The Determinants of Regional Growth and Convergence in China, India, and Russia

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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 nonparametric 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 deepening was identified as the major determinant of regional growth. In Russia, capital deepening impeded positive changes in labor productivity, leaving technological change as the only source of regional growth. In all three countries, rich regions relied more on technological change for their growth than poor ones. 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.

Keywords: Growth, Convergence, Comparative Analysis, Data Envelopment Analysis, Nonparametric

JEL: C14, O57, N10,

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1 Introduction

Over the past decade, China, Russia, and India have become synonyms for fast-growing emerging economies. They are frequently bundled together, as evidenced by common references to Chindia and BRIC (Brazil, Russia, India, and China), and appear as a unified bloc with shared characteristics and a similar pattern of development. In fact, China, Russia, and India are among the largest, most populous, and fastest growing economies in the world, accounting together for about one-half of global growth and more than a quarter of world output in purchasing power terms. Further similarities are to be found in the course of their transition that can be traced back to at least the 1980s when all three countries had still centrally-administered economies marked by government efforts to overcome inefficiencies and stagnation through economic reforms. Their economic 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. Governments in all three countries responded by adopting a broad range of reforms over the period 1991–1993 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. 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 labor. In 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. Lastly, 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.

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. We chose to conduct the growth analysis at the regional rather than at the national level. China, Russia, and India rank among the largest states in the world and are divided into numerous regions the size of countries. The rapid growth observed at the national level could be misleading as it is mostly driven by a few regions which were able to benefit from economic reforms, attract foreign direct investment, absorb advanced technology from abroad, and participate actively in world trade. In addition, the regional focus allows us to expand our analysis and address the issue of increasing regional income inequality which 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 issues such as economic reforms (Chai and Roy, 2007; Das, 2006; Jha, 2003), decentralization (Dethier, 2000; Blanchard and Schleifer, 2001), international trade and finance (Winters and Yusuf, 2007; Broadman, 2007), or sectoral performance (Xu, 2004; Gregory, Nollen, and Tenev, 2007). Recent works that deal explicitly with regional growth issues in China (Miyamoto and Liu, 2005; Henderson, Tochkov, and Badunenko, 2007), Russia (Berkowitz and DeJong, 2002; Brock, 2005), and India (Sachs, Bajpai, and Ramiah, 2002; Krishna, 2004) 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 (e.g., Bosworth and Collins, 2007).

A second feature of this paper is that it uses a nonparametric 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 nonparametric approach allows us to decompose the growth of regional labor productivity into four components attributable to technical efficiency, technological change, and physical and human capital accumulation. Only a handful of studies have employed nonparametric methods to examine regional growth performance in China (Unel and Zebregs, 2006; Henderson, Tochkov, and Badunenko, 2007), 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 $\beta-$ or $\sigma-$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 analyze 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 nonneutral technological change and underscored the advantage of the nonparametric 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 nonparametric 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 others, 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 section describe the methodology and the data, respectively. Section 4 presents the results of the analysis and Section 5 concludes.

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 nonparametric approach to efficiency measurement, Data Envelopment Analysis, 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 cone then presents measure of technical efficiency. The Data Envelopment Analysis is a data driven approach in the sense that it allows data to tell where the frontier lies without prior specifying the functional form of the technology (see Kneip, Park, and Simar (1998) for a proof of consistency for the DEA estimator, as well as Kneip, Simar, and Wilson (2003) for its limiting distribution).

We specify technology to contain four macroeconomic variables: aggregate output and three aggregate inputs—labor, 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 technology as a multiplicative augmentation of physical labor 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 labor input measured in *efficiency* units in region i at time t. The constant returns to scale technology in period t is constructed by using all the data up to that point in time as

$$\mathcal{T}_t = \left\{ \begin{array}{c} \langle Y, \hat{L}, K \rangle \in \Re^3_+ \mid Y \leq \sum\limits_{\tau \leq t} \sum\limits_{i} z_{i\tau} Y_{i\tau},\ \hat{L} \geq \sum\limits_{\tau \leq t} \sum\limits_{i} z_{i\tau} \hat{L}_{i\tau}, \\ K \geq \sum\limits_{\tau \leq t} \sum\limits_{i} z_{i\tau} K_{i\tau},\ z_{i\tau} \geq 0\ \forall\ i, \tau \end{array} \right\}, \tag{1}$$

where $z_{i\tau}$ are the activity levels.

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

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

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-labor 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 labor. Letting b and c stand for the base period and current period respectively, the potential outputs per efficiency unit of labor in the two periods are defined by $\overline{y}_b(\hat{k}_b) = \hat{y}_b/e_b$ and $\overline{y}_c(\hat{k}_c) = \hat{y}_c/e_c$, where e_b and e_c are the values of the efficiency scores in the respective periods as calculated in Eq. (2) above. Hence,

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

Let $\tilde{k}_c = K_c/(L_c H_b)$ denote the ratio of capital to labor 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 labor measured in efficiency units under the counterfactual assumption that human capital were equal to its current-period level. Then $\overline{y}_b(\tilde{k}_c)$ and $\overline{y}_c(\tilde{k}_b)$ are the potential output per efficiency unit of labor at $\tilde{k}_c$ and $\tilde{k}_b$ using the base-period and current-period technologies, respectively. By multiplying the numerator and denominator of Eq. (3) alternatively by $\overline{y}_b(\hat{k}_c)\overline{y}_b(\tilde{k}_c)$ and $\overline{y}_c(\hat{k}_b)\overline{y}_c(\tilde{k}_b)$, we obtain two alternative decompositions of the growth of $\hat{y}$

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(\hat{k}_c)}{\overline{y}_b(\hat{k}_c)} \cdot \frac{\overline{y}_b(\tilde{k}_c)}{\overline{y}_b(\hat{k}_b)} \cdot \frac{\overline{y}_b(\hat{k}_c)}{\overline{y}_b(\tilde{k}_c)}, \tag{4}$$

and

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

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

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

Combining Eq. (4) and (5) with (6), we obtain

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

and

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

Eq. (7) and (8) decompose the growth of labor productivity in the two periods into changes in efficiency, technology, the capital-labor ratio, and human capital accumulation. The decomposition in Eq. (4) measures technological change by the shift in the frontier in the output direction at the current-period capital to effective labor ratio, whereas the decomposition in Eq. (5) measures technological change by the shift in the frontier in the output direction at the base-period capital to effective labor ratio. Similarly, Eq. (7) measures the effect of physical and human capital accumulation along the base-period frontier, whereas Eq. (8) 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 Eq. (3) by $\left(\overline{y}_b(\hat{k}_c)\overline{y}_b(\tilde{k}_c)\right)^{1/2}\left(\overline{y}_c(\hat{k}_b)\overline{y}_c(\tilde{k}_b)\right)^{1/2}$:

$$\begin{aligned}\frac{y_c}{y_b} &= EFF \times (TECH^b \cdot TECH^c)^{1/2} \times (KACC^b \cdot KACC^c)^{1/2} \times (HACC^b \cdot HACC^c)^{1/2} \\ &\equiv EFF \times TECH \times KACC \times HACC. \end{aligned} \tag{9}$$

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 Eq. (9) so that the labor productivity distribution in the current period can be constructed by consecutively multiplying the labor productivity in the base period by each of the four components:

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

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 labor productivity distribution in the base period assuming no efficiency, technological change, or human capital accumulation by looking at the distribution of the variable

$$y^K = KACC \times y_b. \tag{11}$$

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

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

Assuming further no 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

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

It is evident that multiplying the distribution of y^{KEH} by the effect of technological change yields the labor 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 Eq. (11)−(13) is arbitrary and depends on the focus of the analysis on the effect(s) of particular component(s).

2.4 Comparison of Unknown Densities

To back-up the the "eye-ball" test of our distribution analysis, we use nonparametric kernel methods to test formally for the statistical significance of differences between (actual and counterfactual) distributions. Specifically, we follow Kumar and Russell (2002) and choose the test developed by Li (1996) which 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. This test, which works with either independent or dependent data is often used, for example, when testing whether income distributions across two regions, groups, or times are identical. The test statistic used to test for the difference between the two unknown distributions (which goes asymptotically to the standard normal, as shown by Fan and Ullah, 1999), predicated on the integrated square error metric on a space of density functions, $I(f,g) = \int_x (f(x) - g(x))^2 \, dx$, is

$$J = \frac{N b^{\frac{1}{2}} I}{\widehat{\sigma}} \sim N(0,1), \tag{14}$$

where

$$I = \frac{1}{N^2 b} \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} \left[K\left(\frac{x_i - x_j}{b}\right) + K\left(\frac{z_i - z_j}{b}\right) - K\left(\frac{z_i - x_j}{b}\right) - K\left(\frac{x_i - z_j}{b}\right) \right],$$

$$\widehat{\sigma}^2 = \frac{1}{N^2 b \pi^{\frac{1}{2}}} \sum_{i=1}^{N} \sum_{j=1}^{N} \left[K\left(\frac{x_i - x_j}{b}\right) + K\left(\frac{z_i - z_j}{b}\right) + 2K\left(\frac{x_i - z_j}{b}\right) \right],$$

K is the standard normal kernel and b is the optimally chosen bandwidth (see Fan and Ullah (1999); Li (1996); Pagan and Ullah (1999) for further details).

3 Data

China is divided into 33 regions, including 22 provinces, five autonomous regions (mostly ethnic minority areas), four metropolitan areas (Beijing, Shanghai, Tianjin, and Chongqing), and two special administrative regions (Hong Kong and Macau).[1] Our Chinese data set covers 31 regions over the period 1993–2003, excluding Hong and Macau which came under Chinese control only in 1997 and 1999, respectively. Russia is a federation of 89 regions, including 55 provinces (*oblast* or *krai*), 21 republics and 11 autonomous regions (mostly ethnic minority areas), and two federal cities (Moscow and St. Petersburg).[2] Two republics (Chechnya and Ingushetia) were excluded due to lack of data. Furthermore, in accordance with the official reporting standards, 9 autonomous regions were treated as subdivisions of other provinces, and were not listed separately. As a result, our Russian data set covers 78 regions over the period 1994–2003. India is a union of 28 states and 7 union territories (mostly tiny islands or coastal enclaves as well as the city of Dehli).[3] The states of Jammu Kashmir and Mizoram along with 3 union territories (Dadra and Nagar Haveli, Daman and Diu, and Lakshadweep) were excluded due to lack of data.

[1] Figure 1 provides a map of the administrative division of China.
[2] Figure 6 provides a map of the administrative division of Russia.
[3] Figure 12 provides a map of the administrative division of India.

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). Accordingly, our Indian data set covers 27 regions over the period 1993−2003.[4]

Data on output, labor, 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 Labor

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.[5] In absence of data on the number of hours worked, we measure labor as the total number of employed persons aged 15 and above.

Data on the GDP of Russian regions are only available since 1994.[6] Real GDP measured in 1993 constant prices was obtained by deflating the nominal value with the region-specific consumer price index. Labor is measured as the number of employed persons aged 15−72.

India's CSO compiles data on real regional GDP and rebases the series as new benchmark years are adopted. We use the most recent series of real regional output data

[4]Annual data in India is 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.

[5]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).

[6]In contrast to Chinese statistics where overreporting 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).

comprising the period 1993–2003 with base year 1993. 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 labor variable is measured as the sum of main and marginal workers and is linearly interpolated from the census values of 1991 and 2001.

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

$$K_i = \frac{I_i}{(\delta + g_i)}, \tag{15}$$

where I denotes the real value of 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 real with base year 1993 by deflating it with a region-specific fixed investment price index.[7] This price index is available for the majority of provinces from 1993 on. In the few cases (Chongqing, Guangdong, Tianjin, Tibet) where data is missing in certain years we use the respective national fixed investment price index. For the initial value of the capital stock in 1993 (see Eq. (15)) 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]

In contrast to China, 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

[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.

Eq. (15). 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, 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. 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 approximately to the average rate over the 1990s.

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 (Purfield, 2006; Bhide and Shand, 2003). 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.

In 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 over the period 1993−1999, 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 series was linearly extrapolated to the period 2000−2003, and was then 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 Eq. (15), 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). Labor in efficiency units in region i in year t was defined by

$$\hat{L}_{it} = H_{it}L_{it} = h(\epsilon_{it})L_{it} = e^{f(\epsilon_{it})}L_{it}, \tag{16}$$

where

$$f(\epsilon_{it}) = \frac{\theta}{1-\psi}\epsilon_{it}^{1-\psi}. \tag{17}$$

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) estimated that $\psi = 0.58$ using data from Psacharopoulos (1994) for a sample of 56 countries (including China and India, but not Russia). Since the rate of return to education is

$$\frac{d\ln h(\epsilon_{it})}{d\epsilon_{it}} = f'(\epsilon_{it}) = \frac{\theta}{\epsilon_{it}^{\psi}}, \tag{18}$$

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

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. However, 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. Since 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.

Wang and Yao (2003) derived a time series of China's human capital stock in terms of average years of schooling using the perpetual inventory method with the number of graduates at different schooling levels representing the annual changes in the stock. However, their method is difficult to replicate at the regional level in China 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 for 1990 and 2000 were estimated by

$$\epsilon_{it} = \frac{(s_1 N_{1it} + s_2 N_{2it} + s_3 N_{3it} + s_4 N_{4it})}{N_{it}}, \tag{19}$$

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.[9]The average years of schooling for the remaining years were obtained by interpolation. However, they correspond closely to the numbers reported by Zhang, Zhao, Park, and Song (2005) who rely on data from household surveys conducted in several Chinese provinces over the 1988−2001 period.

Previous studies on human capital in Russia drew on data from the Russian Longitudinal Monitoring Survey to obtain average years of schooling (Gorodnichenko and Sabirianova Peter, 2005; Cheidvasser and Benitez-Silva, 2007). Unfortunately, this household survey divides Russia into 8 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 contains 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 Eq. (19) 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.

[9]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). Because the data did not us allow to separate these two groups, the average number of years was adopted as the length of the tertiary education.

Recent studies involving human capital estimates for India have used either census (Playforth and Schuendeln, 2007) or household survey data (Bosworth, Collins, and Virmani, 2007; Gundimeda, Sanyal, Sinha, and Sukhdev, 2007). Since 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 52^{nd} and 61^{st} rounds of the National Sample Survey conducted in 1995−1996 and 2004−2005, respectively.[10] The average years of schooling for these benchmark years were calculated using Eq. (19) 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, 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. For the remaining years of the sample, average years of schooling were obtained through linear interpolation from the benchmark years of the census or survey.

4 Results

This section presents the empirical results for China, Russia, and India. Three issues need to be emphasized. Firstly, since the units of measurement are not equivalent, the results are not directly comparable across the three countries. The purpose of this paper is not a comparison across all regional economies of China, Russia, and India, but rather a comparison of regional tendencies identified separately within each country. Secondly, by using all the previous years data, we preclude implosion of the technological frontier over time as it is difficult to believe that such implosion could occur. Thus, following an approach first suggested by Diewert (1980), we chose to adopt a construction of the technology that precludes such technological degradation. Thirdly, we break down the sample period 1993−2003 into 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

[10] 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 1000 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.

year later caused an adverse shock to growth in all three economies and highlighted their rapidly growing integration with the rest of the world.

4.1 China

4.1.1 Production Frontiers

China's production frontier in 1993, 1998, and 2003 along with scatter plots of output per efficiency unit of labor vs. capital per efficiency unit of labor are presented in Figure 2. Guangdong, Jiangxi, Shanghai, and Zhejiang were the most efficient regional economies in 1993 and therefore defined the "best-practice" frontier for this year. Only Shanghai remained on the frontier in each of the three years. Fujian which was almost on the frontier in 1993 joined the club of most efficient economies in 1998 and retained this position in 2003. Because we preclude implosion of the frontier, the 1993 observations for Jiangxi and Zhejiang, as well as the 1998 observation for Fujian define the frontier in 2003. It is worth mentioning that the frontier shifted up but not by the same proportion for every value of capital per efficiency unit of labor implying that technological change was nonneutral. In fact, the frontier remained constant at the lower levels of capital per efficiency unit of labor over the sample period and was shifted solely by rich regions such as Fujian and especially Shanghai.

The efficiency scores in 1993 (base year) and 2003 (current year) for each region appear in the first two columns of Table 1 and indicate that initially Chinese regions achieved on average relatively high levels of efficiency (81 percent) but became less efficient over the sample period. The fourth column of Table 1 suggests that the mean fall in efficiency was approximately 6 percent. Furthermore, as inferred from Tables 2 and 3 it seems that efficiency deteriorated much more rapidly over the period 1998–2003.

It is evident, however, that efficiency scores vary across regions. The regions with the highest levels of efficiency (90-100 percent) such as 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. In contrast, regions in Western China, such as Tibet and Qinghai, where reforms were slow and their location isolated achieved the lowest efficiency (40-

50 percent). To explore this issue further, we split the sample into three subsamples based on their level of output per worker.[11] The results presented in Table 4 reveal that the overall decline in efficiency stemmed mainly from the abysmal performance of poor regions which recorded a fall of 22 percent on average over the entire sample period. In contrast, rich regions were extremely efficient in every period and managed to move even closer to the production frontier. The remaining regions experienced a deterioration in efficiency that was much less severe than in the case of poor regions.

The negative efficiency scores of poor regions are likely the result of the explosive movement of the frontier between 1993 and 2003. Indeed, 1993 observation of Jiangxi continued to form the 2003 frontier at the lower levels of capital per efficiency unit of labor during this period thus increasing the input−output space to be enveloped and making 2003 observation further from the frontier than they would have been if implosion was allowed. Coastal regions in China, most of which are included in the rich subsample, attracted large inflows of FDI from aborad and gained access to advanced foreign technology through joint ventures. As the frontier shifted upward due to technological change in the rich coastal regions, poor regions, which are located in China's interior and received only scant interest from foreign investors, were not able to keep up with technology advances and experienced a fall in efficiency as their distance from the new frontier increased.

4.1.2 Quadripartite Decomposition of Productivity

As evident from the third column of Table 1, the annual growth of labor 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, labor productivity in the poor regions Ningxia and Guizhou increased by less than half that rate. Tables 2 and 3 also suggest that growth slowed down after 1998 which was probably due in part to the East Asian Financial Crisis. This is further supported by the results for the subsamples in Table 4. 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

[11] Regions which were in the upper quartile over the entire sample period were classified as rich, including Shanghai, Beijing, Tianjin, Guangdong, Liaoning, Zhejiang, Fujian, and Jiangsu. The group of poor regions consisted of those that remained consistently in the lower quartile, including Guangxi, Sha'anxi, Yunnan, Chongqing, Jiangxi, Sichuan, Gansu, and Guizhou. Lastly, the middle group included the rest of the Chinese regions.

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 labor productivity growth are displayed in the last four columns of Tables 1-3. It is obvious that physical capital accumulation is by far the major driving force behind the growth of labor productivity in China. This is consistent with the findings of the other two nonparametric studies on China (Henderson, Tochkov, and Badunenko, 2007; Unel and Zebregs, 2006) although they used different periods and a smaller set of regions. The average contribution of technological change was approximately 12 percent, followed by human capital accumulation with 3.5 percent. The fall in efficiency dragged down the growth of labor productivity by 6.8 percent.

As inferred from Table 4, labor productivity growth in rich regions relied heavily on technological change and human capital accumulation. The contributions of these two components are 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 as compared to 200 percent for physical capital accumulation.

To address the growing income inequality across China's regions, we used at first the traditional approach and regressed labor productivity growth and its four components on the initial level of output per worker. The estimates are presented in Table 5 and the scatterplots along with the fitted regression lines are shown in Figure 3. The statistically significant and positive slope of the regression line in Panel A provides evidence for the divergence of output per worker across China's regions over the 1993−2003 period. This divergence is driven by changes in efficiency, technological change, and human capital accumulation all of which have positively sloping regression lines indicating that rich regions experienced larger changes than poor ones. Physical capital accumulation is the only component of growth leading to convergence across regions which corresponds to its above-average contribution in poor regions described in the previous section.

4.1.3 Analysis of Productivity Distributions

The labor productivity distributions which are kernel-based density estimates are shown in Figure 4.[12] The solid and dashed curves represent the mean-preserving distributions of output per worker in 1993 and 2003, respectively, with the mean shown as a vertical line. It is evident that the distribution in both years is multimodal underlying the potential problems associated with the focus of the regression approach on the first moment of the distribution.[13] 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. Some regions remained at the lower levels of the distribution, but a large group managed to grow faster and move the probability mass to higher income levels. At the same time, the rich regions in the smaller modes were able to grow even faster and drifted even further away creating the long tail of the distribution. 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.

Furthermore, we examined the impact of the four components of labor productivity growth on the shifts of the distribution through counterfactual distributions presented in Figure 5. 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 decreased slightly the probability mass at the lower levels of output per worker but extended the tail of the distribution towards higher levels of income. This further supports the results of the previous sections indicating that technological change was mainly responsible for growth in the rich regions thus contributing to divergence in regional income.

In Panel B of Figure 5, we add physical capital accumulation as a second component that is allowed to vary. The result is a large loss of probability mass at the lower levels of out per worker and gains in the probability mass at higher income levels. This widening

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

[13]We are able to confirm this conjecture statistically. Silverman test of Hall and York (2001) gives the p-values for null hypothesis that distribution of output per worker in unimodal in 1993 and 2003 equal to 0.0951 and 0.0370, respectively.

of the lower mode suggests that a number of provinces with relatively low levels of output per worker in 1993 managed to catch up with richer provinces through capital deepening. This is consistent with our aforementioned findings that capital deepening was the largest contributor to labor productivity growth and that it decreased regional income inequality.

Once we add efficiency changes in Panel C, some minor shifts occur at the lower and higher levels of output making the counterfactual distribution almost indistinguishable from the actual distribution in 2003. Therefore, the effect of the last component, human capital accumulation, seems to be negligible leading to a minor extension of the tail of the distribution towards the top end values of output per worker. This again reflects the relatively small contribution of human capital accumulation to growth found earlier as well as its diverging effect across China's regions.[14]

In Table 6 we present the results of the formal tests for statistical significance of differences between the actual and counterfactual distributions. For the sample period, it is the combination of physical capital accumulation and technological change that cause major shifts in the distribution so that counterfactual and actual distributions are not statistically significantly different from each other. This further supports our previous results showing physical capital accumulation and technological change to be the key determinants of growth. 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 which gained in importance became the second determinant causing major shifts in the distribution.

[14]We also performed the distribution analysis using different sequencing combinations and found that the results are not sensitive to changes in the sequencing order. The shifts in the mean labor productivity are the greatest when capital deepening is introduced; the three other components exert only moderate power. At the same time, both capital deepening and technological change are responsible for the significant shift of the entire labor productivity distribution from the base period to the current one. The results are available from authors upon request.

4.2 Russia

4.2.1 Production Frontiers

Russia's production frontiers in 1994, 1998, and 2003 are depicted in Figure 7. The technological change is not as clearly nonneutral as in the case of China. The frontier shifted up more or less by the same proportion for all levels of capital per efficiency unit of labor. It is fairly evident that Russian regions experienced almost no change from 1994 to 1998—the green triangles (1994) overlay the red circles (1998) and in many cases the 1998 observations are located even closer to the origin than the 1994 observations, implying some productivity deterioration over the 1994−1998 period. In contrast, blue squares (2003) have changed their location shifting dramatically upwards, which indicates positive productivity changes during either the 1994−2003 or the 1998−2003 period.

Komi Republic, Sakha (Yakutia) Republic, Samara Oblast, and Tyumen Oblast define the frontier in 1994. Of these, Tyumen Oblast is the *only* one that remains on the frontier in 1998 and is responsible for its upward shift in 2003. Additionally, given that an implosion of the frontier is precluded, the 1994 observations of Komi Republic and Samara Oblast define the frontier at lower levels of capital per efficiency unit of labor in 1998. Note that neither the 1994 nor the 1998 observations define the frontier in 2003. It was shifted upward only by 2003 observations, making the ruling out of technology degradation obsolete. Accordingly, Altai Republic, the federal city of Moscow, and Tyumen Oblast form the frontier in 2003. Tyumen Oblast shifted the frontier from 1998 to 2003 by even more than from 1994 to 1998. It is noteworthy that Moscow defines the frontier for the middle levels of capital per efficiency unit of labor, while Altai Republic does the same for the lower levels. Thus, a look at the production functions along with the scatterplots of $\hat{y}$ vs. $\hat{k}$ suffices to conclude that Russia went through a severe economic slump in the period 1994−1998 but experienced a phenomenal technological boom in the years 1998−2003.

All three panels of Table 10 suggest that Russian regions were generally quite inefficient in all years observed. The potential gains from removing inefficiency are enormous—up to 45 percent on average in 2003. As one might expect, the performance is fairly heterogeneous across regions depending on their level of output per worker. Rich regions[15]

[15]Regions which were in the highest income quartile over the entire sample period were classified as rich, including Arkhangelsk Oblast, Irkutsk Oblast, Kemerovo Oblast, Khabarovsk Krai, Komi Republic,

are 85–90 percent efficient, the middle regions are roughly 20 percent less efficient than the rich ones, and the poor regions[16] are the least efficient on average at approximately only 50 percent. The fourth column of Table 10 however, reveals that all groups of regions experienced a decline in efficiency. While the entire sample as well as the two subsamples were subject to more or less the same efficiency changes during 1994–2003, analysis of the subperiods discloses some interesting tendencies. In particular, during 1994–1998 poor regions appear to have suffered the most from the efficiency deterioration, while the rich were affected less than the "average" Russian region. The opposite happened during 1998–2003. The 1998 frontier at the lower levels of capital per efficiency unit of labor was defined by some of the 1994 observations, which implies that the 1998 frontier envelops a larger input-output space artificially forcing poor regions further away from the frontier. This explains why poor regions have had larger than average fall in efficiency in the first subperiod. Furthermore, the shift in the 2003 frontier caused by Tyumen Oblast was so radical that regions at the upper levels of capital per efficiency unit of labor were not able to catch-up. Therefore, it was the rich regions that saw the largest decline in efficiency in the second subperiod.

The most efficient Russian regions deserve special attention. The miraculous performance of Tyumen Oblast in all three year under consideration is based on its abundant natural resources. The Tyumen Oil Company (TNK) is one of the 10 largest vertically integrated private oil and gas companies in the world in terms of proven oil reserves. Today the company's proven reserves include 7 billion barrels of crude oil with a production of over 780,000 barrels per day. Another highly efficient region is the Sakha (Yakutia) Republic, one of the most attractive regions for investment in the Far East federal district. Within a short time, Sakha rose to the 18^{th} place from its 44^{th} place in a regional ranking of investment potential in Russia. The region 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, and produces 24 percent of cut diamonds. In addition, it has considerable energy resources as it accounts for 47 percent of explored reserves of

Krasnoyarsk Krai, Magadan Oblast, Moscow (federal city), Moscow Oblast, Republic of Bashkortostan, Republic of Tatarstan, Sakha (Yakutia) Republic, Samara Oblast, Tyumen Oblast, and Vologda Oblast

[16]The group of poor regions consisted of those that remained consistently in the lowest income quartile, including Bryansk Oblast, Chuvash Republic, Ivanovo Oblast, Kaluga Oblast, Kurgan Oblast, Mari El Republic, Penza Oblast, Republic of Adygea, Republic of Dagestan, Republic of Kalmykia, Republic of Mordovia, Republic of North Ossetia-Alania, Tambov Oblast, Tyva Republic, and Vladimir Oblast.

coal and 35 percent of natural gas and oil reserves in Eastern Siberia and the Far East, as well as 22 percent of Russia's water resources.

The Komi Republic which was most efficient in 1994 possesses a unique combination of mineral resources in terms of reserves, deposition conditions, variety, and quality. The gross value of the republic's mineral reserves has been estimated at $11 trillion, or 8 percent of Russia's estimated potential. Its mineral resources include coal, oil, gas, bauxite, titanium ores, salts, gold, diamonds, ores of nonferrous and rare metals, fluorite, shale oil, mineral waters, and building materials. Fuel and energy resources are of special importance (up to 97 percent of the total potential) and will continue to dominate in the near future. The Pechora coal mining basin is Russia's second largest in terms of its stock, and it contains a spectrum of coals for coke and energy production. Export turnover is estimated at $500 million per year. Samara Oblast, among the most efficient regions in 1994, relies mainly on the exploration, extraction, and refining of oil and gas for its growth. In addition, Samara takes the sixth place among Russian regions in terms of the absolute volume of industrial output and the second place among the regions of the Privolzhsky federal district. The gross regional product per capita exceeds the average by 30−40 percent, and the industrial output per capita—by 50 percent. It is also home to the Volzhsky automobile plant, producer of the highly popular car "Lada" which accounts for over 75 percent of all passenger vehicles made in Russia. As per many indicators of socio-economic development, Samara is among the top five regions of Russia. The federal city of Moscow is particularly interesting. It is the capital city and truly is one of the major capital accumulators on the territory of the Russian Federation.

Our findings are broadly in line with the results of the only other known study by Obersteiner (2000) which has employed Data Envelopment Analysis to examine efficiency at the regional level in Russia. Although he focuses only on the industrial sector during the early transitional period of 1987−1993 and does not report the efficiency levels for each region separately, his results indicate that average efficiency was low and decreased in the early 1990s. Moreover, he shows that the best-performing regions that experienced the smallest deterioration in industrial efficiency were those endowed with natural resources that could be extracted and exported, such as Tyumen, Sakha Republic, and Komi Republic. In contrast, the decline was most severe for regions depending on agriculture or the light industry, such as Ivanovo Oblast.

4.2.2 Quadripartite Decomposition of Productivity

The fourth column of Tables 7, 8, and 9 presents the growth of labor productivity for the sample period and the two subperiods, respectively. The averages of productivity growth for the rich, middle, and poor subsamples are given in the fourth column of Table 10. During the ten years under consideration, labor productivity generally increased by 30 percent. However, while poor regions exhibited growth of only 20 percent, rich regions enjoyed a rise in labor productivity of 52 percent. Table 10 reveals quite different growth patterns in the two subperiods. It confirms our previous conclusions from the analysis of the production function (Figure 7) that the first (second) subperiod was characterized by a productivity drop (improvement). Over the period 1994−1998, only Altai Republic, Kabardino-Balkar Republic, Moscow Oblast, and Tyumen Oblast recorded any significant productivity growth. Panel B of Table 10 suggests that poor regions experienced on average the largest decline in productivity of approximately 27 percent. Rich provinces underwent only a moderate decrease of 7 percent. In contrast, Panel C of Table 10 tell us that the second subperiod was associated with a considerable surge in productivity. Furthermore, all regions regardless of their classification enjoyed growth of a similar magnitude, with Kamchatka Krai being the *only* region with a minor productivity decline.

The contributions of change in efficiency, technological change, capital deepening, and human capital accumulation for the entire sample, the two subperiods, and the three subsamples are presented in the last four columns of Tables 7, 8, 9, and 10, respectively. It is clear that 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. While poor regions suffered a decline of almost 18 percent, rich ones lost only roughly 2 percent. Efficiency was the second largest hindrance to growth but unlike the physical capital accumulation, *all* regions lost more or less the same 9 percent in efficiency during 1994−2003 (see Panel A of Table 10). As for the human capital accumulation, it held back growth in *all* years and for *all* regions but since its contribution was close to zero, its impact was minimal.

As in the case with productivity and efficiency changes, the two components, technological change and capital deepening, behave quite differently in the two subperiods.

Remarkably, the fall in efficiency went in unison with productivity decline, while the impact of the other components was negligible in the first subperiod (see Panel B of Table 10 as well as Tables 7, 8, 9). Indeed, the average contribution of technological change, capital deepening, and human capital accumulation was 1.4, -1.5 and -0.5 percent, respectively. Splitting the sample based on wealth tells us that rich regions shifted the frontier slightly upward (mainly the three regions, Chukotka Autonomous Okrug, Magadan Oblast, and Tyumen Oblast). Poor regions did not develop technologically *at all* (recall the regions at lower levels of capital per efficiency unit of labor in Figure 7) during $1994-1998$ period! The average contribution of capital amounted to 1.2 (-3.8) percent for the group of rich (poor) regions.

A completely different story is told by Panel C of Table 10. Firstly, the losses in efficiency are significantly lower than in the first subperiod. Moreover, for rich regions the rate of decline seems to be the same as in the first subperiod but it is twice as high as the average, whereas poor regions lost only 2 percent in efficiency. The contribution of capital deepening increases even further (in negative terms); now it is negative even for the rich regions. The most striking result comes from the fifth column of Panel C of Table 10. If in the first subperiod, technological change was either absent or negligible, in the second subperiod *all* regions reaped the benefits of technological improvement. It is also worth mentioning that such benefits are enjoyed regardless of wealth—rich and poor enjoyed it to the same extent. Hence, the technological change, being the major driving force of productivity growth during $1994-2003$, received a boost not earlier than 1998.

Additionally, we regressed the change in productivity and its four components on the initial (1994) level of output per worker in order to investigate the impact of each component on convergence. First, Panel A of Figure 8 suggests that neither a significant (see Table 11) convergence nor a divergence ensued during the $1994-2003$ period in Russia. Second, the slope coefficients for all four components, presented in Table 11, turn out to be statistically significant but have different signs. While efficiency change and human capital accumulation gave rise to regional divergence, technological change and capital deepening led to convergence. The effects of these two pairs of factors turn out to offset each other. It is noteworthy that rich regions benefited more from technological change and physical capital accumulation, while efficiency change and human capital accumulation impeded productivity growth. The opposite is true for poor regions.

4.2.3 Analysis of Productivity Distributions

Figure 9 shows the mean preserving distributions of output per worker in 1994 and 2003. It is obvious, that the shape of the distribution has somewhat changed. The Li test in Table 12 provides evidence that the two distributions are statistically significantly different from each other. 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 blue dashed distribution stretched to higher levels of output per worker, providing clear 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 the federal city of Moscow forming the mode at the higher levels of income per capita.[17] Similarly, Carluer (2005) using a Markov chains approach 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.

The counterfactual distributions appear in Figures 10 and 11. Panels A in these figures show the isolated effect of efficiency change and technological change. Apparently, efficiency change (Figure 10) and technological change (Table 11) did cause shifts in the distribution, albeit with an opposite effect. Efficiency change made regions poorer; the probability mass increased around zero. At the same time, technological change alone shifted the 1994 distribution to the extent that it closely resembled the 2003 distribution. In contrast, other components, such as capital deepening (Panel B of Figure 10) and human capital accumulation (Panel C of Figure 10) did not contribute at all to the shift of the distribution. Only in combination with technological change does capital deepening have an effect on the 1994 labor productivity distribution (Panel B of Figure 11). Interestingly, when the technological change component is not introduced at all—Figure 10—the shift of the distribution between 1994 and 2003 is defined by the efficiency component.

The results (p-values) of the formal tests for statistical significance of differences between the distributions are shown in Table 12. The first lines of Panels A (entire period), B (first subperiod), and C (second subperiod) indicate that the 1994 distribution is sta-

[17] We performed the calibrated Silverman test of Hall and York (2001) and it rejects unimodality in *both* periods at 5 percent level (p-values of the test in 1994 and 2003 are 0.0110 and 0.000, respectively).

tistically significantly different from the one in 2003, but not from that of 1998. Note that none of the components shifts the 1994 distribution significantly closer to the one in 1998 (see Panel B). Panel A confirms the conclusion from Figures 10 and11 that technological change was the driving force behind the evolution of the income distribution between 1994 and 2003. Lastly, Panel C reveals that it was again technological change that shifted the 1998 distribution making it statistically significantly indistinguishable from its counterpart in 2003.

4.3 India

4.3.1 Production Frontiers

Figure 13 shows India's production frontiers in 1993, 1998, and 2003 along with scatter plots of output per efficient unit of labor versus capital per efficient unit of labor. Interestingly, the production function was defined by a different group of regions for each of the three years. In 1993, the Andaman and Nicobar Island, Dehli, and Tripura were the most efficient regions, whereas in 1998 only Goa achieved this status. In 2003, it was Chandigarh and Pondicherry which defined the frontier, along with the 1993 observations of the Andaman and Nicobar Islands and Tripura. Furthermore, it is evident that technological change was not neutral since the frontier shifted upward by different proportions for every value of capital per efficient unit of labor.[18]

The efficiency scores presented in the first two columns of Tables 13–15 indicate that India's regional economies were not very efficient on average and became even less so over the 1993–2003 period as well as in each of the two subperiods. The mean fall in efficiency over the entire sample period was approximately 3 percent. However, the results for the three subsample in Table 16 reflect large differences between rich and poor regions.[19] Over the entire sample period, rich regions were able to improve their

[18]To check for robustness, we performed the entire analysis for India using the two alternative data sets for human capital described in the Data section (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 authors upon request.

[19]Regions which were in the upper quartile over the entire sample period were classified as rich, including Dehli, Chandigrah, Goa, Pondicherry, and Punjab. The group of poor regions consisted of those that remained consistently in the lower quartile, including Uttar Pradesh, Madhya Pradesh, Assam, Manipur, Orissa, and Bihar. Lastly, the middle group included the rest of India's regions.

efficiency by almost 3 percent on average, while the efficiency score for poor regions decreased by 17 percent but remained largely unchanged for the remaining regions. In the period after 1998, all three subsamples experienced a deterioration of efficiency, but again the largest decrease was recorded by the poor and the smallest by the rich regions.

Mukherjee and Ray (2005) used nonparametric 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. Nevertheless, it is interesting to note that they provided efficiency rankings for the manufacturing sector of 22 regions in India over the period 1986−1999 and found that Goa, Dehli, and Chandigarh ranked consistently at the top. Our results similarly indicate that these three regions had efficiency scores between 0.9 and 1 for the entire sample period as well as for each of the two subperiods. 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.

4.3.2 Quadripartite Decomposition of Productivity

Over the period 1993−2003, the average annual growth of labor productivity of India's regional economies was approximately 4.4 percent, as shown in the third column of Table 13. The fastest growing region was Pondicherry with 16 percent, whereas the Andaman and Nicobar Islands exhibited a negative growth rate of 2.9 percent. Productivity growth for the entire sample was slightly slower after 1998 as evident from Tables 14 and 15. The results for the subsamples in Table 16 suggest that the growth rate of 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 contributions of efficiency, technological change, physical and human capital accumulation to labor productivity growth appear in the last four columns of Tables 13−15. Physical capital accumulation is evidently the largest determinant of growth with 30 percent, followed by technological change with 18 percent. Human capital accumulation contributed only 2 percent to labor productivity growth, while efficiency change had a negative effect on growth. The relative proportions were similar for the period 1993−1998, but in the second subperiod technological change became the major contributor to growth with 15 percent as opposed to 12 percent for physical capital accumulation.

The results for the subsamples provide some interesting insights. The main driving force behind the growth of rich regions was technological change with 35 percent, whereas physical capital accumulation contributed only 13 percent. For poor regions, these numbers were almost exactly reversed with physical capital accumulation and technological change accounting for 41 percent and 13 percent, respectively. 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. The relative proportions were very similar in the first subperiod. As for the 1998−2003 period, technological change became the leading determinant of labor 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 important role of technological change for labor 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 nonparametric 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 that technological change grew in importance over the 1990s to become a larger contributor to growth than physical capital accumulation.

We use the standard method of regressing labor productivity growth as well as its four components on the initial level of output per worker in 1993 to address the issue of regional income convergence. The scatterplots with the fitted regression lines are shown in Figure 14 and the estimated coefficients in Table 17. The results provide no evidence for convergence or divergence across Indian provinces over the sample period. The only statistically significant slope coefficients were found for technological change and physical capital accumulation, albeit with different signs. The positive sign for technological change indicates that this component contributed to a growing income gap across Indian regions, whereas the downward sloping regression line in Panel D of Figure 14 suggests that physical capital accumulation resulted in narrowing this gap.

4.3.3 Analysis of Productivity Distributions

The labor productivity distributions resulting from the kernel-based density estimates appear in Figure 15. The solid and dashed curves represent the mean-preserving distributions of output per worker in 1993 and 2003, respectively, with the mean shown as a vertical line. The obvious multimodality of the distribution in 2003 underlines again the advantage of the nonparametric over the regression approach.[20] 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 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 findings of the only other known nonparametric study of distributional dynamics at the regional level in India by Bandyopadhyay (2006). She shows that since the 1970s and well 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.

The counterfactual distributions highlighting the impact of each of the four components of labor productivity growth on the shifts of the distribution are displayed in Figure 16. 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. But 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.

[20]Using the calibrated Silverman test of Hall and York (2001) we reject the null hypothesis that distribution of output per worker is unimodal in 2003 at any conventional level (p-value is 0.0030); we fail to reject such hypothesis in 1993 (p-value is 0.4364).

Adding human capital accumulation in Panel B does not lead to any major changes in the distribution which confirms our results that human capital is a relatively small contributor to labor productivity growth. However, when technological changes is added in Panel C the counterfactual distribution changes noticeably emphasizing the important role of this component found earlier. 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. Efficiency change which accounts for the differences between the counterfactual and the actual 2003 distribution in Panel C appears to have a relatively modest impact which results mainly in shaping more clearly the three modes.[21]

The formal tests for statistical significance of differences between the actual and counterfactual distributions appear in Table 18. The results indicate that the actual distributions for 1993 and 2003 are significantly different from each other. However, the null hypothesis that the counterfactual and the actual distributions are equal could not be rejected for any of the components of labor productivity growth or any combination thereof. The only exception is human capital accumulation which as the smallest contributing factor did not cause a major shift in the 1993 distribution. For the two subperiods, the actual and counterfactual distributions were found to be indistinguishable.

4.4 Comparative Analysis

4.4.1 Production Frontiers

The production frontiers of China, Russia, and India were generally defined by two types of regions: metropolises and regions with a favorable geographic location. The metropolitan areas included either capital cities (Moscow, Dehli) or major financial, in-

[21]Introducing components in other sequences did not change the results. Technological change and efficiency change were always responsible for shifting the mean of the labor productivity distribution, whereas the other two components had a much smaller impact. However, only technological change contributed to a statistically significant change in the shape of the distribution. The results are available from the authors upon request.

dustrial, or administrative centers (Chandigarh, Shanghai). The second group consisted of regions located along the coast (Fujian, Zhejiang, Guangdong; Goa, Pondicherry) or covering an area rich in natural resources (Tyumen Oblast, Sakha Republic, Komi Republic). All these regions were the wealthiest in their respective countries and shared not only the highest levels of efficiency but were also responsible for significant shifts of the frontier over the 1990s. The technological change was clearly nonneutral in the case of China and India as the frontier shifted up only at the higher levels of capital per efficiency unit of labor but remained largely constant at the lower levels. In Russia, the frontier experienced an upward move for all levels of capital per efficient unit of labor as the regions recovered from the initial difficulties of the economic transition after 1998.

Chinese regions were on average the most efficient economies with respect to their frontier, followed by Indian regions, with Russian regions being distant third. Poor regions in each of the three countries followed a similar ranking, however the rich regions were on average very close to their respective frontiers and barely differed in terms of efficiency scores. This is probably because rich regions in all three countries were able to benefit from economic reforms early in the reform period, developed export industries relying on joint ventures with foreign firms, and were exposed to competition on world markets. Furthermore, all regions experienced on average a decline in efficiency over the period 1993−2003. The deterioration was most severe in Russia and least severe in India, with China in between. For China and India, the subsamples provide a quite different picture. Rich regions were actually able to improve their efficiency slightly in contrast to a major fall in efficiency scores recorded in poor regions.

4.4.2 Quadripartite Decomposition of Productivity

With an average annual growth of 14.5 percent over a decade, China's regional economies remained unrivaled. Russian and Indian regions grew in contrast by 3 and 4 percent, respectively. In all three countries, rich regions exhibited much higher growth rates than poor ones. For China and India, the difference in growth rates between the first and the second subperiods was marginal, but in the case of Russia growth was negative during the 1994−1998 period and turned positive in the following period.

The quadripartite decomposition indicates that physical capital accumulation was the major contributor to regional growth in India and China, followed by technological change. This can be explained by the ability of these two countries to attract record amounts of foreign direct investment and the availability of a large pool of domestic savings. In Russia, on the contrary, technological change was the driving force behind growth whereas capital deepening was an impediment to growth. In all three countries, human capital accumulation played only a marginal role in the growth process. Another common feature across China, Russia, and India was that wealthy regions relied more on technological change for their growth than poor ones. For rich regions, technological change was a relatively important contributor to growth in China, the major one in India, and the only one in Russia. For poor regions, physical capital accumulation was the largest component of growth in China and India, but also the largest obstacle to growth in Russia. These patterns for rich and poor provinces remained largely unchanged in China in the two subperiods. This was also true for Russia except that the magnitudes of the contributions soared dramatically after 1998. In the case of India, poor regions relied on physical capital accumulation for growth over the 1993−1998 period, but technological change replaced it as the largest contributor after 1998.

4.4.3 Analysis of Productivity Distributions

The distributions of output per worker for China, Russia, and India show the existence of multiple modes underscoring the importance of using a nonparametric approach instead of the standard regression approach. The large mode at the lower levels of output per worker and the one or more modes at the higher levels reflect the regional income inequality in each of the three countries. Over the 1993−2003 period, the distributions experienced a major shift which affected the shape and location of the modes. In all three countries, the mode at the lower levels of output per worker widened considerably indicating that a group of regions managed to grow faster than the majority of regions thus catching up with the rich regions. This led to the emergence of another mode which was more pronounced for India and Russia. At the same time, however, rich provinces were able to grow even faster leaving all other regions behind. This can be inferred from the tail of the distribution which lengthened significantly over the sample period and signaled growing income divergence between rich and poor regions.

The analysis of the counterfactual distributions demonstrates that the largest changes in the shape of the distribution were caused by physical capital accumulation in China and India, and technological change in Russia confirming our findings that these components were also the major contributors to growth in the three countries, respectively. In China and India, physical capital accumulation was responsible for convergence in output per worker levels of rich and poor regions, as it led to a widening of the larger mode rather than a lengthening of the tail of the distribution. In contrast, the decline in capital per worker in Russia was greater for poor regions than for rich ones, and thus resulted in a growing income gap across regions. In all three countries, technological change was the key driving force behind divergence as it brought about an extension of the tail of the distribution towards higher levels of output per worker. Human capital accumulation did not result in any significant shifts of the distribution and was largely irrelevant in the context of regional convergence in China, Russia, and India.

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. In particular, we employed nonparametric 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 and India), 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 nonparametric 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 nonparametric 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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6 China

Table 1: Efficiency scores and percentage change of quadripartite decomposition indexes, 1993−2003

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Anhui	0.89	0.79	160.05	−11.88	2.07	179.77	3.35
Beijing	0.81	0.76	148.77	−5.84	55.18	63.32	4.25
Chongqing	0.89	0.62	155.57	−30.30	4.45	245.61	1.57
Fujian	0.99	1.00	185.30	1.14	6.07	151.05	5.93
Gansu	0.75	0.55	133.32	−25.65	2.60	198.07	2.62
Guangdong	1.00	0.96	144.20	−3.89	16.35	105.99	6.02
Guangxi	0.97	0.73	118.09	−25.21	2.00	180.30	2.00
Guizhou	0.76	0.52	91.68	−31.78	0.87	173.68	1.79
Hainan	0.78	0.67	103.19	−14.91	12.18	100.71	6.06
Hebei	0.82	0.76	168.52	−6.84	5.69	167.80	1.84
Heilongjiang	0.79	0.89	125.46	12.10	8.14	81.91	2.24
Henan	0.86	0.77	121.96	−10.34	1.45	137.18	2.88
Hubei	0.86	0.75	160.81	−12.66	5.13	177.73	2.27
Hunan	0.87	0.77	128.83	−11.46	1.82	147.30	2.63
Inner Mongolia	0.70	0.74	157.29	6.34	5.83	125.39	1.43
Jiangsu	0.90	0.90	209.83	−0.31	10.79	161.13	7.43
Jiangxi	1.00	0.75	116.79	−25.18	1.71	178.56	2.26
Jilin	0.75	0.88	171.92	16.41	5.60	118.62	1.18
Liaoning	0.91	0.97	139.20	6.23	16.49	84.60	4.71
Ningxia	0.53	0.45	94.59	−14.75	7.40	102.99	4.69
Qinghai	0.44	0.47	115.18	7.88	13.60	67.39	4.90
Sha'anxi	0.68	0.56	114.75	−17.54	4.68	142.70	2.51
Shandong	0.88	0.88	143.15	−0.61	5.57	127.62	1.81
Shanghai	1.00	1.00	195.39	0.00	76.76	61.20	3.66
Shanxi	0.61	0.65	132.41	7.37	6.12	98.96	2.52
Sichuan	0.88	0.70	147.07	−20.10	2.73	195.10	1.99
Tianjin	0.72	0.96	219.30	34.83	39.78	62.05	4.55
Tibet	0.55	0.55	174.01	0.06	11.56	130.23	6.63
Xinjiang	0.69	0.70	109.04	2.20	13.81	70.50	5.41
Yunnan	0.83	0.63	104.73	−23.65	4.06	152.00	2.25
Zhejiang	1.00	0.89	200.46	−11.27	16.29	176.17	5.44
Average	0.81	0.75	144.87	−6.76	11.83	134.38	3.51

Table 2: Efficiency scores and percentage change of quadripartite decomposition indexes, 1993−1998

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Anhui	0.89	0.91	80.42	1.69	0.00	76.42	0.57
Beijing	0.81	0.84	69.16	3.68	19.57	33.10	2.52
Chongqing	0.89	0.80	67.15	−10.26	0.00	86.00	0.14
Fujian	0.99	1.00	90.86	1.14	5.09	77.56	1.13
Gansu	0.75	0.65	47.59	−12.96	0.00	69.00	0.33
Guangdong	1.00	0.97	67.56	−3.37	3.11	66.37	1.08
Guangxi	0.97	0.81	49.08	−16.38	0.00	77.95	0.20
Guizhou	0.76	0.67	44.89	−12.48	0.01	65.20	0.20
Hainan	0.78	0.64	44.20	−17.97	2.98	68.86	1.09
Hebei	0.82	0.79	74.23	−3.34	2.94	72.98	1.23
Heilongjiang	0.79	0.82	38.40	3.68	6.57	24.09	0.94
Henan	0.86	0.83	57.15	−4.49	0.00	63.67	0.54
Hubei	0.86	0.82	76.72	−4.83	1.28	81.22	1.17
Hunan	0.87	0.85	52.65	−3.10	0.00	56.87	0.42
Inner Mongolia	0.70	0.74	57.07	6.82	2.72	41.65	1.05
Jiangsu	0.90	0.89	85.39	−1.44	5.12	76.42	1.42
Jiangxi	1.00	0.90	41.90	−10.10	0.00	57.51	0.21
Jilin	0.75	0.84	85.71	11.38	3.82	59.42	0.74
Liaoning	0.91	0.92	56.22	1.09	4.85	46.15	0.85
Ningxia	0.53	0.51	36.94	−3.47	5.37	32.75	1.42
Qinghai	0.44	0.46	38.98	5.74	8.05	20.54	0.91
Sha'anxi	0.68	0.63	46.43	−7.51	0.77	55.05	1.32
Shandong	0.88	0.93	52.07	4.86	1.83	40.65	1.25
Shanghai	1.00	1.00	72.15	0.00	29.32	30.40	2.08
Shanxi	0.61	0.67	56.31	10.85	3.25	34.42	1.60
Sichuan	0.88	0.78	60.06	−11.38	0.00	80.19	0.24
Tianjin	0.72	0.88	82.11	23.02	9.90	30.60	3.15
Tibet	0.55	0.57	76.84	4.03	5.82	58.20	1.54
Xinjiang	0.69	0.67	47.58	−3.10	4.94	43.84	0.90
Yunnan	0.83	0.72	49.66	−13.17	0.67	69.29	1.13
Zhejiang	1.00	0.94	93.31	−5.76	2.94	97.72	0.79
Average	0.81	0.79	61.25	−2.16	4.22	57.87	1.04

Table 3: Efficiency scores and percentage change of quadripartite decomposition indexes, 1998−2003

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Anhui	1.00	0.82	44.13	−18.27	0.00	75.84	0.29
Beijing	0.85	0.76	47.07	−10.16	22.16	30.90	2.38
Chongqing	0.89	0.63	52.90	−29.09	0.00	115.20	0.20
Fujian	1.00	1.00	49.48	0.00	7.60	36.68	1.64
Gansu	0.72	0.57	58.09	−20.31	0.00	97.91	0.24
Guangdong	0.99	0.96	45.74	−3.00	13.87	30.00	1.49
Guangxi	0.90	0.76	46.29	−15.63	0.00	73.07	0.18
Guizhou	0.75	0.56	32.29	−24.96	0.00	75.97	0.19
Hainan	0.66	0.67	40.91	1.09	14.01	20.37	1.58
Hebei	0.82	0.76	54.12	−6.25	4.76	54.18	1.79
Heilongjiang	0.83	0.89	62.91	7.24	6.93	40.63	1.03
Henan	0.91	0.82	41.24	−10.13	0.00	56.78	0.24
Hubei	0.87	0.75	47.59	−13.62	0.56	66.47	2.06
Hunan	0.94	0.81	49.90	−13.61	0.00	73.18	0.20
Inner Mongolia	0.77	0.74	63.81	−3.56	5.17	59.47	1.27
Jiangsu	0.89	0.90	67.12	1.10	7.72	50.94	1.67
Jiangxi	1.00	0.78	52.77	−21.59	0.00	94.49	0.18
Jilin	0.85	0.88	46.42	2.87	4.10	35.18	1.15
Liaoning	0.94	0.97	53.11	2.83	13.01	30.16	1.23
Ningxia	0.52	0.45	42.09	−12.90	7.09	50.12	1.47
Qinghai	0.46	0.47	54.83	1.38	9.20	37.83	1.46
Sha'anxi	0.68	0.57	46.66	−17.04	0.00	75.00	1.01
Shandong	0.97	0.88	59.90	−9.25	3.85	66.66	1.80
Shanghai	1.00	1.00	71.58	0.00	39.04	21.26	1.77
Shanxi	0.69	0.65	48.68	−6.10	3.68	50.60	1.41
Sichuan	0.86	0.73	54.36	−15.75	0.00	82.88	0.18
Tianjin	0.90	0.96	75.33	6.99	15.78	39.93	1.16
Tibet	0.57	0.55	54.95	−3.94	7.88	47.61	1.29
Xinjiang	0.68	0.70	41.65	2.80	14.01	19.07	1.50
Yunnan	0.78	0.64	36.80	−17.75	0.00	65.78	0.32
Zhejiang	0.96	0.89	55.43	−7.12	11.02	48.33	1.62
Average	0.83	0.76	51.55	−8.18	6.82	55.56	1.10

Table 4: Mean Percentage Changes of the Quadripartite Decomposition Indices by Wealth Classification

Category	TE_b[4a]	TE_c[4a]	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Panel A: The whole period, 1993−2003							
Poor[4b]	0.85	0.67	124.96	−21.81	3.07	177.78	2.12
Middle[4d]	0.82	0.79	136.58	−3.73	6.97	125.19	3.32
Rich[4c]	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 1^{st} 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 2^{nd} 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

[4a] b stands for base period, c—for current; efficiencies are weighted due to Färe and Zelenyuk (2003).
[4b] Poor are regions, which consistently remained in the lower quartile of output per worker;
[4c] Rich are regions, which consistently remained in the upper quartile of output per worker;
[4d] Other than 'rich' and 'poor.'

Figure 1: Administrative Division of China

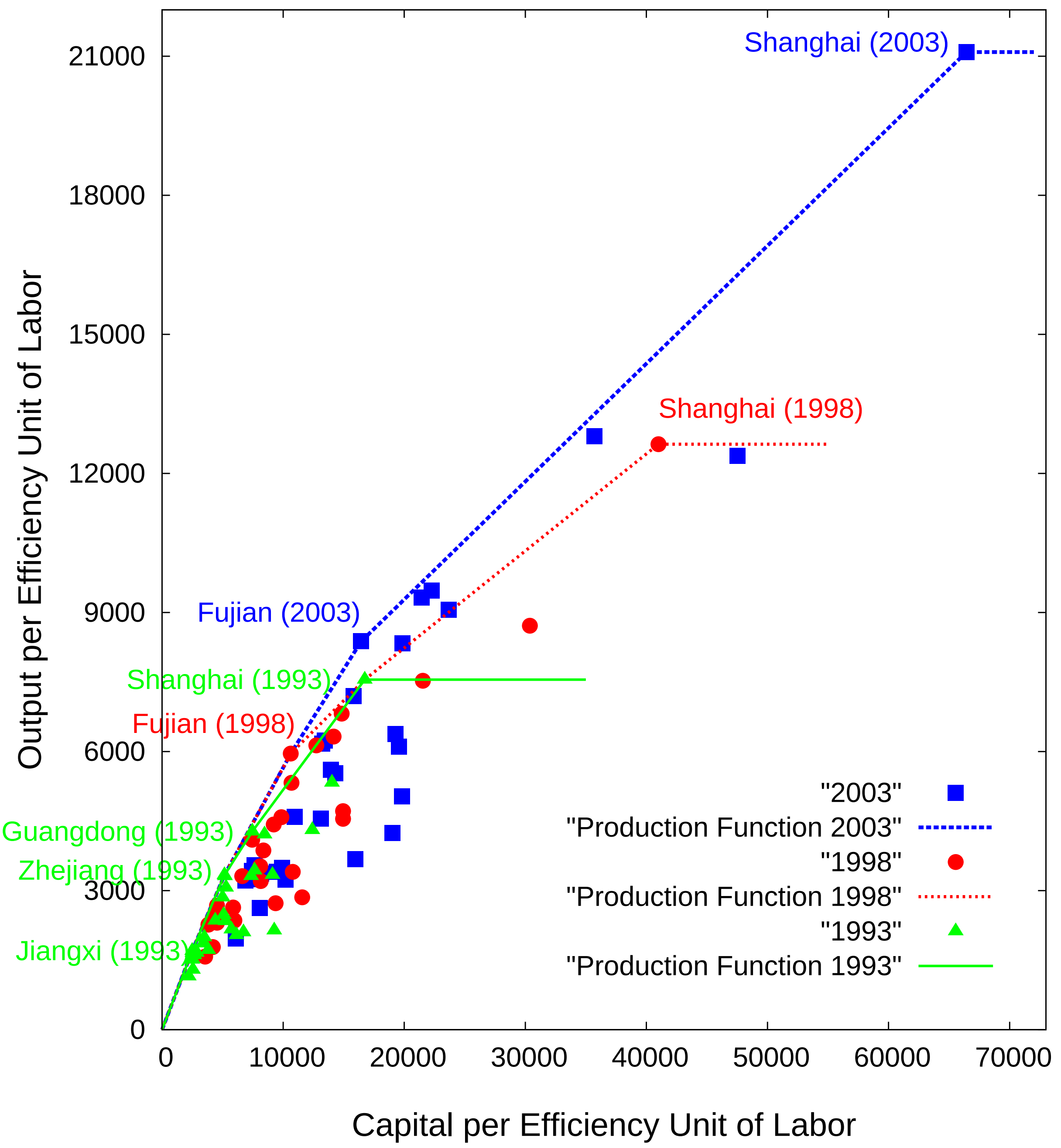

Figure 2: Estimated Best-Practice Production Frontiers for China in 1993, 1998, in 2003

Table 5: Growth Regressions of the Percentage Change in Output per Worker and the Four Decomposition Indices on Output per Worker in Base Period

Regression	(A)	(B)	(C)	(D)	(E)
	(PROD−1) ×100	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Constant	120.53	-19.06	-13.92	188.41	2.44
	0.000	0.001	0.000	0.000	0.000
Slope	3.9E-03	2.0E-03	4.2E-03	-8.8E-03	1.7E-04
	0.002	0.032	0.000	0.000	0.053

Notes: p-values under estimates, based on "heteroskedasticity-consistent" estimators for the variance (Huber, 1981; White, 1980).

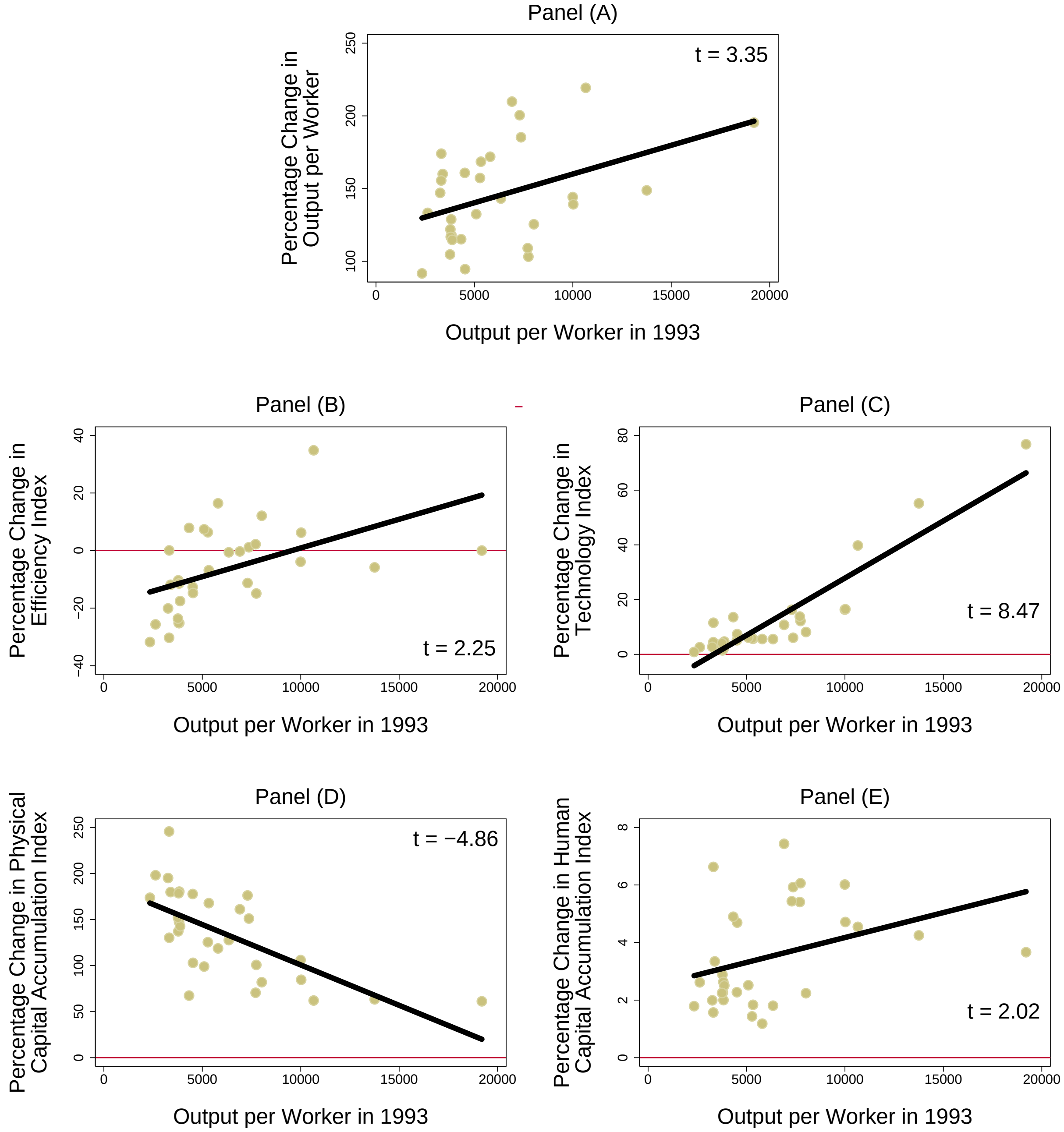

Figure 3: Percentage change (from 1993 to 2003) in output per worker and four decomposition indexes, plotted against output per worker in 1993

Note: Each panel contains a GLS regression line.

Table 6: Distribution Hypothesis Tests (p-values)

	H_0: Distributions are equal H_1: Distributions are not equal	Bootstrap p-value
	Panel A: The whole period, 1993−2003	
1	$g(y_{2003})$ vs. $f(y_{1993})$	0.0000
2	$g(y_{2003})$ vs. $f(y_{1993} \times EFF)$	0.0000
3	$g(y_{2003})$ vs. $f(y_{1993} \times TECH)$	0.0002
4	$g(y_{2003})$ vs. $f(y_{1993} \times KACC)$	0.0036
5	$g(y_{2003})$ vs. $f(y_{1993} \times HACC)$	0.0000
6	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times TECH)$	0.0000
7	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times KACC)$	0.0350
8	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times HACC)$	0.0000
9	$g(y_{2003})$ vs. $f(y_{1993} \times TECH \times KACC)$	0.3362
10	$g(y_{2003})$ vs. $f(y_{1993} \times TECH \times HACC)$	0.0000
11	$g(y_{2003})$ vs. $f(y_{1993} \times KACC \times HACC)$	0.0084
12	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times TECH \times KACC)$	0.9430
13	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times TECH \times HACC)$	0.0000
14	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times KACC \times HACC)$	0.0602
15	$g(y_{2003})$ vs. $f(y_{1993} \times TECH \times KACC \times HACC)$	0.5620
	Panel B: The 1^{st} sub-period, 1993−1998	
1	$g(y_{1998})$ vs. $f(y_{1993})$	0.0010
2	$g(y_{1998})$ vs. $f(y_{1993} \times EFF)$	0.0038
3	$g(y_{1998})$ vs. $f(y_{1993} \times TECH)$	0.0050
4	$g(y_{1998})$ vs. $f(y_{1993} \times KACC)$	0.2874
5	$g(y_{1998})$ vs. $f(y_{1993} \times HACC)$	0.0002
6	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times TECH)$	0.0258
7	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times KACC)$	0.6972
8	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times HACC)$	0.0054
9	$g(y_{1998})$ vs. $f(y_{1993} \times TECH \times KACC)$	0.8366
10	$g(y_{1998})$ vs. $f(y_{1993} \times TECH \times HACC)$	0.0090
11	$g(y_{1998})$ vs. $f(y_{1993} \times KACC \times HACC)$	0.3992
12	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times TECH \times KACC)$	0.9950
13	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times TECH \times HACC)$	0.0318
14	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times KACC \times HACC)$	0.7798
15	$g(y_{1998})$ vs. $f(y_{1993} \times TECH \times KACC \times HACC)$	0.8862
	Panel C: The 2^{nd} sub-period, 1998−2003	
1	$g(y_{2003})$ vs. $f(y_{1998})$	0.0002
2	$g(y_{2003})$ vs. $f(y_{1998} \times EFF)$	0.0044

(*continued on next page*)

Table 6 (*Continued*)

	H_0: Distributions are equal H_1: Distributions are not equal	Bootstrap p-value
3	$g(y_{2003})$ vs. $f(y_{1998} \times TECH)$	0.0300
4	$g(y_{2003})$ vs. $f(y_{1998} \times KACC)$	0.0352
5	$g(y_{2003})$ vs. $f(y_{1998} \times HACC)$	0.0010
6	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times TECH)$	0.0808
7	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times KACC)$	0.1540
8	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times HACC)$	0.0074
9	$g(y_{2003})$ vs. $f(y_{1998} \times TECH \times KACC)$	0.7016
10	$g(y_{2003})$ vs. $f(y_{1998} \times TECH \times HACC)$	0.0470
11	$g(y_{2003})$ vs. $f(y_{1998} \times KACC \times HACC)$	0.0496
12	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times TECH \times KACC)$	0.9900
13	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times TECH \times HACC)$	0.1286
14	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times KACC \times HACC)$	0.2706
15	$g(y_{2003})$ vs. $f(y_{1998} \times TECH \times KACC \times HACC)$	0.8176

Notes: We used the bootstrapped Li (1996) Tests with 5000 bootstrap replications and the Sheather and Jones (1991) bandwidth.

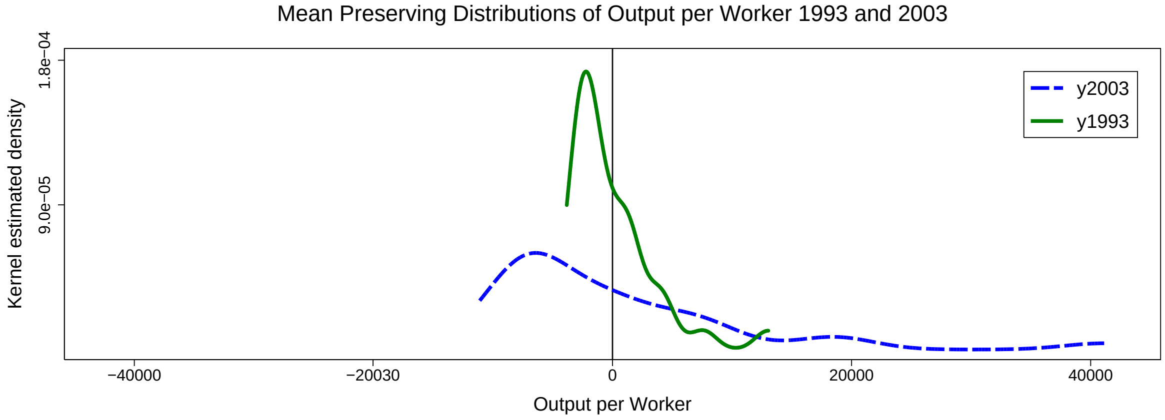

Figure 4: Actual Output per Worker Distributions

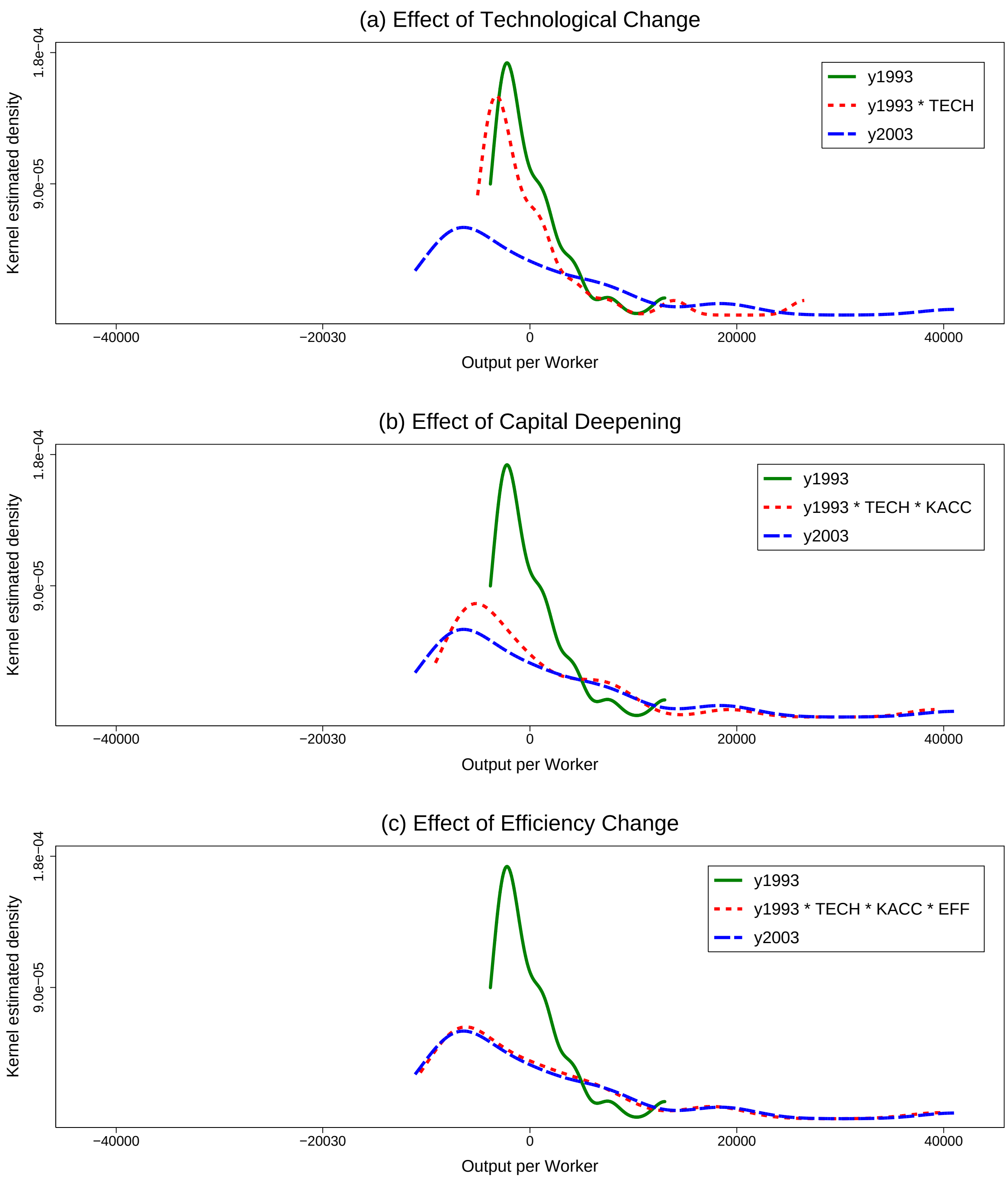

Figure 5: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: TECH, KACC, and EFF

Notes: 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.

7 Russia

Table 7: Efficiency scores and percentage change of quadripartite decomposition indexes, 1994−2003

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Altai Krai	0.54	0.48	14.63	−11.71	56.93	−17.12	−0.18
Altai Republic	0.73	1.00	98.04	37.48	63.70	−11.71	−0.33
Amur Oblast	0.65	0.53	9.72	−18.34	64.12	−17.57	−0.69
Arkhangelsk Oblast	0.69	0.71	42.73	3.03	58.15	−11.53	−0.99
Astrakhan Oblast	0.35	0.39	71.41	13.90	58.57	−4.24	−0.90
Belgorod Oblast	0.55	0.48	25.73	−13.56	56.36	−5.87	−1.18
Bryansk Oblast	0.57	0.41	−8.39	−29.06	62.74	−20.43	−0.27
Buryat Republic	0.69	0.56	13.18	−17.86	58.55	−12.29	−0.92
Chelyabinsk Oblast	0.69	0.67	20.54	−3.41	58.11	−20.29	−0.98
Chita Oblast	0.57	0.40	2.10	−28.95	58.98	−9.07	−0.59
Chukotka Autonomous Okrug	0.48	0.40	117.38	−16.53	159.02	1.21	−0.67
Chuvash Republic	0.50	0.38	−2.50	−24.14	58.00	−18.45	−0.25
Irkutsk Oblast	0.95	0.77	8.16	−19.44	57.18	−13.62	−1.11
Ivanovo Oblast	0.61	0.43	5.99	−28.71	65.19	−9.73	−0.29
Jewish Autonomous Oblast	0.40	0.29	7.24	−26.57	78.56	−17.16	−1.26
Kabardino-Balkar Republic	0.44	0.62	70.47	39.10	61.33	−23.81	−0.29
Kaliningrad Oblast	0.51	0.56	47.24	10.01	56.09	−14.01	−0.28
Kaluga Oblast	0.56	0.52	22.81	−7.94	59.04	−15.93	−0.23
Kamchatka Krai	0.73	0.43	−11.60	−41.26	69.74	−10.40	−1.06
Karachay-Cherkess Republic	0.34	0.32	22.54	−6.29	68.47	−21.87	−0.66
Kemerovo Oblast	0.75	0.58	16.46	−22.65	58.75	−4.33	−0.86
Khabarovsk Krai	0.60	0.59	38.60	−1.61	58.63	−10.51	−0.77
Kirov Oblast	0.59	0.50	7.33	−16.04	57.11	−18.43	−0.25
Komi Republic	1.00	0.92	39.57	−8.25	59.11	−3.57	−0.86
Kostroma Oblast	0.62	0.43	6.49	−30.59	56.95	−1.92	−0.34
Krasnodar Krai	0.50	0.45	61.36	−10.17	56.17	15.78	−0.66
Krasnoyarsk Krai	0.76	0.61	15.67	−20.48	66.28	−11.27	−1.40
Kurgan Oblast	0.53	0.37	−15.90	−29.19	58.45	−24.76	−0.38
Kursk Oblast	0.46	0.34	−8.79	−26.79	56.19	−19.84	−0.50
Leningrad Oblast	0.54	0.68	80.28	24.83	58.37	−7.85	−1.04
Lipetsk Oblast	0.69	0.68	33.22	−0.86	56.17	−13.38	−0.67

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Table 7 (*Continued*)

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Magadan Oblast	0.86	0.47	39.99	−44.85	162.61	−0.38	−2.98
Mari El Republic	0.53	0.36	−12.73	−33.23	61.23	−18.65	−0.35
Moscow (federal city)	0.89	1.00	118.97	11.74	58.24	24.95	−0.89
Moscow Oblast	0.66	0.77	88.46	17.08	55.53	4.26	−0.74
Murmansk Oblast	0.68	0.40	−9.36	−40.67	67.81	−7.85	−1.20
Nizhny Novgorod Oblast	0.76	0.47	−5.82	−38.13	54.40	−1.22	−0.19
Novgorod Oblast	0.45	0.49	65.97	8.82	57.79	−2.49	−0.88
Novosibirsk Oblast	0.46	0.57	63.87	24.12	58.15	−15.68	−0.99
Omsk Oblast	0.59	0.68	49.06	15.43	56.47	−17.02	−0.54
Orenburg Oblast	0.63	0.54	11.09	−14.64	56.75	−16.36	−0.73
Oryol Oblast	0.44	0.52	64.89	18.37	55.31	−10.09	−0.24
Penza Oblast	0.37	0.32	6.55	−14.11	56.71	−20.59	−0.31
Perm Krai	0.74	0.50	0.65	−31.88	58.66	−6.19	−0.73
Primorsky Krai	0.54	0.60	40.67	11.45	57.93	−19.35	−0.91
Pskov Oblast	0.53	0.60	34.62	13.71	58.43	−25.14	−0.18
Republic of Adygea	0.48	0.29	−9.82	−38.82	61.40	−8.48	−0.22
Republic of Bashkortostan	0.81	0.70	38.12	−12.62	58.07	0.83	−0.82
Republic of Dagestan	0.40	0.78	98.89	95.08	64.62	−37.80	−0.43
Republic of Kalmykia	0.24	0.26	68.62	8.42	58.95	−1.67	−0.49
Republic of Karelia	0.58	0.46	5.48	−19.69	59.09	−16.81	−0.77
Republic of Khakassia	0.66	0.39	−23.89	−41.51	64.37	−19.96	−1.09
Republic of Mordovia	0.41	0.38	24.76	−6.59	61.61	−17.15	−0.25
Republic of North Ossetia-Alania	0.42	0.47	40.01	12.93	62.93	−23.65	−0.33
Republic of Tatarstan	0.54	0.61	69.92	12.63	58.52	−4.08	−0.79
Rostov Oblast	0.44	0.43	25.44	−2.47	56.79	−17.59	−0.45
Ryazan Oblast	0.62	0.49	7.06	−21.45	56.05	−12.17	−0.56
Sakha (Yakutia) Republic	1.00	0.79	60.79	−20.81	103.61	1.64	−1.90
Sakhalin Oblast	0.44	0.38	67.64	−14.08	88.52	4.49	−0.95
Samara Oblast	1.00	0.76	15.68	−23.89	54.51	−1.12	−0.52
Saratov Oblast	0.49	0.41	14.06	−16.58	57.58	−12.43	−0.91
Smolensk Oblast	0.61	0.47	2.06	−22.82	56.04	−14.86	−0.47
St. Petersburg (federal city)	0.73	0.81	65.46	12.23	59.63	−7.37	−0.29
Stavropol Krai	0.48	0.42	7.03	−14.17	56.28	−19.87	−0.42
Sverdlovsk Oblast	0.81	0.65	5.68	−19.51	56.54	−15.38	−0.88

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Table 7 (*Continued*)

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Tambov Oblast	0.46	0.48	29.70	3.94	57.57	−20.58	−0.29
Tomsk Oblast	0.59	0.55	37.27	−6.18	69.93	−12.77	−1.30
Tula Oblast	0.64	0.57	19.25	−10.77	58.08	−15.25	−0.24
Tver Oblast	0.71	0.54	19.36	−24.35	55.72	1.61	−0.29
Tyumen Oblast	1.00	1.00	154.54	0.00	147.73	4.76	−1.92
Tyva Republic	0.48	0.46	38.75	−4.37	61.77	−9.96	−0.39
Udmurt Republic	0.61	0.58	20.17	−5.44	56.96	−18.68	−0.43
Ulyanovsk Oblast	0.81	0.45	−22.11	−43.87	59.00	−12.42	−0.35
Vladimir Oblast	0.63	0.57	21.63	−10.35	62.34	−16.21	−0.26
Volgograd Oblast	0.68	0.56	10.65	−17.32	56.43	−14.07	−0.44
Vologda Oblast	0.92	0.90	35.05	−1.69	56.81	−11.24	−1.31
Voronezh Oblast	0.58	0.52	21.07	−11.71	59.16	−13.59	−0.29
Yaroslavl Oblast	0.77	0.71	20.43	−7.12	56.39	−16.63	−0.55
Average	0.61	0.55	30.73	−9.00	64.10	−11.34	−0.68

Table 8: Efficiency scores and percentage change of quadripartite decomposition indexes, 1994−1998

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Altai Krai	0.54	0.42	−25.90	−23.21	0.00	−2.89	−0.64
Altai Republic	0.73	0.80	15.46	10.53	0.00	4.46	0.00
Amur Oblast	0.65	0.49	−29.90	−25.51	1.43	−6.32	−0.96
Arkhangelsk Oblast	0.69	0.59	−14.48	−13.95	0.00	−0.10	−0.53
Astrakhan Oblast	0.35	0.33	−2.49	−4.88	0.00	3.04	−0.51
Belgorod Oblast	0.55	0.49	−11.03	−11.35	0.00	0.99	−0.62
Bryansk Oblast	0.57	0.38	−35.31	−34.02	0.00	−1.95	0.00
Buryat Republic	0.69	0.46	−33.95	−32.91	0.00	−1.05	−0.50
Chelyabinsk Oblast	0.69	0.52	−29.51	−24.48	0.00	−6.17	−0.52
Chita Oblast	0.57	0.39	−29.18	−30.94	0.55	3.00	−0.98
Chukotka Autonomous Okrug	0.48	0.39	−1.26	−18.80	23.91	0.00	−1.86
Chuvash Republic	0.50	0.38	−26.50	−24.05	0.00	−3.24	0.00
Irkutsk Oblast	0.95	0.80	−16.95	−15.70	0.00	−0.92	−0.57
Ivanovo Oblast	0.61	0.41	−31.24	−32.97	0.00	2.58	0.00
Jewish Autonomous Oblast	0.40	0.20	−45.67	−49.56	6.12	2.30	−0.78
Kabardino-Balkar Republic	0.44	0.53	18.74	20.11	0.00	−1.15	0.00
Kaliningrad Oblast	0.51	0.38	−32.84	−24.78	0.00	−10.42	−0.32
Kaluga Oblast	0.56	0.38	−36.37	−31.99	0.00	−6.44	0.00
Kamchatka Krai	0.73	0.68	−7.76	−6.55	2.89	−3.18	−0.92
Karachay-Cherkess Republic	0.34	0.30	−12.09	−13.11	3.92	−1.78	−0.88
Kemerovo Oblast	0.75	0.54	−26.47	−28.09	0.00	2.77	−0.50
Khabarovsk Krai	0.60	0.67	4.43	10.36	0.00	−4.88	−0.51
Kirov Oblast	0.59	0.51	−19.58	−14.37	0.00	−5.64	−0.47
Komi Republic	1.00	0.91	−6.66	−8.52	0.46	2.59	−1.00
Kostroma Oblast	0.62	0.47	−21.53	−24.02	0.00	3.29	0.00
Krasnodar Krai	0.50	0.46	−6.87	−9.50	0.00	3.44	−0.52
Krasnoyarsk Krai	0.76	0.67	−15.53	−12.50	2.05	−4.49	−0.94
Kurgan Oblast	0.53	0.35	−36.95	−34.16	0.00	−3.65	−0.62
Kursk Oblast	0.46	0.40	−20.47	−14.49	0.00	−6.47	−0.57
Leningrad Oblast	0.54	0.51	−13.48	−7.08	0.01	−6.38	−0.54
Lipetsk Oblast	0.69	0.46	−34.10	−32.69	0.01	−1.51	−0.59
Magadan Oblast	0.86	0.65	−8.05	−24.38	23.91	0.01	−1.88
Mari El Republic	0.53	0.37	−32.80	−30.25	0.01	−3.66	0.00
Moscow (federal city)	0.89	0.80	−0.80	−11.05	0.00	11.53	0.00

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Table 8 (*Continued*)

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Moscow Oblast	0.66	0.76	22.86	15.97	0.00	6.55	−0.56
Murmansk Oblast	0.68	0.52	−22.42	−23.60	2.57	−0.07	−0.93
Nizhny Novgorod Oblast	0.76	0.46	−36.74	−39.40	0.01	4.83	−0.44
Novgorod Oblast	0.45	0.47	4.29	5.01	0.00	−0.11	−0.58
Novosibirsk Oblast	0.46	0.41	−9.36	−10.03	0.00	1.27	−0.51
Omsk Oblast	0.59	0.53	−15.45	−9.46	0.00	−6.03	−0.62
Orenburg Oblast	0.63	0.44	−31.98	−29.92	0.00	−2.39	−0.56
Oryol Oblast	0.44	0.43	−1.02	−1.06	0.00	0.71	−0.66
Penza Oblast	0.37	0.26	−32.41	−28.74	0.02	−4.60	−0.59
Perm Krai	0.74	0.54	−26.95	−27.34	0.00	1.04	−0.50
Primorsky Krai	0.54	0.52	−9.29	−4.47	0.00	−4.54	−0.53
Pskov Oblast	0.53	0.44	−18.96	−16.38	0.00	−2.46	−0.64
Republic of Adygea	0.48	0.41	−15.82	−13.95	0.00	−2.17	0.00
Republic of Bashkortostan	0.81	0.67	−14.49	−16.48	0.00	2.97	−0.56
Republic of Dagestan	0.40	0.36	−24.05	−9.31	0.00	−16.25	0.00
Republic of Kalmykia	0.24	0.19	−23.09	−20.88	0.01	−2.32	−0.50
Republic of Karelia	0.58	0.40	−31.40	−30.86	0.30	−0.08	−1.01
Republic of Khakassia	0.66	0.41	−40.00	−37.87	1.87	−4.28	−0.95
Republic of Mordovia	0.41	0.39	−12.91	−5.83	0.01	−7.53	0.00
Republic of North Ossetia-Alania	0.42	0.36	−16.29	−13.86	0.00	−2.81	0.00
Republic of Tatarstan	0.54	0.58	7.23	6.94	0.00	0.79	−0.52
Rostov Oblast	0.44	0.38	−18.41	−14.90	0.00	−3.52	−0.62
Ryazan Oblast	0.62	0.37	−40.27	−39.85	0.01	−0.08	−0.62
Sakha (Yakutia) Republic	1.00	0.87	−8.41	−13.28	8.22	−1.70	−0.73
Sakhalin Oblast	0.44	0.35	−13.11	−22.01	6.23	5.72	−0.80
Samara Oblast	1.00	0.79	−18.43	−21.31	0.01	4.34	−0.66
Saratov Oblast	0.49	0.33	−36.75	−33.85	0.00	−3.82	−0.58
Smolensk Oblast	0.61	0.44	−30.40	−27.46	0.00	−3.46	−0.60
St. Petersburg (federal city)	0.73	0.74	−5.43	2.45	0.00	−7.69	0.00
Stavropol Krai	0.48	0.42	−17.13	−12.36	0.00	−4.90	−0.57
Sverdlovsk Oblast	0.81	0.61	−26.54	−23.86	0.00	−2.96	−0.57
Tambov Oblast	0.46	0.36	−24.19	−22.59	0.00	−1.45	−0.62
Tomsk Oblast	0.59	0.49	−19.06	−16.82	2.98	−4.64	−0.91
Tula Oblast	0.64	0.53	−21.14	−16.92	0.00	−5.08	0.00

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Table 8 (*Continued*)

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Tver Oblast	0.71	0.54	−20.53	−24.53	0.00	5.30	0.00
Tyumen Oblast	1.00	1.00	21.59	0.00	22.34	0.59	−1.19
Tyva Republic	0.48	0.34	−28.69	−29.49	0.00	1.14	0.00
Udmurt Republic	0.61	0.49	−23.45	−20.04	0.00	−3.68	−0.62
Ulyanovsk Oblast	0.81	0.54	−32.01	−33.10	0.00	1.64	0.00
Vladimir Oblast	0.63	0.50	−25.00	−20.82	0.00	−5.28	0.00
Volgograd Oblast	0.68	0.51	−24.71	−25.15	0.00	1.21	−0.62
Vologda Oblast	0.92	0.71	−24.27	−22.31	0.00	−1.95	−0.59
Voronezh Oblast	0.58	0.44	−25.50	−24.56	0.00	−1.26	0.00
Yaroslavl Oblast	0.77	0.56	−30.87	−27.21	0.00	−4.45	−0.61
Average	0.61	0.50	−18.82	−18.34	1.41	−1.48	−0.52

Table 9: Efficiency scores and percentage change of quadripartite decomposition indexes, 1998−2003

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Altai Krai	0.52	0.48	54.71	−7.68	95.45	−14.23	−0.04
Altai Republic	1.00	1.00	71.51	0.00	102.38	−15.13	−0.15
Amur Oblast	0.54	0.53	56.51	−0.45	80.09	−12.58	−0.14
Arkhangelsk Oblast	0.68	0.71	66.90	3.53	86.26	−13.22	−0.26
Astrakhan Oblast	0.37	0.39	75.79	5.15	82.46	−8.17	−0.22
Belgorod Oblast	0.60	0.48	41.32	−20.17	93.19	−8.04	−0.36
Bryansk Oblast	0.47	0.41	41.61	−13.55	102.41	−18.99	−0.10
Buryat Republic	0.52	0.56	71.34	7.55	83.52	−12.99	−0.24
Chelyabinsk Oblast	0.61	0.67	71.01	10.21	88.06	−17.28	−0.25
Chita Oblast	0.43	0.40	44.18	−5.74	80.13	−15.02	−0.07
Chukotka Autonomous Okrug	0.39	0.40	120.15	2.81	112.75	0.00	0.66
Chuvash Republic	0.48	0.38	32.65	−20.51	97.72	−15.52	−0.10
Irkutsk Oblast	0.95	0.77	30.23	−19.39	90.55	−14.95	−0.31
Ivanovo Oblast	0.51	0.43	54.14	−14.47	104.50	−11.78	−0.10
Jewish Autonomous Oblast	0.21	0.29	97.40	39.75	83.03	−22.52	−0.40
Kabardino-Balkar Republic	0.67	0.62	43.58	−7.52	101.19	−22.73	−0.13
Kaliningrad Oblast	0.48	0.56	119.22	16.40	95.86	−3.63	−0.22
Kaluga Oblast	0.48	0.52	93.03	8.34	99.07	−10.43	−0.08
Kamchatka Krai	0.73	0.43	−4.17	−41.61	78.96	−8.07	−0.23
Karachay-Cherkess Republic	0.32	0.32	39.38	1.23	81.52	−24.05	−0.13
Kemerovo Oblast	0.61	0.58	58.39	−4.88	81.28	−7.95	−0.21
Khabarovsk Krai	0.77	0.59	32.73	−22.48	83.77	−6.69	−0.16
Kirov Oblast	0.64	0.50	33.46	−22.16	95.87	−12.39	−0.09
Komi Republic	1.00	0.92	49.52	−8.25	78.54	−8.52	−0.22
Kostroma Oblast	0.59	0.43	35.70	−27.26	96.10	−4.63	−0.24
Krasnodar Krai	0.57	0.45	73.26	−20.08	91.02	13.60	−0.10
Krasnoyarsk Krai	0.73	0.61	36.93	−16.36	78.35	−8.01	−0.21
Kurgan Oblast	0.43	0.37	33.39	−13.40	96.32	−21.48	−0.07
Kursk Oblast	0.48	0.34	14.69	−28.85	92.26	−15.87	−0.34
Leningrad Oblast	0.60	0.68	108.37	14.11	86.23	−1.64	−0.32
Lipetsk Oblast	0.56	0.68	102.14	22.11	92.36	−13.75	−0.23
Magadan Oblast	0.65	0.47	52.24	−27.07	111.93	−0.38	−1.12
Mari El Republic	0.46	0.36	29.87	−23.24	101.12	−15.71	−0.20
Moscow (federal city)	1.00	1.00	120.73	0.00	94.56	13.66	−0.18

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Table 9 (*Continued*)

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Moscow Oblast	0.93	0.77	53.39	−17.66	93.28	−3.42	−0.20
Murmansk Oblast	0.56	0.40	16.84	−27.82	78.96	−9.27	−0.32
Nizhny Novgorod Oblast	0.57	0.47	48.88	−17.49	94.24	−7.04	−0.07
Novgorod Oblast	0.56	0.49	59.15	−13.13	88.81	−2.78	−0.19
Novosibirsk Oblast	0.47	0.57	80.79	20.68	86.00	−19.26	−0.25
Omsk Oblast	0.66	0.68	76.30	3.06	94.59	−11.90	−0.21
Orenburg Oblast	0.52	0.54	63.32	2.82	90.72	−16.64	−0.09
Oryol Oblast	0.54	0.52	66.59	−4.27	95.11	−10.69	−0.14
Penza Oblast	0.32	0.32	57.63	0.00	92.73	−18.15	−0.08
Perm Krai	0.61	0.50	37.78	−17.53	82.28	−8.22	−0.14
Primorsky Krai	0.60	0.60	55.08	0.18	88.91	−17.89	−0.20
Pskov Oblast	0.55	0.60	66.12	9.11	96.87	−22.63	−0.04
Republic of Adygea	0.51	0.29	7.13	−42.82	100.78	−6.64	−0.05
Republic of Bashkortostan	0.79	0.70	61.52	−10.74	85.91	−2.51	−0.16
Republic of Dagestan	0.45	0.78	161.87	72.98	105.72	−26.41	0.00
Republic of Kalmykia	0.21	0.26	119.26	20.10	81.07	0.83	−0.01
Republic of Karelia	0.44	0.46	53.77	4.44	82.53	−19.22	−0.15
Republic of Khakassia	0.45	0.39	26.86	−13.51	80.50	−18.46	−0.36
Republic of Mordovia	0.48	0.38	43.26	−20.24	102.07	−11.03	−0.08
Republic of North Ossetia-Alania	0.45	0.47	67.25	5.42	102.81	−21.65	−0.16
Republic of Tatarstan	0.66	0.61	58.47	−8.31	83.33	−5.58	−0.16
Rostov Oblast	0.47	0.43	53.74	−6.87	94.71	−15.04	−0.21
Ryazan Oblast	0.46	0.49	79.23	6.60	93.95	−12.98	−0.38
Sakha (Yakutia) Republic	0.89	0.79	75.55	−11.20	89.50	4.80	−0.45
Sakhalin Oblast	0.36	0.38	92.94	6.15	86.87	−2.53	−0.22
Samara Oblast	0.97	0.76	41.81	−21.65	94.07	−6.63	−0.11
Saratov Oblast	0.39	0.41	80.32	5.61	90.99	−10.43	−0.19
Smolensk Oblast	0.54	0.47	46.62	−12.60	93.29	−12.97	−0.28
St. Petersburg (federal city)	0.92	0.81	74.96	−11.91	99.62	−0.37	−0.12
Stavropol Krai	0.51	0.42	29.15	−18.20	91.91	−17.54	−0.23
Sverdlovsk Oblast	0.73	0.65	43.86	−11.60	91.56	−14.89	−0.19
Tambov Oblast	0.44	0.48	71.07	9.55	95.04	−19.92	−0.02
Tomsk Oblast	0.53	0.55	69.59	4.68	78.71	−9.05	−0.33
Tula Oblast	0.66	0.57	51.22	−14.28	97.87	−10.76	−0.09

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Table 9 (*Continued*)

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Tver Oblast	0.67	0.54	50.20	−20.51	95.13	−2.97	−0.20
Tyumen Oblast	1.00	1.00	109.34	0.00	103.07	4.01	−0.89
Tyva Republic	0.42	0.46	94.58	8.97	100.71	−10.85	−0.21
Udmurt Republic	0.60	0.58	56.98	−3.87	94.82	−16.01	−0.20
Ulyanovsk Oblast	0.68	0.45	14.55	−33.08	97.96	−13.37	−0.19
Vladimir Oblast	0.62	0.57	62.17	−8.97	102.57	−11.96	−0.10
Volgograd Oblast	0.62	0.56	46.97	−9.26	93.63	−16.18	−0.21
Vologda Oblast	0.86	0.90	78.31	4.81	92.16	−11.09	−0.42
Voronezh Oblast	0.55	0.52	62.51	−6.53	98.49	−12.29	−0.13
Yaroslavl Oblast	0.69	0.71	74.21	3.91	94.24	−13.36	−0.38
Average	0.59	0.55	60.81	−5.50	92.27	−10.90	−0.20

Table 10: Mean Percentage Changes of the Quadripartite Decomposition Indices by Wealth Classification

Category	TE_b[10a]	TE_c[10a]	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
			Panel A: The whole period, 1994−2003				
Poor[10b]	0.51	0.48	20.56	−7.08	60.84	−17.60	−0.32
Middle[10d]	0.63	0.56	27.21	−9.66	61.95	−12.19	−0.64
Rich[10c]	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 1^{st} 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 2^{nd} 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

[10a] b stands for base period, c—for current; efficiencies are weighted due to Färe and Zelenyuk (2003).
[10b] Poor are regions, which consistently remained in the lower quartile of output per worker;
[10c] Rich are regions, which consistently remained in the upper quartile of output per worker;
[10d] Other than 'rich' and 'poor.'

Figure 6: Administrative Division of Russia

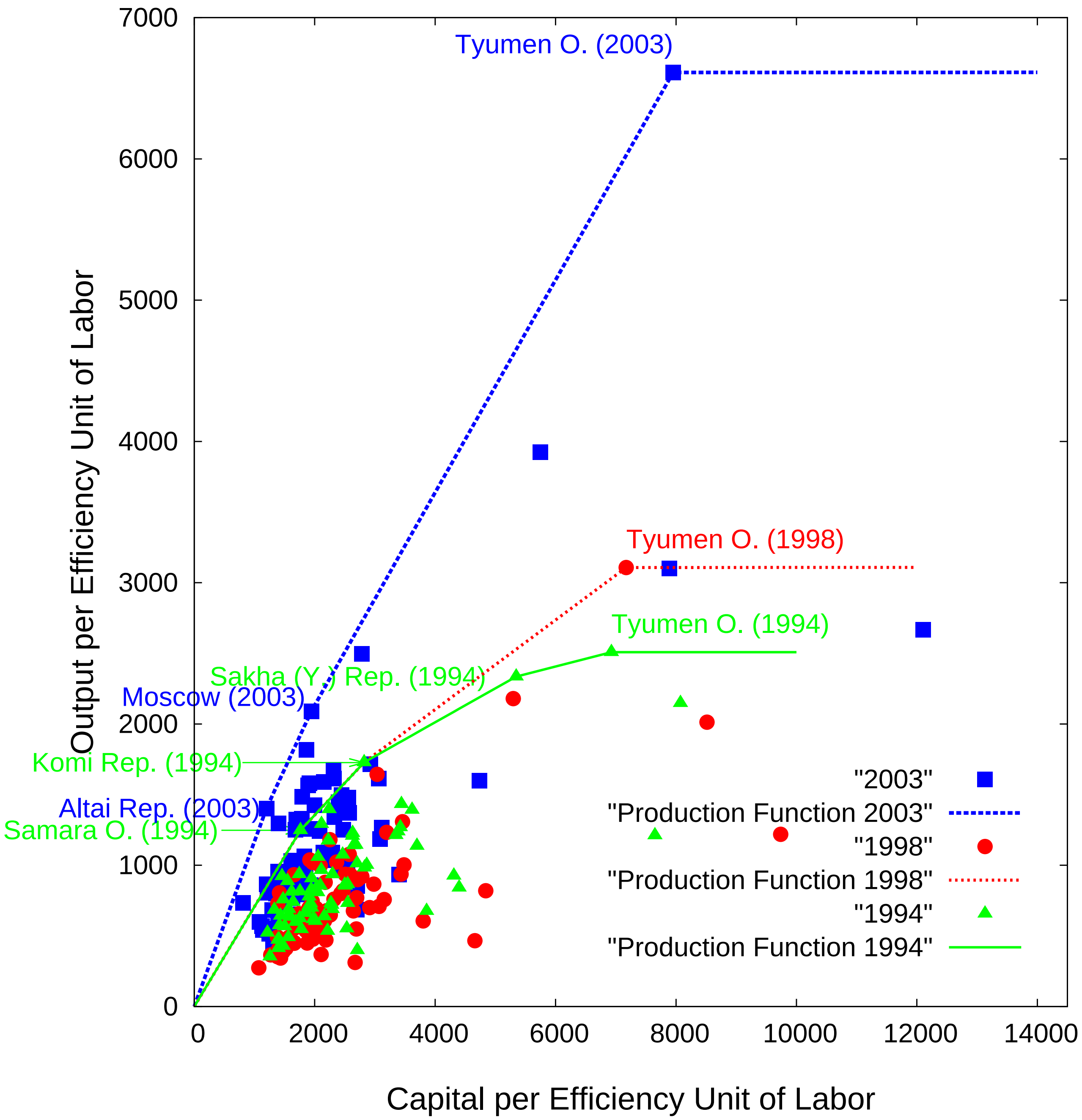

Figure 7: Estimated Best-Practice Production Frontiers for Russia in 1994, 1998, and 2003

Table 11: Growth Regressions of the Percentage Change in Output per Worker and the Four Decomposition Indices on Output per Worker in Base Period

Regression	(A)	(B)	(C)	(D)	(E)
	(PROD−1) ×100	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Constant	19.31	6.65	37.03	−19.51	0.15
	0.158	0.407	0.000	0.000	0.187
Slope	4.6E-03	-6.3E-03	1.1E-02	3.3E-03	-3.4E-04
	0.413	0.027	0.001	0.000	0.000

Notes: *p*-values under estimates, based on "heteroskedasticity-consistent" estimators for the variance (Huber, 1981; White, 1980).

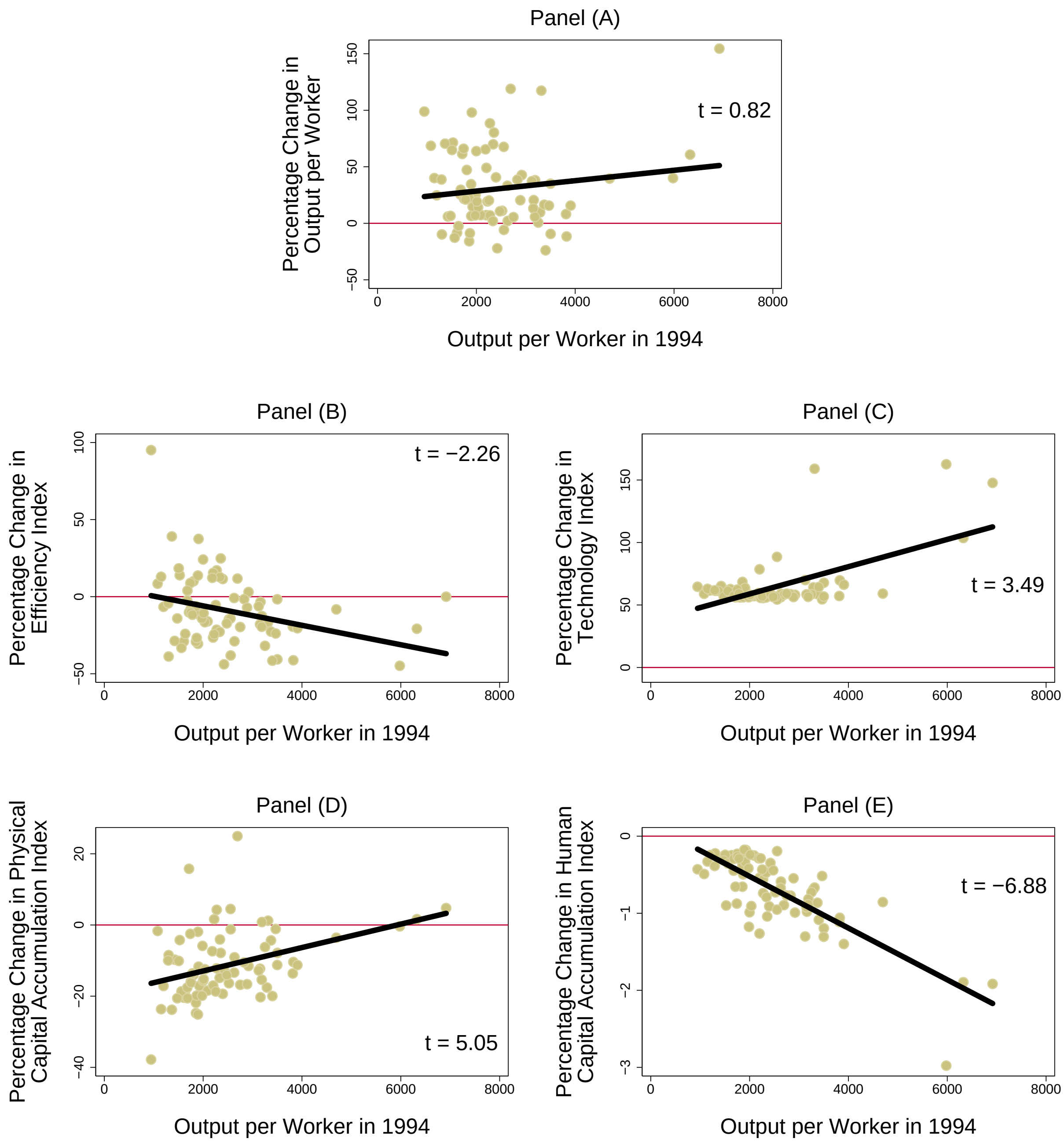

Figure 8: Percentage change (from 1994 to 2003) in output per worker and four decomposition indexes, plotted against output per worker in 1994

Note: Each panel contains a GLS regression line.

Table 12: Distribution Hypothesis Tests (p-values)

	H_0: Distributions are equal H_1: Distributions are not equal	Bootstrap p-value
	Panel A: The whole period, 1994−2003	
1	$g(y_{2003})$ vs. $f(y_{1994})$	0.0096
2	$g(y_{2003})$ vs. $f(y_{1994} \times EFF)$	0.0004
3	$g(y_{2003})$ vs. $f(y_{1994} \times TECH)$	0.6192
4	$g(y_{2003})$ vs. $f(y_{1994} \times KACC)$	0.0122
5	$g(y_{2003})$ vs. $f(y_{1994} \times HACC)$	0.0090
6	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times TECH)$	0.9148
7	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times KACC)$	0.0004
8	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times HACC)$	0.0000
9	$g(y_{2003})$ vs. $f(y_{1994} \times TECH \times KACC)$	0.2230
10	$g(y_{2003})$ vs. $f(y_{1994} \times TECH \times HACC)$	0.7540
11	$g(y_{2003})$ vs. $f(y_{1994} \times KACC \times HACC)$	0.0114
12	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times TECH \times KACC)$	0.9950
13	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times TECH \times HACC)$	0.9092
14	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times KACC \times HACC)$	0.0004
15	$g(y_{2003})$ vs. $f(y_{1994} \times TECH \times KACC \times HACC)$	0.3582
	Panel B: The 1^{st} sub-period, 1994−1998	
1	$g(y_{1998})$ vs. $f(y_{1994})$	0.9256
2	$g(y_{1998})$ vs. $f(y_{1994} \times EFF)$	0.9584
3	$g(y_{1998})$ vs. $f(y_{1994} \times TECH)$	0.9194
4	$g(y_{1998})$ vs. $f(y_{1994} \times KACC)$	0.9576
5	$g(y_{1998})$ vs. $f(y_{1994} \times HACC)$	0.8862
6	$g(y_{1998})$ vs. $f(y_{1994} \times EFF \times TECH)$	0.9670
7	$g(y_{1998})$ vs. $f(y_{1994} \times EFF \times KACC)$	0.9638
8	$g(y_{1998})$ vs. $f(y_{1994} \times EFF \times HACC)$	0.9310
9	$g(y_{1998})$ vs. $f(y_{1994} \times TECH \times KACC)$	0.7270
10	$g(y_{1998})$ vs. $f(y_{1994} \times TECH \times HACC)$	0.9680
11	$g(y_{1998})$ vs. $f(y_{1994} \times KACC \times HACC)$	0.9992
12	$g(y_{1998})$ vs. $f(y_{1994} \times EFF \times TECH \times KACC)$	0.9978
13	$g(y_{1998})$ vs. $f(y_{1994} \times EFF \times TECH \times HACC)$	0.9622
14	$g(y_{1998})$ vs. $f(y_{1994} \times EFF \times KACC \times HACC)$	0.9502
15	$g(y_{1998})$ vs. $f(y_{1994} \times TECH \times KACC \times HACC)$	0.7766
	Panel C: The 2^{nd} sub-period, 1998−2004	
1	$g(y_{2003})$ vs. $f(y_{1994})$	0.0002
2	$g(y_{2003})$ vs. $f(y_{1994} \times EFF)$	0.0000

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Table 12 (*Continued*)

	H_0: Distributions are equal H_1: Distributions are not equal	Bootstrap p-value
3	$g(y_{2003})$ vs. $f(y_{1994} \times TECH)$	0.8404
4	$g(y_{2003})$ vs. $f(y_{1994} \times KACC)$	0.0002
5	$g(y_{2003})$ vs. $f(y_{1994} \times HACC)$	0.0000
6	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times TECH)$	0.9746
7	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times KACC)$	0.0000
8	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times HACC)$	0.0002
9	$g(y_{2003})$ vs. $f(y_{1994} \times TECH \times KACC)$	0.7884
10	$g(y_{2003})$ vs. $f(y_{1994} \times TECH \times HACC)$	0.8520
11	$g(y_{2003})$ vs. $f(y_{1994} \times KACC \times HACC)$	0.0010
12	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times TECH \times KACC)$	0.9996
13	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times TECH \times HACC)$	0.9756
14	$g(y_{2003})$ vs. $f(y_{1994} \times EFF \times KACC \times HACC)$	0.0000
15	$g(y_{2003})$ vs. $f(y_{1994} \times TECH \times KACC \times HACC)$	0.8104

Notes: We used the bootstrapped Li (1996) Tests with 5000 bootstrap replications and the Sheather and Jones (1991) bandwidth.

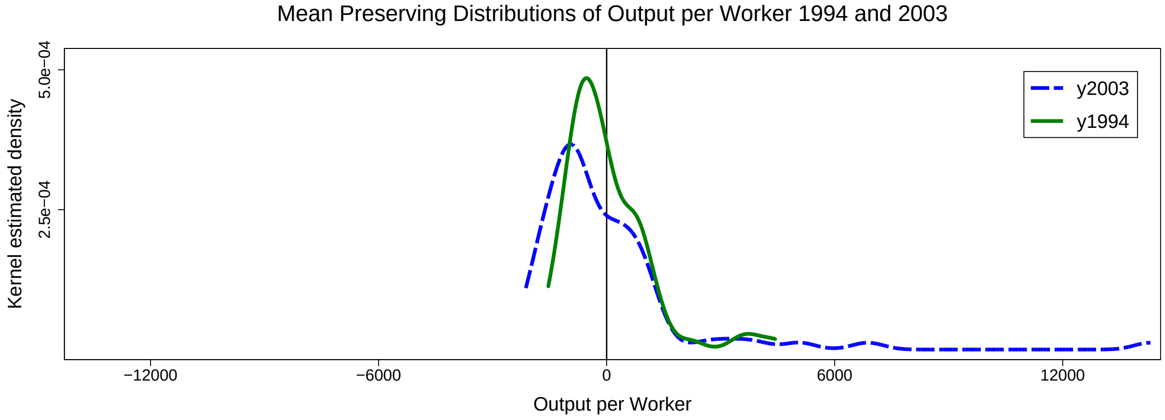

Figure 9: Actual Output per Worker Distributions

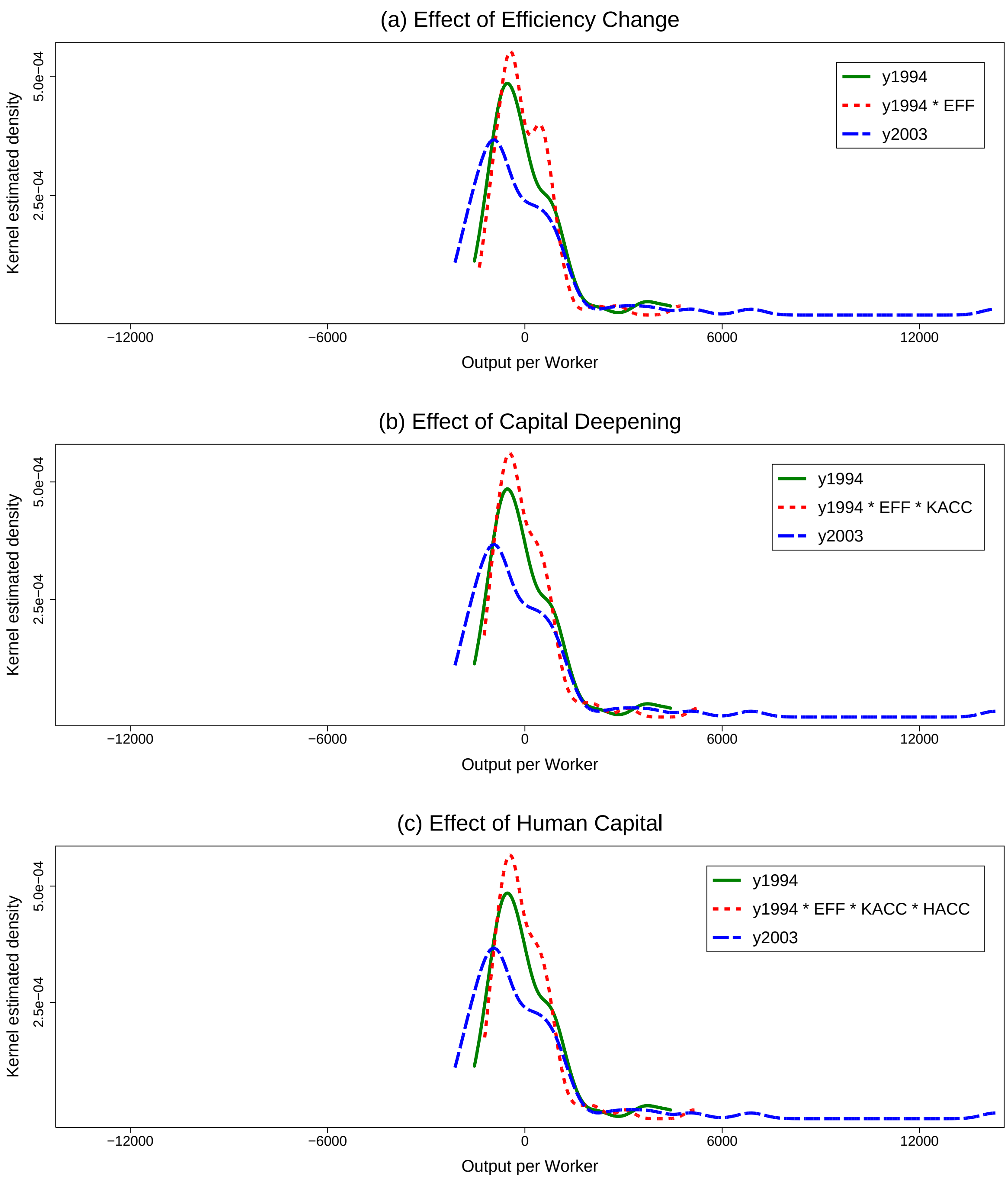

Figure 10: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: EFF, KACC, and HACC

Notes: 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.

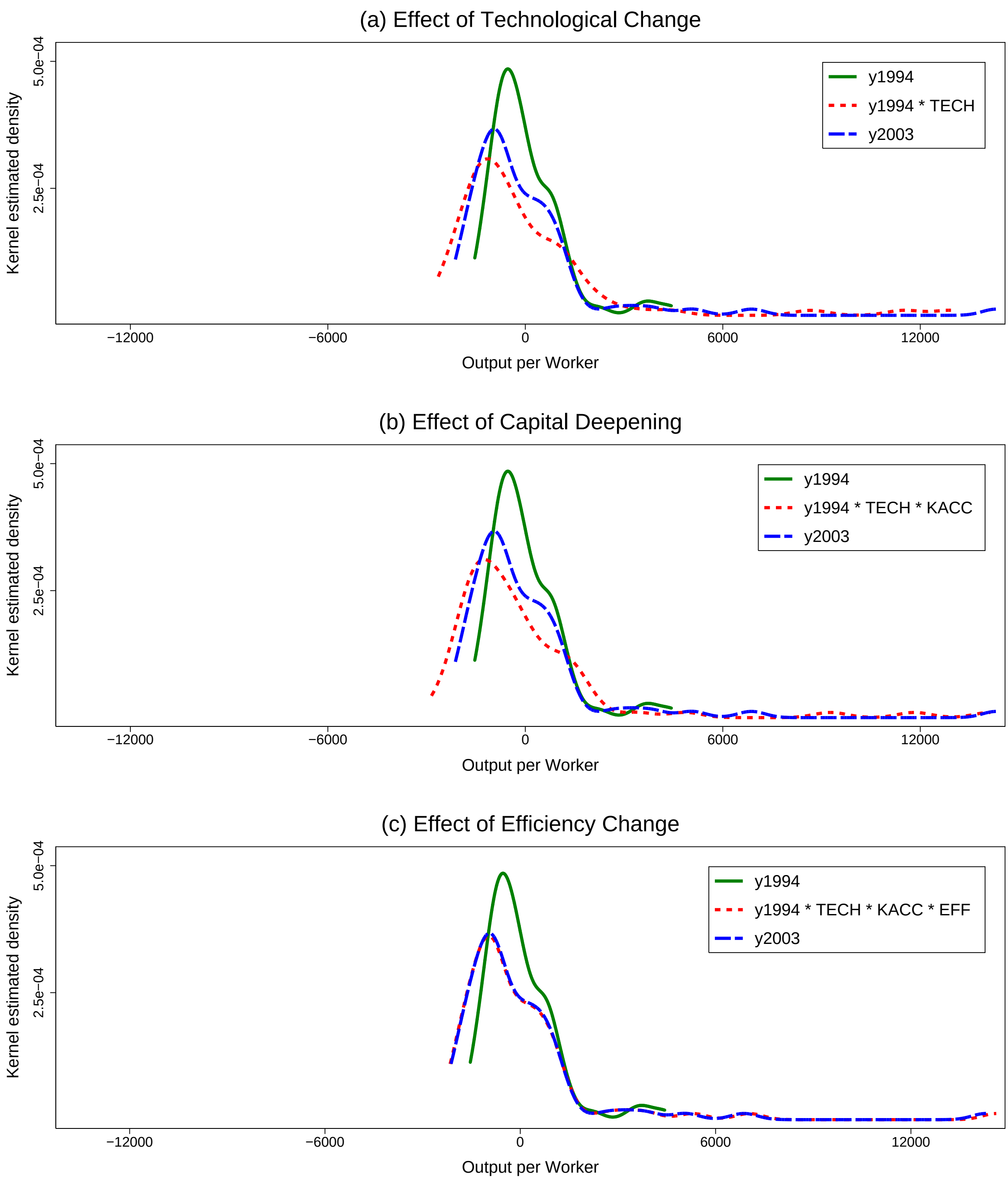

Figure 11: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: TECH, KACC, and EFF

Notes: 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 technological change, capital deepening, and efficiency change on the 1994 distribution.

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Table 13: Efficiency scores and percentage change of quadripartite decomposition indexes, 1993−2003

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Andaman & Nicobar	1.00	0.56	−2.88	−43.62	21.51	42.43	−0.47
Andhra Pradesh	0.64	0.66	52.99	3.04	0.58	44.33	2.28
Arunachal Pradesh	0.46	0.33	22.66	−27.78	52.96	0.00	11.04
Assam	0.35	0.39	17.57	13.09	25.55	−18.49	1.58
Bihar	0.65	0.55	11.19	−14.77	0.00	31.57	−0.85
Chandigarh	0.92	1.00	61.63	8.60	52.24	−0.06	−2.18
Dehli	1.00	0.96	52.21	−3.88	36.76	12.68	2.76
Goa	0.94	0.98	70.00	4.72	42.57	9.11	4.35
Gujarat	0.62	0.60	63.69	−2.98	18.46	39.82	1.86
Haryana	0.82	0.71	15.60	−12.49	13.25	15.52	0.97
Himachal Pradesh	0.49	0.39	44.57	−21.46	16.54	53.21	3.10
Karnataka	0.67	0.54	53.35	−18.40	6.94	70.41	3.12
Kerala	0.54	0.68	58.51	26.03	9.87	13.48	0.87
Madhya Pradesh	0.60	0.52	23.45	−13.72	0.01	41.08	1.41
Maharashtra	0.62	0.62	40.70	−0.96	20.58	14.68	2.74
Manipur	0.69	0.37	29.47	−46.05	2.83	121.99	5.13
Meghalaya	0.72	0.63	51.74	−12.92	0.00	68.13	3.64
Nagaland	0.46	0.53	27.59	15.23	10.02	−4.26	5.12
Orissa	0.31	0.28	31.61	−11.49	49.32	−2.37	2.00
Pondicherry	0.61	1.00	163.92	64.45	52.94	−0.01	4.94
Punjab	0.93	0.81	7.27	−13.59	9.10	14.32	−0.47
Rajasthan	0.59	0.61	48.03	3.26	1.20	39.48	1.57
Sikkim	0.51	0.51	70.74	1.05	31.71	25.43	2.28
Tamil Nadu	0.52	0.58	43.76	12.33	6.77	17.73	1.82
Tripura	1.00	0.85	67.51	−15.05	0.00	96.38	0.41
Uttar Pradesh	0.75	0.53	21.20	−29.77	0.00	71.82	0.45
West Bengal	0.54	0.87	49.62	60.54	0.00	−6.64	−0.17
Average	0.66	0.63	44.36	−2.84	17.84	30.07	2.20

Table 14: Efficiency scores and percentage change of quadripartite decomposition indexes, 1993−1998

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Andaman & Nicobar	1.00	0.80	−0.06	−19.51	4.78	19.75	−1.05
Andhra Pradesh	0.64	0.61	21.83	−4.06	0.00	26.44	0.43
Arunachal Pradesh	0.46	0.34	4.06	−26.53	33.23	−0.01	6.32
Assam	0.35	0.31	0.98	−9.76	17.86	−5.55	0.52
Bihar	0.65	0.59	9.46	−8.73	0.00	20.42	−0.41
Chandigarh	0.92	0.92	29.61	0.26	31.83	−1.06	−0.90
Dehli	1.00	0.96	27.11	−3.72	20.01	8.37	1.51
Goa	0.94	1.00	45.60	6.77	25.63	6.66	1.77
Gujarat	0.62	0.69	37.49	10.46	4.41	18.31	0.77
Haryana	0.82	0.73	2.07	−10.53	5.58	7.76	0.27
Himachal Pradesh	0.49	0.46	21.98	−6.99	3.17	25.45	1.34
Karnataka	0.67	0.58	32.08	−12.39	0.77	46.63	2.02
Kerala	0.54	0.59	21.86	9.62	3.95	6.50	0.42
Madhya Pradesh	0.60	0.54	13.32	−10.38	0.00	26.20	0.20
Maharashtra	0.62	0.62	18.88	−0.42	8.70	8.71	1.02
Manipur	0.69	0.49	11.30	−29.32	0.00	55.62	1.18
Meghalaya	0.72	0.71	22.82	−1.21	0.00	23.66	0.54
Nagaland	0.46	0.43	−1.15	−7.22	5.91	−1.44	2.06
Orissa	0.31	0.26	11.54	−16.83	33.25	0.01	0.64
Pondicherry	0.61	0.81	81.91	33.61	33.24	0.00	2.19
Punjab	0.93	0.86	3.50	−7.40	3.89	8.51	−0.85
Rajasthan	0.59	0.61	33.13	3.75	0.00	27.96	0.29
Sikkim	0.51	0.45	28.93	−11.32	19.19	20.20	1.49
Tamil Nadu	0.52	0.59	28.97	14.58	2.24	8.50	1.47
Tripura	1.00	0.74	24.41	−26.03	0.01	67.91	0.16
Uttar Pradesh	0.75	0.59	10.02	−21.84	0.00	40.53	0.17
West Bengal	0.54	0.67	21.65	22.08	0.00	−0.29	−0.06
Average	0.66	0.63	20.86	−4.93	9.54	17.25	0.87

Table 15: Efficiency scores and percentage change of quadripartite decomposition indexes, 1998−2003

Region	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Andaman & Nicobar	0.89	0.57	−2.82	−36.03	14.58	32.30	0.22
Andhra Pradesh	0.85	0.77	25.57	−8.95	19.19	15.43	0.25
Arunachal Pradesh	0.34	0.33	17.87	−1.70	14.81	0.01	4.44
Assam	0.34	0.44	16.43	28.39	13.15	−20.19	0.43
Bihar	0.85	0.68	1.58	−19.85	12.73	12.42	0.00
Chandigarh	0.93	1.00	24.71	7.43	16.16	0.21	−0.28
Dehli	0.97	0.96	19.75	−1.27	15.16	4.11	1.17
Goa	1.00	0.98	16.76	−1.92	14.37	0.78	3.27
Gujarat	0.77	0.61	19.05	−19.80	14.11	29.51	0.45
Haryana	0.83	0.76	13.26	−8.29	12.70	9.18	0.36
Himachal Pradesh	0.53	0.40	18.52	−24.98	13.37	38.42	0.67
Karnataka	0.77	0.59	16.11	−23.50	14.17	31.77	0.89
Kerala	0.69	0.73	30.08	6.10	12.17	9.02	0.26
Madhya Pradesh	0.74	0.61	8.94	−17.83	19.59	10.49	0.33
Maharashtra	0.68	0.64	18.36	−5.14	14.00	8.81	0.58
Manipur	0.66	0.42	16.33	−35.88	14.37	57.92	0.45
Meghalaya	0.96	0.74	23.55	−23.30	15.88	38.18	0.59
Nagaland	0.51	0.61	29.07	18.62	13.32	−5.18	1.27
Orissa	0.26	0.28	17.99	7.35	15.23	−5.40	0.83
Pondicherry	0.81	1.00	45.08	23.08	14.79	0.00	2.70
Punjab	1.00	0.88	3.64	−12.49	11.90	5.68	0.15
Rajasthan	0.86	0.71	11.19	−16.79	18.21	12.51	0.48
Sikkim	0.45	0.51	32.42	13.94	14.57	0.20	1.24
Tamil Nadu	0.72	0.63	11.47	−12.02	12.57	12.13	0.37
Tripura	1.00	0.99	34.64	−1.43	15.49	17.80	0.40
Uttar Pradesh	0.80	0.62	10.16	−22.77	17.91	20.79	0.13
West Bengal	0.93	1.00	23.00	8.06	20.23	−5.13	−0.21
Average	0.75	0.68	18.62	−6.70	14.99	12.29	0.79

Table 16: Mean Percentage Changes of the Quadripartite Decomposition Indices by Wealth Classification

Category	TE_b[16a]	TE_c[16a]	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
			Panel A: The whole period, 1993−2003				
Poor[16a]	0.63	0.50	22.41	−17.12	12.95	40.93	1.62
Middle[16c]	0.61	0.65	47.40	0.63	12.59	32.51	2.71
Rich[16b]	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 1^{st} 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 2^{nd} 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

[16a] b stands for base period, c—for current; efficiencies are weighted due to Färe and Zelenyuk (2003).
[16b] Poor are regions, which consistently remained in the lower quartile of output per worker;
[16c] Rich are regions, which consistently remained in the upper quartile of output per worker;
[16d] Other than 'rich' and 'poor.'

Figure 12: Administrative Division of India

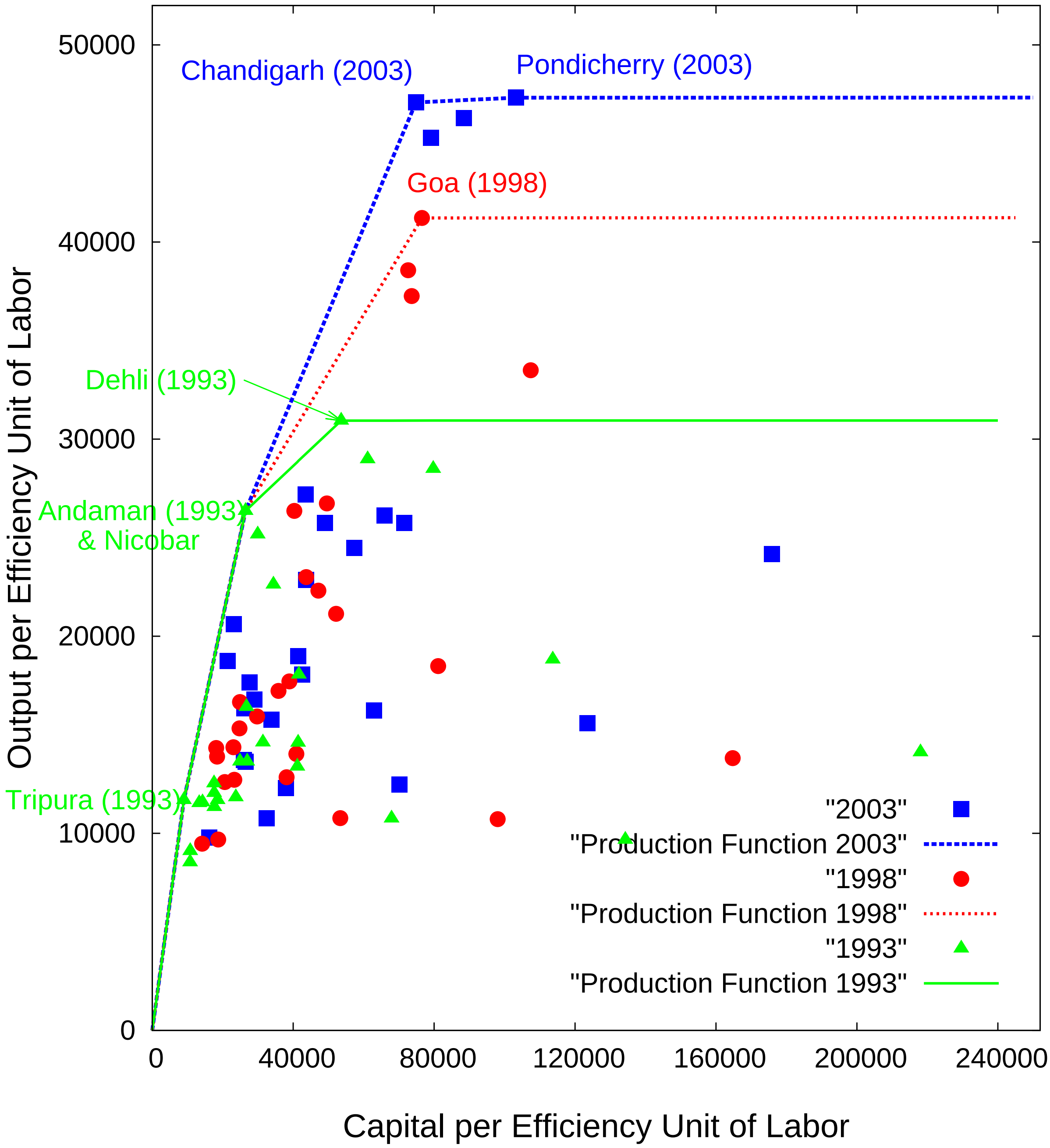

Figure 13: Estimated Best-Practice Production Frontiers for India in 1993, 1998, and 2003

Table 17: Growth Regressions of the Percentage Change in Output per Worker and the Four Decomposition Indices on Output per Worker in Base Period

Regression	(A)	(B)	(C)	(D)	(E)
	(PROD−1) ×100	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100	(HACC−1) ×100
Constant	35.59	-9.15	3.02	43.45	7.92
	0.000	0.276	0.707	0.003	0.003
Slope	3.1E-04	1.4E-04	6.8E-04	-6.9E-04	-9.4E-05
	0.374	0.557	0.003	0.031	0.199

Notes: *p*-values under estimates, based on "heteroskedasticity-consistent" estimators for the variance (Huber, 1981; White, 1980).

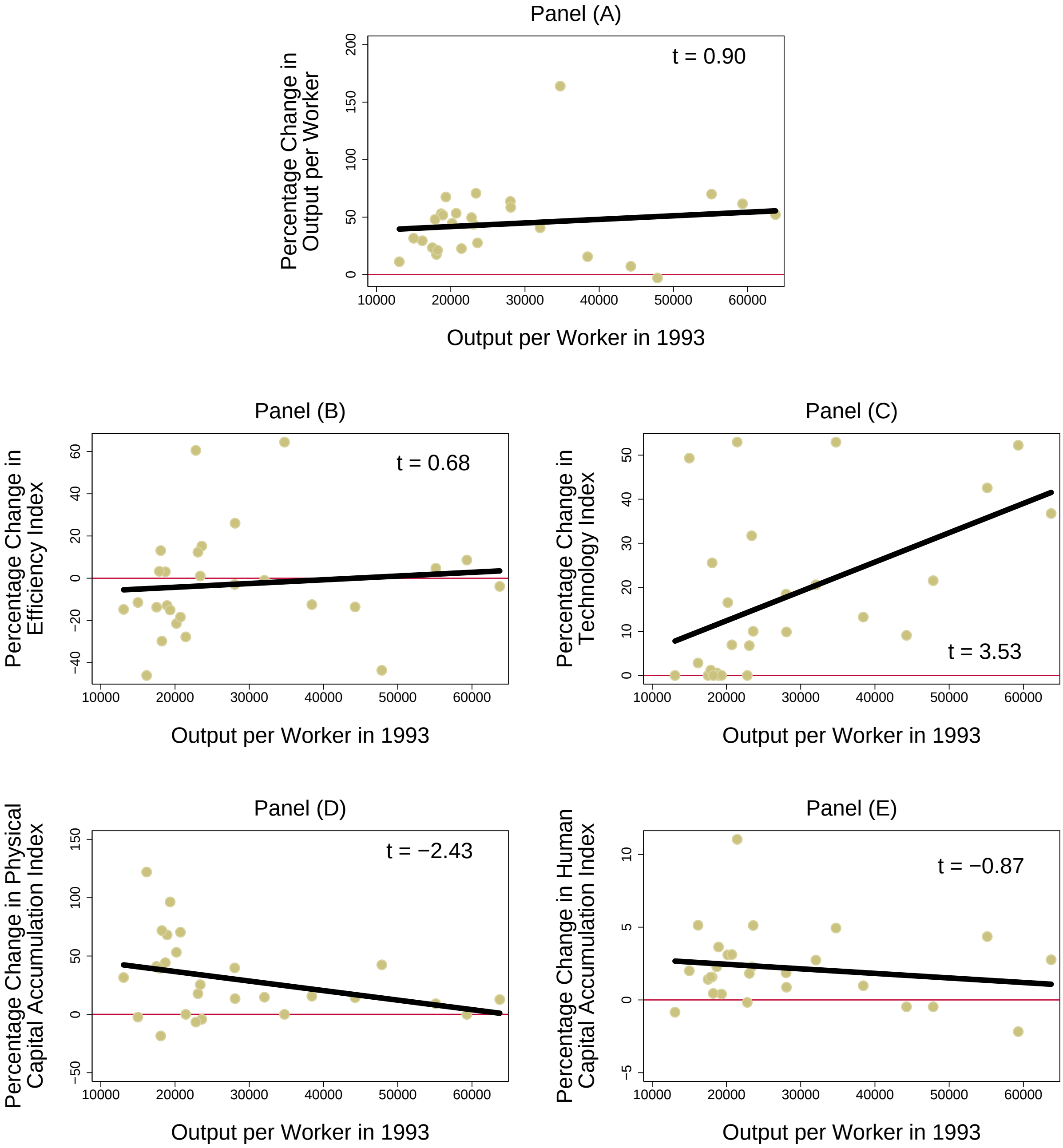

Figure 14: Percentage change (from 1993 to 2003) in output per worker and four decomposition indexes, plotted against output per worker in 1993

Note: Each panel contains a GLS regression line.

Table 18: Distribution Hypothesis Tests (p-values)

	H_0: Distributions are equal H_1: Distributions are not equal	Bootstrap p-value
	Panel A: The whole period, 1993−2003	
1	$g(y_{2003})$ vs. $f(y_{1993})$	0.0070
2	$g(y_{2003})$ vs. $f(y_{1993} \times EFF)$	0.1268
3	$g(y_{2003})$ vs. $f(y_{1993} \times TECH)$	0.7786
4	$g(y_{2003})$ vs. $f(y_{1993} \times KACC)$	0.0804
5	$g(y_{2003})$ vs. $f(y_{1993} \times HACC)$	0.0136
6	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times TECH)$	0.9494
7	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times KACC)$	0.1060
8	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times HACC)$	0.1468
9	$g(y_{2003})$ vs. $f(y_{1993} \times TECH \times KACC)$	0.9702
10	$g(y_{2003})$ vs. $f(y_{1993} \times TECH \times HACC)$	0.9660
11	$g(y_{2003})$ vs. $f(y_{1993} \times KACC \times HACC)$	0.1294
12	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times TECH \times KACC)$	0.9470
13	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times TECH \times HACC)$	0.8238
14	$g(y_{2003})$ vs. $f(y_{1993} \times EFF \times KACC \times HACC)$	0.0752
15	$g(y_{2003})$ vs. $f(y_{1993} \times TECH \times KACC \times HACC)$	0.9612
	Panel B: The 1^{st} sub-period, 1993−1998	
1	$g(y_{1998})$ vs. $f(y_{1993})$	0.0938
2	$g(y_{1998})$ vs. $f(y_{1993} \times EFF)$	0.8052
3	$g(y_{1998})$ vs. $f(y_{1993} \times TECH)$	0.9096
4	$g(y_{1998})$ vs. $f(y_{1993} \times KACC)$	0.1426
5	$g(y_{1998})$ vs. $f(y_{1993} \times HACC)$	0.1186
6	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times TECH)$	0.8138
7	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times KACC)$	0.5336
8	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times HACC)$	0.8226
9	$g(y_{1998})$ vs. $f(y_{1993} \times TECH \times KACC)$	0.7828
10	$g(y_{1998})$ vs. $f(y_{1993} \times TECH \times HACC)$	0.8734
11	$g(y_{1998})$ vs. $f(y_{1993} \times KACC \times HACC)$	0.1384
12	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times TECH \times KACC)$	0.9994
13	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times TECH \times HACC)$	0.8296
14	$g(y_{1998})$ vs. $f(y_{1993} \times EFF \times KACC \times HACC)$	0.5502
15	$g(y_{1998})$ vs. $f(y_{1993} \times TECH \times KACC \times HACC)$	0.7926
	Panel C: The 2^{nd} sub-period, 1998−2003	
1	$g(y_{2003})$ vs. $f(y_{1998})$	0.2436
2	$g(y_{2003})$ vs. $f(y_{1998} \times EFF)$	0.6348

(*continued on next page*)

Table 18 (*Continued*)

	H_0: Distributions are equal H_1: Distributions are not equal	Bootstrap p-value
3	$g(y_{2003})$ vs. $f(y_{1998} \times TECH)$	0.8420
4	$g(y_{2003})$ vs. $f(y_{1998} \times KACC)$	0.6156
5	$g(y_{2003})$ vs. $f(y_{1998} \times HACC)$	0.3414
6	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times TECH)$	0.8824
7	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times KACC)$	0.5876
8	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times HACC)$	0.6996
9	$g(y_{2003})$ vs. $f(y_{1998} \times TECH \times KACC)$	0.8920
10	$g(y_{2003})$ vs. $f(y_{1998} \times TECH \times HACC)$	0.8642
11	$g(y_{2003})$ vs. $f(y_{1998} \times KACC \times HACC)$	0.6888
12	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times TECH \times KACC)$	0.9956
13	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times TECH \times HACC)$	0.9084
14	$g(y_{2003})$ vs. $f(y_{1998} \times EFF \times KACC \times HACC)$	0.6134
15	$g(y_{2003})$ vs. $f(y_{1998} \times TECH \times KACC \times HACC)$	0.9318

Notes: We used the bootstrapped Li (1996) Tests with 5000 bootstrap replications and the Sheather and Jones (1991) bandwidth.

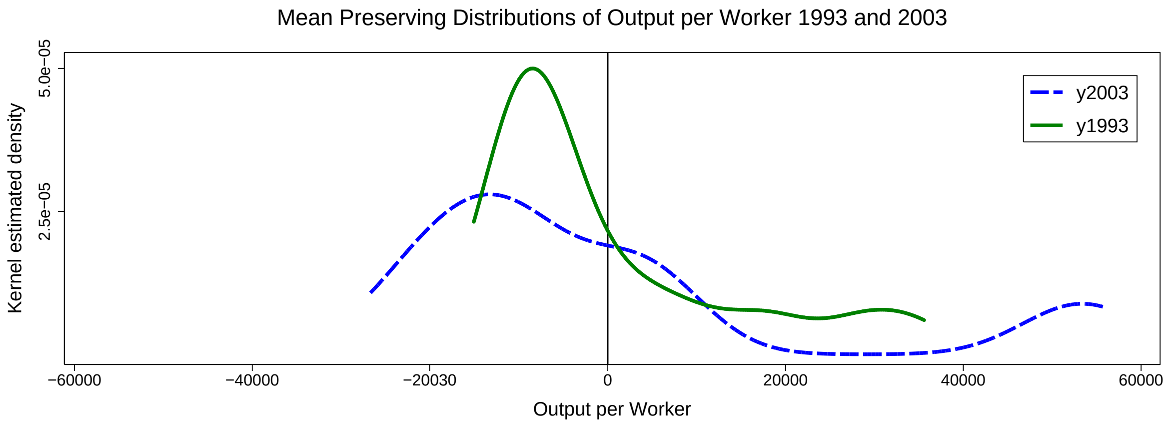

Figure 15: Actual Output per Worker Distributions

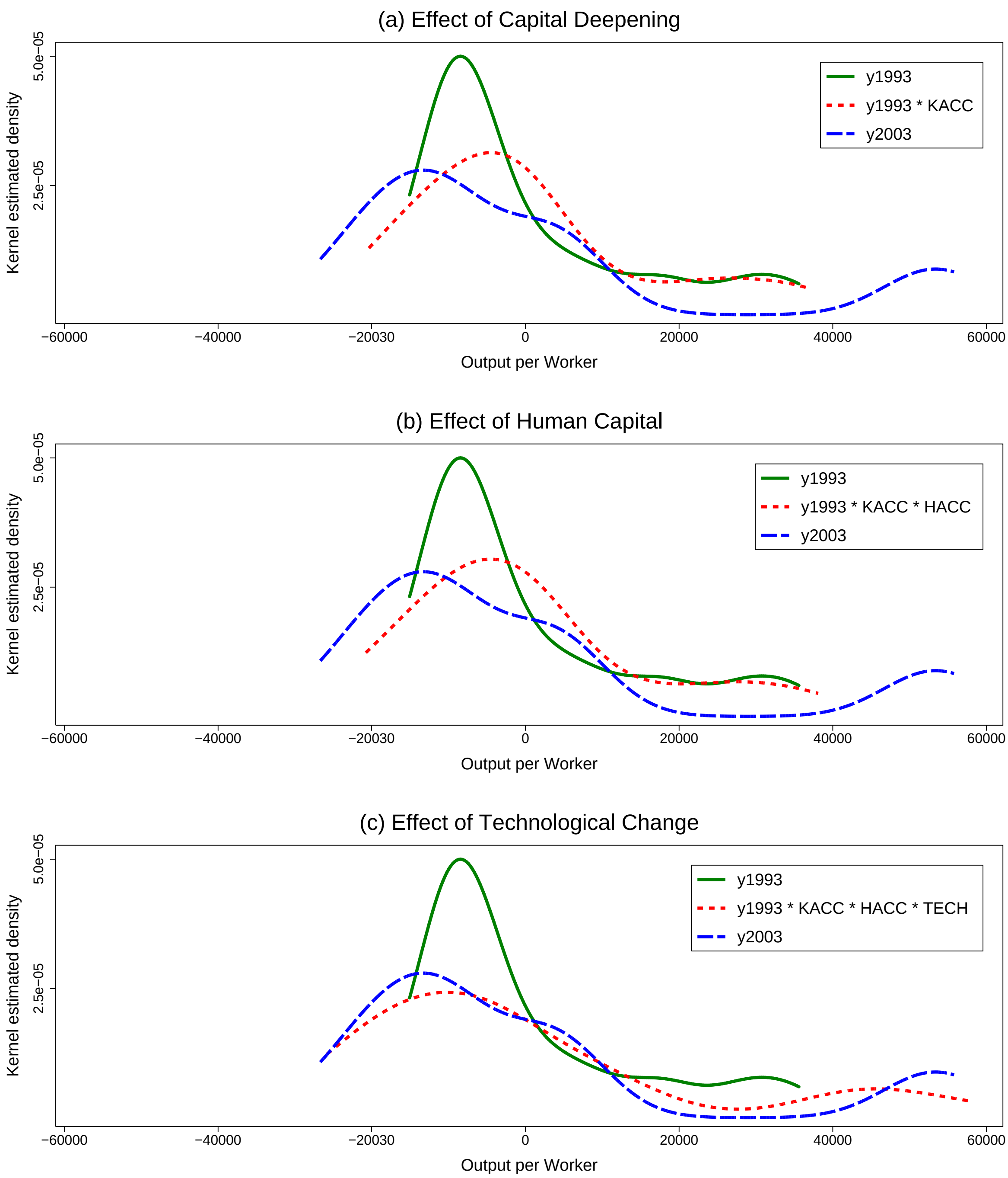

Figure 16: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: KACC, HACC, and TECH

Notes: 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.