et al.*, 2007; Gundimeda *et al.*, 2007). As both data sources may provide valuable information on education levels at the regional level, we derived two sets of average years of schooling to avoid choosing one over the other. We obtained data from the two most recent censuses in 1991 and 2001, and the 52nd and 61st rounds of the National Sample Survey conducted in 1995–1996 and 2004–2005, respectively.[14] The average years of schooling were calculated using Equation (18) with N representing the number of individuals aged 15–80 years, and j taking the value of 1 for primary, 2 for middle, 3 for secondary, 4 for higher secondary and 5 for graduate (tertiary) level. The schooling cycles (s_j) were assumed to be 5 years for primary, 8 years for middle, 10 years for secondary, 12 years for higher secondary and 16 years for tertiary education.

[13] The number of graduates at the tertiary level includes those with a junior college degree (15 years) and those with a university degree (16 years). As the data did not allow us to separate these two groups, the average number of years was adopted as the length of the tertiary education.

[14] Although the National Sample Survey is conducted annually, reporting of educational data at the regional level is inconsistent. For most years the survey supplies the number of persons per 1,000 aged 7–80 years by educational level, making it impossible to calculate the average schooling years of the working-age population. Only the 1995–1996 and 2004–2005 surveys present data on persons aged 15–80 years.

4. Results

This section presents the empirical results for the sample period 1993–2003 as well as for two subperiods, 1993–1998 and 1998–2003. The year 1998 was chosen as a breakpoint not only because it is the midpoint of the sample period but because the Asian Financial Crisis in 1997 and the related Russian Rouble Crisis a year later caused an adverse shock to growth in all three economies and highlighted their rapidly growing integration with the rest of the world. Furthermore, given the large income inequalities, the results are also reported for the subsamples of rich and poor regions which included those that remained consistently in the upper and lower quartiles, respectively, over the entire sample period. Lastly, although the analysis was conducted separately for each country due to different units of measurement, the resulting relative efficiency levels, percentage contributions to growth and changes in the income distribution were compared across the three countries.

4.1 Efficiency

The efficiency scores of Chinese regions shown in the first two columns of Table 1 indicate that average efficiency levels were relatively high in 1993 but declined by 2003. The deterioration in efficiency was more rapid after 1998 and stemmed mainly from the abysmal performance of poor regions which recorded a fall of 22 percent on average over the entire sample period. By contrast, rich regions were extremely efficient in every period and managed to move even closer to the production frontier.

The regions with the highest levels of efficiency (90–100 percent), including Shanghai, Fujian, Jiangsu, Zhejiang and Guangdong, were on the forefront of economic reforms in China, benefitted from foreign capital and technology attracted to the Special Economic Zones established in these regions in the 1980s, and profited from their costal location as they developed dynamic export-oriented industries. These regions defined the production frontier and were responsible for its large upward shifts between 1993 and 2003.[15] By contrast, regions in western China, such as Tibet, Ningxia and Qinghai, where reforms were slow and their location isolated achieved the lowest efficiency (40–50 percent).[16] As the frontier shifted upward due

[15] The frontier shifted up but not by the same proportion for every value of capital per efficiency unit of labour implying that technological change was non-neutral. In fact, the frontier remained constant at the lower levels of capital per efficiency unit of labour.

[16] While it is a well-established fact that coastal regions in China are more developed and more dynamic than their counterparts in the interior of the country, the overwhelming majority of existing studies examine different types of convergence but, in contrast to our study, fail to decompose regional growth and quantify and explain the contribution of the resulting components, including efficiency, to the divergence between coastal and interior regions.

Table 1. Efficiency levels and components of labour productivity change for Chinese regions

Category	TE_b*	TE_c*	Productivity change	(EFF-1) × 100	(TECH − 1) × 100	(KACC − 1) × 100	(HACC − 1) × 100
Panel A: The whole period, 1993–2003							
Poor	0.85	0.67	124.96	−21.81	3.07	177.78	2.12
Middle	0.82	0.79	136.58	−3.73	6.97	125.19	3.32
Rich	0.94	0.93	180.31	2.61	29.71	108.19	5.25
All regions	0.81	0.75	144.87	−6.76	11.83	134.38	3.51
Panel B: The first sub-period, 1993–1998							
Poor	0.85	0.76	52.08	−9.49	0.49	67.45	0.51
Middle	0.82	0.83	57.69	−0.64	3.14	53.08	1.01
Rich	0.94	0.94	77.10	2.29	9.99	57.29	1.63
All regions	0.81	0.79	61.25	−2.16	4.22	57.87	1.04
Panel C: The second sub-period, 1998–2003							
Poor	0.84	0.69	47.77	−18.90	0.46	81.99	0.36
Middle	0.87	0.80	50.07	−6.21	5.17	51.89	1.21
Rich	0.95	0.93	58.11	−1.17	16.27	36.02	1.62
All regions	0.83	0.76	51.55	−8.18	6.82	55.56	1.10

***Notes*:** *'b' stands for first and 'c' for the last year of the period in question; efficiencies are weighted as in Färe and Zelenyuk (2003).
Poor implies regions which consistently remained in the lower quartile of output per worker. Rich implies regions which consistently remained in the upper quartile of output per worker. Middle implies other than 'rich' and 'poor'.

to technological change in the rich coastal regions, poor regions were not able to keep up and experienced a fall in relative efficiency as their distance from the new frontier increased.

The first two columns of Table 2 suggest that, in contrast to China, Russian regions were generally quite inefficient with respect to their own frontier in all years observed. The potential gains from removing inefficiencies are enormous – up to 45 percent on average in 2003. As in China, the performance is fairly heterogeneous across regions. Rich regions were 85–90 percent efficient, whereas poor regions are the least efficient at approximately only 50 percent. The fourth column of Table 2 reveals that all groups of regions experienced more or less the same decline in efficiency during 1994–2003. The analysis of the subperiods provides a more nuanced picture. During 1994–1998 poor regions appear to have suffered the largest declines in efficiency, while the rich were the least affected. This can be explained by the growing distance of poor regions from the benchmark frontier as it was shifted upward by rich regions. During 1998–2003 this trend was reversed as

Table 2. Efficiency levels and components of labour productivity change for Russian regions

Category	TE_b*	TE_c*	Productivity change	(EFF − 1) × 100	(TECH − 1) × 100	(KACC − 1) × 100	(HACC − 1) × 100
Panel A: The whole period, 1994–2003							
Poor	0.51	0.48	20.56	−7.08	60.84	−17.60	−0.32
Middle	0.63	0.56	27.21	−9.66	61.95	−12.19	−0.64
Rich	0.85	0.86	52.18	−8.79	74.25	−2.35	−1.19
All regions	0.61	0.55	30.73	−9.00	64.10	−11.34	−0.68
Panel B: The first sub-period, 1994–1998							
Poor	0.51	0.38	−26.77	−23.53	0.00	−3.84	−0.15
Middle	0.63	0.50	−20.17	−19.23	1.10	−1.59	−0.57
Rich	0.85	0.79	−6.56	−10.29	3.80	1.21	−0.71
All regions	0.61	0.50	−18.82	−18.34	1.41	−1.48	−0.52
Panel C: The second sub-period, 1998–2003							
Poor	0.47	0.48	64.59	−2.12	98.98	−14.65	−0.09
Middle	0.60	0.56	59.33	−4.95	90.95	−11.75	−0.19
Rich	0.90	0.86	61.74	−10.64	89.77	−4.43	−0.34
All regions	0.59	0.55	60.81	−5.50	92.27	−10.90	−0.20

***Notes*:** *'b' stands for first and 'c' for the last year of the period in question; efficiencies are weighted as in Färe and Zelenyuk (2003).
Poor implies regions which consistently remained in the lower quartile of output per worker. Rich implies regions which consistently remained in the upper quartile of output per worker. Middle implies other than 'rich' and 'poor'.

rich regions experienced larger decreases in efficiency due to the extraordinary performance of a few regions such as Tyumen Oblast within the rich category.

The production frontier in Russia and its upward movements were determined by a group of highly efficient regions, including Tyumen, Sakha, Komi and Samara, which have in common that they are rich in natural resources and their production constitutes a large share of Russian exports. Tyumen Oblast is home to the Tyumen Oil Company (TNK) which is one of the 10 largest vertically-integrated private oil and gas companies in the world in terms of proven oil reserves. Sakha (Yakutia) Republic has become one of the most attractive regions for investment in the Far East federal district. It possesses unique natural resources and extracts 100 percent of stibium, 98 percent of diamonds, 40 percent of tin and 15 percent of gold in Russia. In addition, it has considerable energy resources as it accounts for 47 percent of explored reserves of coal and 35 percent of natural gas and oil reserves in Eastern Siberia and the Far East.

The Komi Republic is abundant in coal, oil, gas, bauxite, titanium ores, salts, gold, diamonds, ores of non-ferrous and rare metals, fluorite, shale oil and building materials. The gross value of its mineral reserves has been put at $11 trillion or 8 percent of Russia's estimated potential. Komi is also home to the Pechora coal mining basin, Russia's second largest in terms of its stock. The economy of Samara Oblast relies mainly on the exploration, extraction and refining of oil and gas for its growth. It is also home to the Volzhsky automobile plant, which accounts for over 75 percent of all passenger vehicles made in Russia. The federal city of Moscow is also among the most efficient regions due to its role as the administrative and financial centre of Russia.

The only other known study which has employed Data Envelopment Analysis to examine efficiency at the regional level in Russia is Obersteiner (2000). In contrast to our paper, it focuses only on the industrial sector during the late Soviet and early transitional period (1987–1993), fails to explore efficiency differences between poor and rich regions and does not examine other components of growth besides efficiency. Although Obersteiner (2000) does not report the efficiency levels for each region separately, his estimates suggest that average efficiency was low and decreased in the early 1990s. Our results indicate that this decline has continued at the aggregate level over the 1990s and early 2000s. Moreover, his findings show that in the final years of the Soviet Union the best-performing regions with the smallest deterioration in industrial efficiency were Tyumen, Sakha Republic and Komi Republic, the same regions that achieved the highest level of aggregate efficiency in our sample for the period 1994–2003.

It is evident from the first two columns of Table 3 that India's regional economies were as inefficient with respect to their own production function as their Russian counterparts. Moreover, average efficiency declined over the 1993–2003 period; however, whereas rich regions were able to improve their efficiency by almost 3 percent, the efficiency scores for poor regions decreased by 17 percent. In the period after 1998, both subsamples experienced a deterioration in efficiency, but again the larger decline was recorded by the poor regions.[17]

In contrast to China and Russia where the most efficient regions reflected the trade patterns of each country with the rest of the world, the regions defining the production frontier in India were found to be a more diverse group. They ranged from Delhi, the capital and second most important commercial centre after Mumbai, to Haryana, a manufacturing region that produces a significant share of India's industrial output. The city of Gurgaon which has become a major outsourcing and offshoring hub since the late 1990s is also located in Haryana. Other efficient regions included Punjab, the largest agricultural producer in India, and its capital Chandigarh, as well as Goa and Pondicherry, two small coastal enclaves that rely largely on tourism and fishing respectively.

[17] As in China, technological change in India was non-neutral as the frontier shifted upward by different proportions for every value of capital per efficiency unit of labour.

Table 3. Efficiency levels and components of labour productivity change for Indian regions

Category	TE_b*	TE_c*	Productivity change	(EFF − 1) × 100	(TECH − 1) × 100	(KACC − 1) × 100	(HACC − 1) × 100
Panel A: The whole period, 1994–2003							
Poor	0.63	0.50	22.41	−17.12	12.95	40.93	1.62
Middle	0.61	0.65	47.40	0.63	12.59	32.51	2.71
Rich	0.95	0.90	58.69	2.78	35.85	13.08	1.49
All regions	0.66	0.63	44.36	−2.84	17.84	30.07	2.20
Panel B: The first sub-period, 1993–1998							
Poor	0.63	0.53	9.44	−16.14	8.52	22.87	0.38
Middle	0.61	0.63	21.27	−3.08	5.81	19.09	1.23
Rich	0.95	0.91	31.28	1.67	19.90	7.04	0.44
All regions	0.66	0.63	20.86	−4.93	9.54	17.25	0.87
Panel C: The second sub-period, 1998–2003							
Poor	0.72	0.58	11.90	−10.10	15.50	12.67	0.36
Middle	0.77	0.71	21.61	−6.61	14.99	14.18	0.80
Rich	0.98	0.92	17.85	−3.53	14.49	7.18	1.20
All regions	0.75	0.68	18.62	−6.70	14.99	12.29	0.79

***Notes*:** *'b' stands for the first and 'c' for the last year of the period in question; efficiencies are weighted as in Färe and Zelenyuk (2003).
Poor implies regions which consistently remained in the lower quartile of output per worker. Rich implies regions which consistently remained in the upper quartile of output per worker. Middle implies other than 'rich' and 'poor'.

Mukherjee and Ray (2005) used non-parametric methods to estimate the efficiency at the regional level in India; however, they focused only on the manufacturing sector, and therefore their results are not directly comparable with ours.[18] Nevertheless, they reported that Goa, Delhi and Chandigarh ranked consistently at the top over the period 1986–1999 which is in line with our results. Furthermore, Mukherjee and Ray (2005) show that there is no convergence in efficiency scores which corroborates our findings of different trends in efficiency changes for rich and poor regions.

[18] Besides the more narrow focus on manufacturing, Mukherjee and Ray (2005) differs from our study in several key aspects. The authors do not include human capital in the production function, use a smaller sample of Indian states and do not decompose labour productivity to examine the contribution of additional components besides efficiency.

4.2 Quadripartite decomposition of productivity

As evident from the third column of Table 1, the annual growth of labour productivity in China's regions was on average 14.5 percent over the period 1993–2003. Whereas the rich coastal regions Zhejiang and Jiangsu grew by more than 20 percent, labour productivity in the poor regions Ningxia and Guizhou increased by less than half that rate. Growth slowed down after 1998 which was most probably caused by the East Asian Financial Crisis. This is further supported by the results for the subsamples. The growth rate of rich regions which are more dependent on exports and were thus more affected by the financial crisis decreased from 77 percent over the 1993–1998 period to 58 percent after 1998, whereas the drop for poor provinces was only from 52 to 48 percent.

The contributions of efficiency, technological change, physical and human capital accumulation to labour productivity growth are displayed in the last four columns of Table 1. It is obvious that physical capital accumulation is by far the most important driving force behind the growth of labour productivity in China. This is broadly consistent with the findings of the other two non-parametric studies on China (Henderson *et al.*, 2007; Unel and Zebregs, 2006), although the results are not directly comparable due to differences in methodology and data.[19] The average contribution of technological change was approximately 12 percent, followed by human capital accumulation with 3.5 percent.

Labour productivity growth in rich regions relied heavily on technological change and human capital accumulation. The contributions of these two components were well above the regional average with 30 and 5 percent, respectively, and contrast with the 3 and 2 percent for poor regions. The extreme case was Shanghai where technological change was more important for growth than physical capital accumulation. As for poor regions, their growth was driven largely by physical capital accumulation which contributed not only more than the regional average but also exceeded the rate of capital deepening in rich regions. In Sichuan and Gansu, for instance, technological change and human capital accumulation contributed only around 2 percent each compared with 200 percent for physical capital accumulation.

The growth rates of labour productivity in Russia appear in the third column of Table 2. During the 10 years under consideration, labour productivity increased by 30 percent which is five times less than in China. However, rich regions enjoyed a rise in labour productivity of 52 percent compared with only 20 percent in poor regions. Moreover, there are significant differences between the two subperiods. Russia went through a severe economic slump in 1994–1997 when only a handful of regions recorded any productivity growth, including Moscow and Tyumen Oblast. Poor regions in general experienced much larger drops in growth than rich

[19] For instance, Unel and Zebregs (2006) use a smaller number of Chinese provinces, focus on the period before 1998 and do not include human capital into the production function.

regions. The period after 1998 was characterized by a surge in productivity, whereby all regions regardless of their classification enjoyed growth of a similar magnitude.[20]

The contributions of the four growth components are presented in the last four columns of Table 2. It is clear that in contrast to China, technological change is the only factor driving productivity growth at the regional level in Russia. The other three components impeded productivity growth on average, with physical capital accumulation being the main obstacle experiencing an average decline of 12 percent and affecting poor regions more seriously than rich ones.[21] Efficiency was the second largest hindrance to growth but unlike the physical capital accumulation, *all* regions lost approximately the same percentage during 1994–2003. As for human capital accumulation, it held back growth in *all* years and for *all* regions but as its contribution was close to zero, its impact was minimal.

Technological change and capital deepening behave quite differently in the two subperiods. During 1994–1998, neither of them contributed significantly to productivity growth which was almost entirely driven by a deterioration in efficiency. After 1998, the share of technological change increases dramatically for all groups of regions turning into the only positive contributor to growth. By contrast, physical capital accumulation continued to deteriorate. Hence, technological change as the major driving force of productivity growth during 1994–2003 received a boost not earlier than 1998.

Over the period 1993–2003, the average annual growth of labour productivity of India's regional economies was approximately 4.4 percent, as shown in the third column of Table 3. This is higher than in Russia but far below the growth rate of Chinese regions. Productivity growth for the entire sample slowed down after 1998. The growth rate for rich regions over the entire sample period was almost three times higher than the growth of poor regions. Over the second subperiod, the differences in growth rates narrowed and the middle group of regions managed to grow faster than the group of rich regions.

The shares of the four components in labour productivity growth of Indian regions appear in the last four columns of Table 3.[22] As in China, physical

[20] The technological change in Russia was not as clearly non-neutral as in the case of China and India. Especially in the second subperiod, the frontier shifted up more or less by the same proportion for all levels of capital per efficiency unit of labour.

[21] Although the decline in Russia's capital stock after the breakdown of the Soviet Union is a well-known fact, to our knowledge no studies exist that have examined this issue at the regional level and have quantified the extent to which the physical capital deterioration has impeded regional growth and has contributed to the growing divergence across Russian regions.

[22] To check for robustness, we performed the entire analysis for India using the two alternative datasets for human capital described in Section 3 (census vs. household survey). While there were some minor quantitative differences in the results, the major conclusions did not change. The full set of results is available from the authors upon request.

capital accumulation was the largest determinant of growth, followed by technological change. The contribution of human capital accumulation was relatively small, while efficiency change had a negative effect. In the first subperiod these trends remained the same; however, after 1998 technological change surpassed physical capital accumulation as the major contributor to growth.

The results for the subsamples also provide some interesting insights. Productivity growth in rich regions was mainly driven by technological change, followed by physical capital accumulation. For poor regions, these numbers were almost exactly reversed. Poor and rich regions did not differ much in terms of the share of human capital accumulation; however, as mentioned above, efficiency in poor regions suffered a severe fall, while it improved slightly in rich regions. During 1998–2003, technological change became the leading determinant of labour productivity growth for each of the three subsamples. Physical capital accumulation remained crucial for the growth of poor regions, but was much less important for rich regions.

The key role of technological change for labour productivity growth in India was highlighted by Bosworth *et al.* (2007) who employed standard growth accounting and found that at the national level the contribution of physical capital accumulation and total factor productivity were at par over the 1993–1999 period, but that the latter's growth was almost twice as high as the former's over the 1999–2004 period. At the subnational level, Kumar (2004) used a non-parametric technique to decompose total factor productivity in the manufacturing sector of 15 Indian regions into efficiency and technological change. He showed that over the 1990s technological change was the most significant factor behind total factor productivity growth in manufacturing, and that efficiency in many regions either deteriorated or remained constant. Kumar's results, although not directly comparable with ours due to his sectoral focus and a smaller sample, are largely in line with our findings about the growing importance of technological change in India over the 1990s.[23]

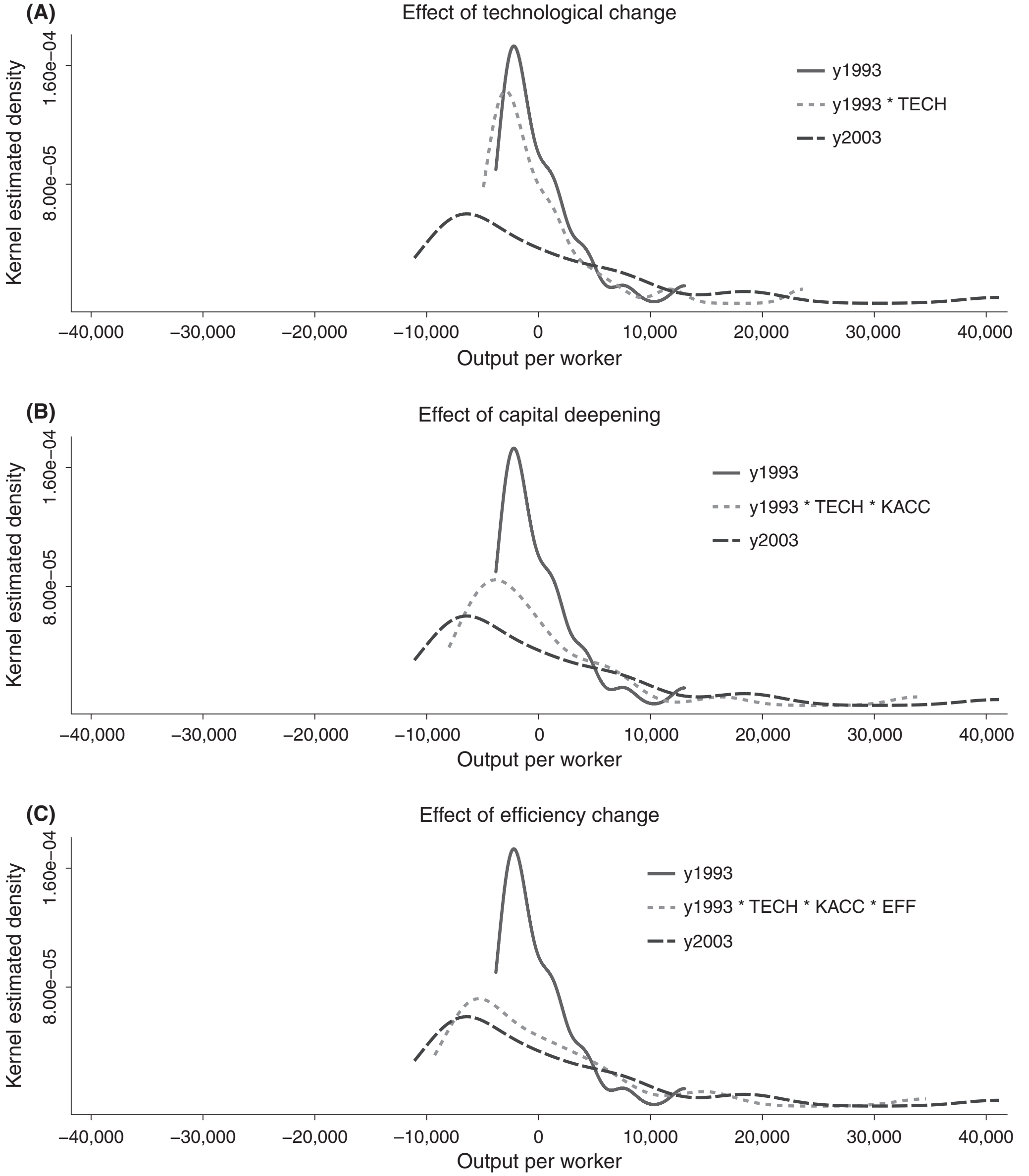
4.3 Analysis of productivity distributions

The labour productivity distributions for China are shown in Figure 1 as solid and dashed lines.[24] The solid and dashed curves represent the mean-preserving distributions of output per worker in 1993 and 2003, respectively. It is evident that the distribution in both years is multimodal underlying the potential problems

[23] Besides a smaller sample and the focus on a single sector, Kumar (2004) differs from our study in several major points. He uses the Malmquist index which measures TFP growth over time rather than at a given point in time. Moreover, he decomposes total factor productivity (TFP) rather than labour productivity failing to account for the contributions of physical capital and human capital accumulation. Lastly, he uses the book value of fixed assets of manufacturing firms which is likely to distort the true value of capital.

[24] The figures for the subperiods are not included here to conserve space, but they are available from the authors upon request.

Figure 1. Shifts in the distribution of output per worker for Chinese regions



Note: In each panel, the solid curve is the actual 1993 distribution and the dashed curve is the actual 2003 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of technological change, capital deepening and efficiency change on the 1993 distribution.

associated with the focus of the regression approach on the first moment of the distribution.[25] In 1993, the majority of regions were concentrated around a relatively low value of output per worker, whereas rich regions were grouped in several smaller modes. By 2003, the distribution had shifted with a dramatic increase in variance reflecting the income divergence across China's regions. Despite differences in the sample period and the data used, these results largely match the findings of Aziz and Duenwald (2001) who also applied the distribution approach to study the issue of income divergence across China's regions.[26]

The counterfactual distributions presented in Figure 1 illustrate the impact of the four components of labour productivity growth on the shifts of the distribution in China. In Panel A we observe the shift in the distribution assuming that technological change is the only varying component of growth. When comparing the 1993 distribution and the dotted line representing the counterfactual one, it is evident that technological change mainly extended the tail of the distribution towards higher levels of income. In other words, technological change led to income divergence across China's regions as it contributed more to the growth of rich regions than to the growth of poor ones.

In Panel B, we add physical capital accumulation as a second component that is allowed to vary. The result is a large loss in the probability mass at the lower levels of output per worker and gains in the probability mass at higher income levels. This widening of the lower mode suggests that a number of relatively poor regions managed to catch up with richer regions through capital deepening. Physical capital accumulations has thus resulted in a narrowing of the regional income gap in China. Efficiency changes (Panel C) and human capital cause only minor shifts in the distribution.[27]

Figure 2 shows the mean preserving distributions of output per worker in Russia in 1994 and 2003 as solid and dashed lines respectively. While most regions were clustered close to zero in 1994, in 2003 less probability mass was concentrated around the mode. As the rich regions became even wealthier, the right tail of the dashed distribution stretched to higher levels of output per worker, providing clear

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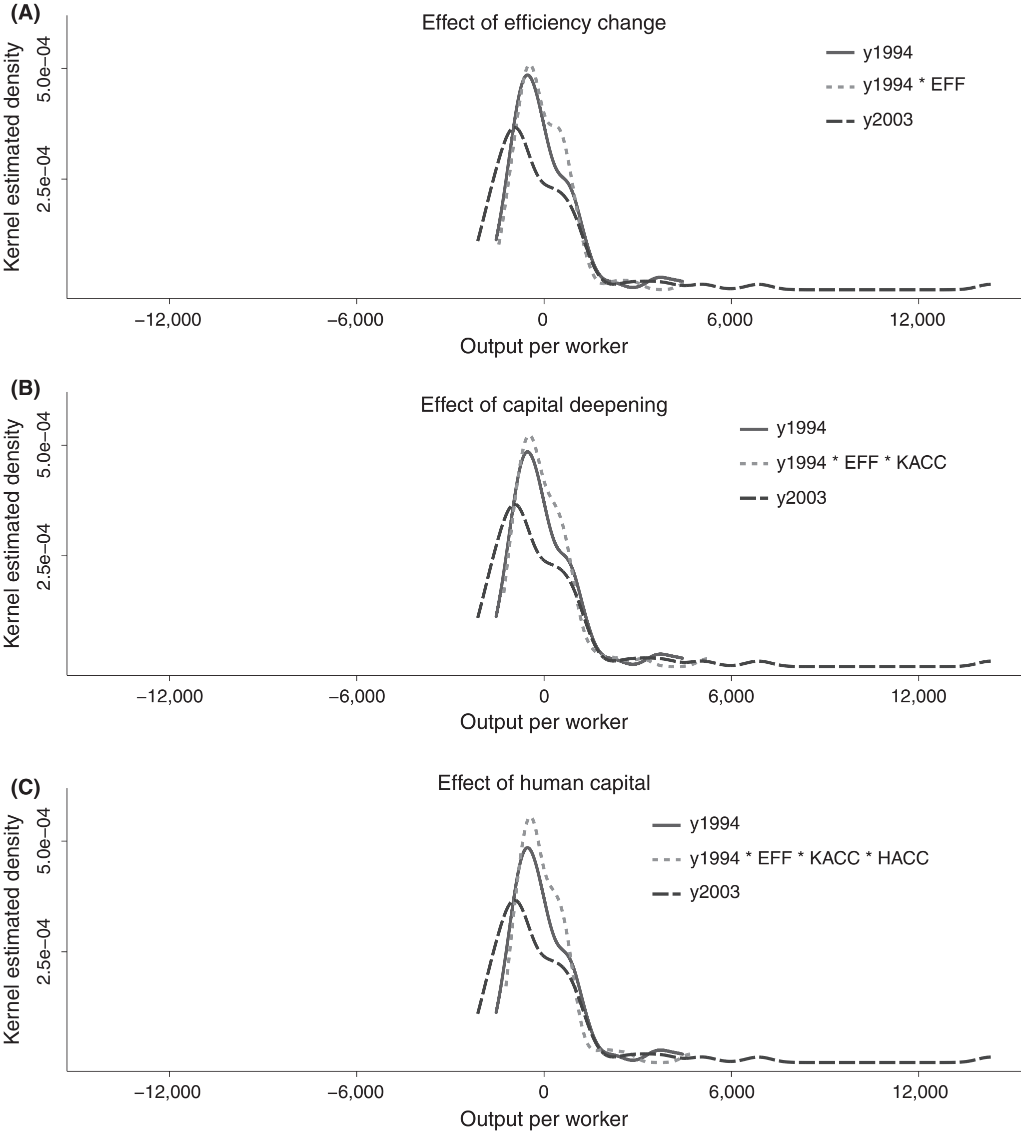
[25] We are able to confirm this conjecture statistically. The calibrated Silverman (1981) test of Hall and York (2001) shows the p-values for the null hypothesis that the distribution of output per worker is unimodal in 1993 and 2003 to be 0.095 and 0.037, respectively.

[26] The study by Aziz and Duenwald (2001) mostly describes the distribution of labour productivity, whereas our paper identifies the growth components responsible for the shifts of the distribution and quantifies the extent of their effect. In addition, their sample period ends in 1997, while ours extends to 2003.

[27] We also performed the distribution analysis using different sequencing combinations for all three countries and found that the results are not sensitive to changes in the sequencing order. Furthermore, we formally test for statistical significance of differences between (actual and counterfactual) distributions using the test developed by Li (1996). The Li test tests the null hypothesis $H_0 : f(x) = g(x)$ for all x against the alternative $H_1 : f(x) \neq g(x)$ for some x (for further details, see Fan and Ullah, 1999; Li, 1996; Pagan and Ullah, 1999). These tests confirmed that capital deepening and after 1998 also technological change were enough to render the two distributions indistinguishable from each other. The full set of results is available from the authors upon request.

Figure 2. Shifts in the distribution of output per worker for Russian regions



***Note*:** In each panel, the solid curve is the actual 1994 distribution and the dashed curve is the actual 2003 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of efficiency change, capital deepening and human capital accumulation on the 1994 distribution.

evidence for the widening income gap between rich and poor regions. This affirms the divergence found by previous studies on income distribution dynamics of Russian regions. Herzfeld (2006) who used the same sample of regions showed the evolution of the income distribution from a unimodal to a bimodal over the period 1994–2002 with Tyumen, the Sakha Republic and Moscow forming the mode at the higher levels of income per capita.[28] Similarly, Carluer (2005) identified two regional clubs in Russia and demonstrated the increasing polarization in the income distribution over the 1990s. The regions in each of the two clubs broadly correspond to our rich and poor subsamples.[29]

The counterfactual distributions appear in three panels of Figure 2. Panel A shows the isolated effect of efficiency change. Apparently, efficiency change did cause shifts in the distribution, albeit with an opposite effect. Efficiency change made regions poorer; the probability mass increased around zero. By contrast, other components, such as capital deepening (Panel B) and human capital accumulation (Panel C) did not contribute at all to the shift of the distribution. The isolated effect of technological change can be deduced from the difference between counterfactual distribution of $y^{EKH} = (y_{1994} \times \text{EFF} \times \text{KACC} \times \text{HACC})$ and that of y_{2004} (Panel C). It is obvious that technological change alone shifted the 1994 distribution to the extent that it closely resembled the 2003 distribution. Only in combination with technological change does capital deepening have an effect on the 1994 labour productivity distribution.[30]

The labour productivity distributions for Indian regions appear in Figure 3. The solid and dashed curves represent the mean-preserving distributions of output per worker in 1993 and 2003, respectively. The obvious multimodality of the distribution in 2003 underlines again the advantage of the non-parametric procedure over the regression approach.[31] In 1993, the majority of regions were clustered around a relatively low value of output per worker while rich regions were grouped in several smaller modes. By 2003, the lower mode had widened considerably with a large number of regions moving to higher levels of output per worker and creating

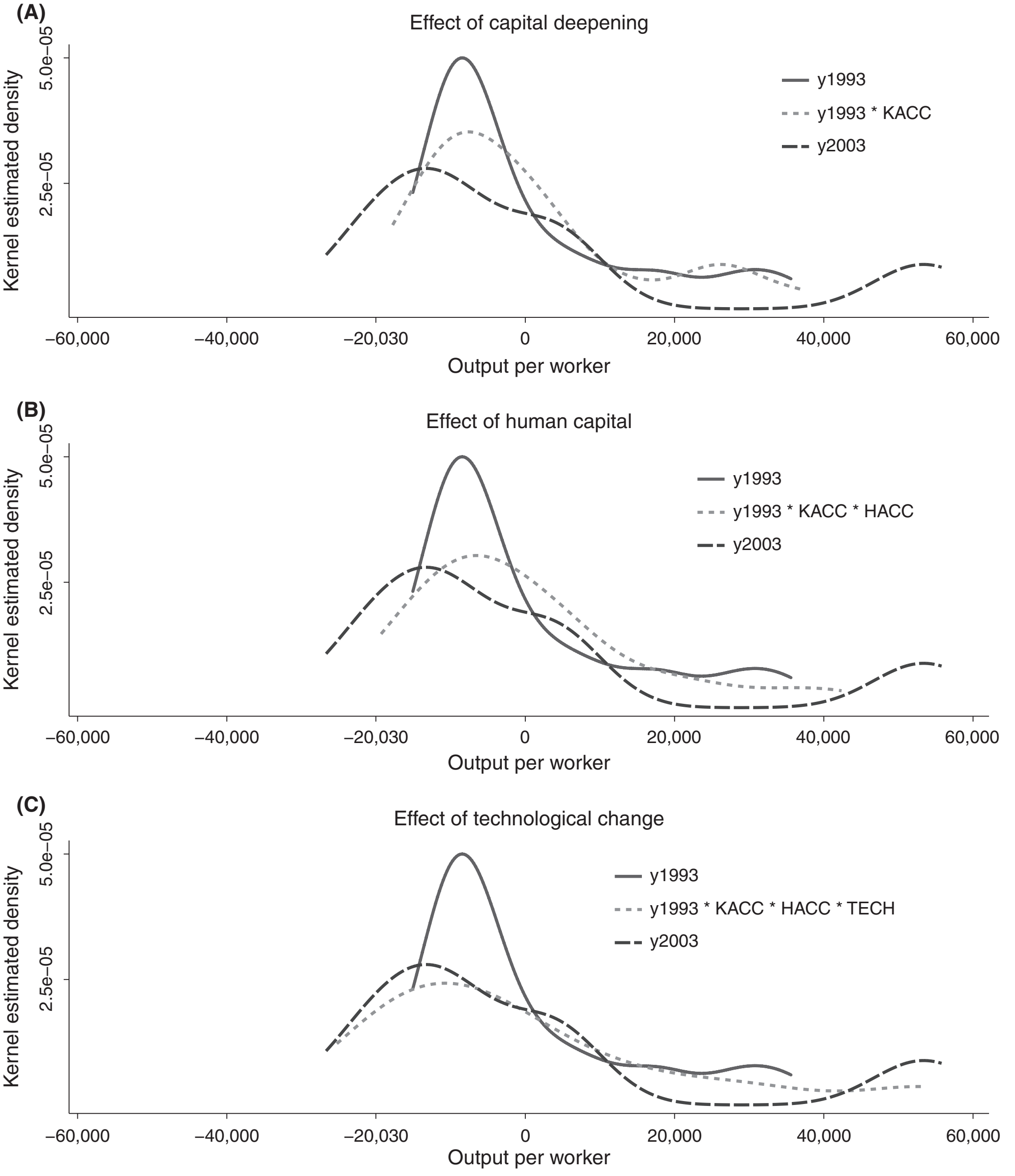
[28] In contrast to Herzfeld (2006), we reject unimodality in *both* periods at the 5 percent level (p-values in 1994 and 2003 were 0.011 and 0.000, respectively, using the calibrated Silverman (1981) test of Hall and York, 2001). An additional important difference to our study is that Herzfeld (2006) does not examine the factors responsible for the shifts of the distribution.

[29] The main difference to our study is that Carluer (2005) used a Markov chains approach and did not examine the contributions of the various growth components to the dynamics of the distribution. Furthermore, his sample period (1985–1999) includes 7 years of unreliable Soviet regional data which cannot be easily linked to data from the post-Soviet period due to changes in statistical methodology.

[30] This evidence is backed by the results of the Li test, which show the p-values of the difference between the actual 2004 distribution, y_{2004}, and the counterfactual distributions, $y_{1994} \times \text{TECH}$, $y_{1994} \times \text{TECH} \times \text{KACC}$, $y_{1994} \times \text{TECH} \times \text{HACC}$, $y_{1994} \times \text{EFF} \times \text{TECH} \times \text{KACC}$, and $y_{1994} \times \text{EFF} \times \text{TECH} \times \text{HACC}$ to be 0.62, 0.22, 0.75, 0.99 and 0.91, respectively.

[31] Using the calibrated Silverman (1981) test of Hall and York (2001) we reject the null hypothesis that the distribution of output per worker is unimodal in 2003 at any conventional level (p-value is 0.003); we fail to reject the same hypothesis for 1993 (p-value is 0.436).

Figure 3. Shifts in the distribution of output per worker for Indian regions



***Note*:** In each panel, the solid curve is the actual 1993 distribution and the dashed curve is the actual 2003 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of capital deepening, human capital accumulation and technological change on the 1993 distribution.

what seems to be a new mode. At the same time, rich regions shifted to even higher income levels extending the tail of the distribution and concentrating around a very pronounced mode. This evidence essentially confirms the trend found for earlier periods by the only other known non-parametric study of distributional dynamics at the regional level in India by Bandyopadhyay (2006). She shows that since the 1970s and into the 1990s the polarization across Indian states increased leading to the emergence of two convergence clubs, one at each end of the distribution, which correspond to the two modes in our study.[32]

The counterfactual distributions highlighting the impact of each of the four components of labour productivity growth on the shifts of the distribution are displayed in Figure 3. Panel A shows the dotted line of the counterfactual distribution assuming that there is only physical capital accumulation. The larger mode at the lower level of output per worker widens dramatically indicating a divergence among the regions that were poor in 1993. However, the fact that the tail of the distribution remains unchanged suggests that over the period 1993–2003 some previously poor regions were able to catch up through capital deepening with the rich regions.

Adding human capital accumulation in Panel B does not lead to any major shifts in the distribution; however, when technological change is added in Panel C the counterfactual distribution changes noticeably. In fact, there are two changes in the distribution. The first one is a further widening of the lower mode and the emergence of an adjacent mode. This widening, however, is also accompanied by the extension of both tails of the distribution indicating the divergence across Indian regions caused by technological change. Part of the probability mass that shifted to the right due to physical capital accumulation moves back to the left while a prominent mode emerges at the higher levels of output per worker.[33]

We also performed the distribution analysis for the two subperiods for each of the countries, which provided additional insights into the evolution of the labour productivity distribution. In China over the period 1993–1998, capital deepening alone (or in any combination with other components) was enough to render the actual and counterfactual distributions indistinguishable from each other, whereas after 1998 technological change gained in importance to become the second determinant causing major shifts in the distribution. The case of Russia is interesting because although actual distributions in both subperiods were significantly different from each other, the shifts of the distribution in the first subperiod were not caused by any single component. The driving effect of technological change started

[32] In contrast to our study, Bandyopadhyay (2006) includes only 17 states in her sample and does not examine the effect of the various components of labour productivity on the shifts of the distribution. Furthermore, the sample period in her study ends with 1993 which marks the first year of our sample period.

[33] The null hypothesis that the counterfactual and the actual distributions are equal could not be rejected for any of the components of labour productivity growth except human capital accumulation.

only after 1998. For India, we found that the actual and counterfactual distributions were not significantly different from each other in the two subperiods.

5. Conclusion

This paper represents the first known comparative analysis of regional growth and convergence in China, Russia and India using a unified methodological framework. Our approach to the investigation of patterns of productivity growth is essentially akin to growth accounting. It decomposes the labour productivity into four components attributable to technological catch-up, technological change, physical and capital accumulations. This allows us to measure the magnitude of each of these components and study their role in growth and convergence. As mentioned in the beginning, such an analysis of components' contributions to growth is therefore consistent with more than one growth theory. Moreover, this approach has three major advantages over standard growth accounting: (i) it does not require neutrality of technological change, or (ii) adhering to a specific functional form of the technology and (iii) allows the modelling of inefficiency of regional economies. We have employed non-parametric techniques to identify the sources of growth for regional economies in the three countries and their role in the increasing regional income inequality over the period of market transition.

Our results indicate that the rapid growth at the national level in China, Russia and India was driven by wealthy regions with highly efficient economies located mostly along the coast (China) or in areas rich in natural resources (Russia), thus reflecting the specialization of each country in the world economy. The lack of proportional development at all levels of output per worker which was most pronounced in China and India repudiates the usual assumption of the neutrality of technological change and underscores the advantage of the non-parametric approach.

Our findings suggest that physical capital accumulation was the largest contributor to regional growth in China and India increasing the probability of a slow down in their growth in the future. In Russia, technological change was the only source of growth as capital investment dropped dramatically and efficiency deteriorated during the period of market transition. Consequently, Russian regions could boost their growth relative to their counterparts in China and India if they manage to reverse these negative trends. Furthermore, we showed that in all three countries rich regions relied more on technological change for their growth than poor ones providing them with the potential for sustainable growth in the long run. The analysis of the income distributions for China, Russia and India offered further proof of the advantage of non-parametric methods over the standard regression approach as it revealed the existence of multiple modes. Our results indicate that the income divergence across regions in all three countries was mainly due to rapid technological advances in the rich regions that were not matched by poor regions. Some regional economies at the lower levels of output per worker managed to grow faster and achieve a certain level of catch up due to higher rates of capital accumulation in China and India or a less severe deterioration of efficiency in Russia; however, this convergence was not enough to reverse the growing income inequality caused by technological change. The income divergence across regions is likely to remain a major issue in the future unless poor regions manage to grow faster by relying on technological change as a more sustainable source of growth.

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