Binghamton University (SUNY) Department of Economics
Working Paper 0609 (2006)

A Drive up the Capital Coast? Contributions to Post-Reform Growth Across Chinese Provinces

Daniel J. Henderson*
Department of Economics
State University of New York at Binghamton

Kiril Tochkov†
Department of Economics
Texas Christian University

Oleg Badunenko‡
Department of Economics
European University Viadrina

Abstract

We use nonparametric production-frontier methods to decompose the growth of labor productivity of Chinese provinces in the post-reform period. These techniques, combined with kernel density estimates, allow us to decompose the shift in the distribution of labor productivity without the need for many assumptions common in the empirical growth literature. We find that (1) the distribution of output per worker across Chinese provinces is multimodal, (2) technology change is decidedly nonneutral, (3) physical capital accumulation has been the major driving force behind the growth performance of Chinese provinces and (4) it attempts to drive convergence between provinces, but (5) minimal technological progress and human capital accumulation are key factors responsible for the regional disparities in China.

JEL: C14, O50, P27
Keywords: Convergence, Data Envelopment Analysis, Growth, Nonparametric

*Corresponding author: Daniel J. Henderson, Department of Economics, State University of New York, Binghamton, NY 13902-6000, U.S.A., Phone: 1-607-777-4480, Fax: 1-607-777-2681, e-mail: djhender@binghamton.edu.

†Kiril Tochkov, Department of Economics, Texas Christian University, TCU Box 298510, Fort Worth, TX 76129-0001, U.S.A., Phone: 1-817-257-7554, Fax: 1-817-257-5058, e-mail: k.tochkov@tcu.edu.

‡Oleg Badunenko, Department of Economics, European University Viadrina, Große Scharrnstraße 59, Frankfurt (Oder), 15230, Germany, Phone: +49(0)33555342946, Fax: +49(0)33555342959, e-mail: badunenko@uni-ffo.de.

1 Introduction

Since the introduction of market reforms, beginning in 1978, the Chinese economy has exhibited phenomenal growth, arguably qualifying it as another East Asian "miracle". However, the unprecedented economic boom at the national level conceals uneven growth patterns across provinces. Although economic reforms have been beneficial to all regional economies in China, in general, those located along the coast of China have been able to grow much faster than interior provinces in the Central and Western parts of the country.

The issue of uneven regional development in China has attracted a considerable amount of empirical research (for an overview, see Kanbur and Zhang 2001, and Lu and Wang 2002). Studies usually focus on income inequality across provinces (inter-provincial inequality), but also often group provinces in larger regions (e.g., coastal and interior) and examine inequality within a given region (intra-regional inequality) or between regions (inter-regional inequality). Despite differences in methodology, data sources, and time periods, most authors agree that inter-provincial disparities narrowed initially over the 1980s but have widened since the late 1980s and early 1990s. Evidence in favor of convergence in the 1980s appears to be largely attributed to declining intra-regional inequality within the group of coastal provinces. By contrast, the inter-regional inequality, especially between the coastal and interior regions, has been increasing since the start of the market transition in 1978, and has become much more pronounced over the 1990s, thereby contributing to the widening of the income gap across provinces (Jian et al. 1996; Lee 2000; Fujita and Hu 2001; Yao and Zhang 2001).

A broad range of reasons have been forwarded to explain the growing regional discrepancies in China. The advantageous geographical location of coastal provinces enabled them to engage in international trade, whereas interior provinces largely failed to integrate into the world economy and thus benefit from globalization. Besides the varying degree of openness across provinces, the uneven distribution of domestic and foreign capital investment has been identified as a major determinant of regional inequality. Coastal areas were the main beneficiaries of the large inflows of foreign direct investment as well as domestic capital (Zhang and Zhang 2003). In the labor-intensive export industries, foreign capital was combined with cheap labor supplied either via migration from interior provinces or from rural surplus labor within the coastal provinces (Fu 2004; Fujita and Hu 2001). A more developed infrastructure and higher levels of human capital in the coastal provinces gave a further boost to growth (Fleisher and Chen 1997; Demurger 2001).

The preferential policies extended to coastal provinces by the central government in the context of an unbalanced coast-oriented development strategy have also been blamed for the discrepancy in growth rates and income levels across regions (Demurger et al. 2002; Lu and Wang 2002). These policies included tax breaks as well as permission to operate special economic zones that offered lucrative business conditions to foreign firms and joint-ventures, and facilitated the inflow of disproportionately large amounts of foreign capital. Aside from spill-over effects among coastal provinces, the rapid growth along the coast largely failed to spread to the interior regions, resulting in increases in regional inequality (Ying 2000; Fu 2004).

The objective of this paper is to determine the sources of growth at the provincial level in China and to examine their impact on regional inequality. It differs from previous works in two major aspects. First, the study uses a nonparametric production-frontier approach allowing a more comprehensive decomposition of growth. Second, we examine inter-provincial convergence by analyzing the entire distribution of provincial output per worker and its dynamics over the sample period.

The nonparametric production-frontier approach to decomposing productivity growth was started by Färe et al. (1994). Since then, many papers have used nonparametric production-frontier methods with cross-country data (Kumar and Russell 2002; Henderson and Russell 2005; Los and Timmer 2005; Henderson and Zelenyuk 2007). A major benefit of this type of approach is that there is no need to specify a functional form for the technology, no need to make the assumption that technological change is neutral, or to make assumptions about market structure or the absence of market imperfections. The purpose of using this approach here is to address the debate in the empirical literature. Specifically, the question of whether the rapid economic growth of China over the reform period was driven primarily by total factor productivity growth or by factor accumulation. This issue has been addressed in the literature using national-level (Borensztein and Ostry 1996; Hu and Khan 1997; Young 2000; Wang and Yao 2003), sectoral-level (Jefferson, Rawski and Zheng 1996;

Kong, Robert and Wan 1999; Fu 2005) and provincial-level (Fleisher and Chen 1997; Ezaki and Sun 1999; Arayama and Miyoshi 2004; Miyamoto and Liu 2005) data.

Virtually all of these studies use the conventional growth-accounting method to estimate total factor productivity growth as a residual of output growth after subtracting the contribution of relevant inputs. This type of approach however relies crucially on the assumptions that the form of the production function is known and that there is neutral technological change. In this study, we instead use the nonparametric production-frontier method given in Henderson and Russell (2005) which avoids the limitations of the conventional approach and allows us to decompose the growth of labor productivity into four components attributable to technological catch-up (movements towards the frontier), technological change (shifts in the frontier), and physical and human capital accumulation (movements along the frontier).

We estimate the contribution to growth of each of the four components for 28 Chinese provinces over the period 1978-2000. In addition, we split the sample into two sub-periods to find evidence for a turning point proposed in the literature (Fujita and Hu 2001; Lu and Wang 2002) regarding the rise of regional inequality. Moreover, we try to shed light on the possible sources for regional disparities by estimating the relative importance of each growth component for different sub-samples categorized according to geographical location (coastal, interior) and level of output per worker (rich, middle, poor).

The second feature of this study is that it examines inter-provincial convergence by analyzing the entire distribution of provincial output per worker and its dynamics between 1978 and 2000. Previous studies rely mostly on estimating the relationship between the growth rate and the initial output level to detect convergence. However, this approach focuses only on the first moment of the labor productivity distribution, and thus provides only a partial view of the convergence process. It could also lead to biased results when the distribution of labor productivity is multimodal (Quah 1993, 1996, 1997).

For completeness, we first follow a regression approach and estimate whether each of the four growth components contributed to convergence across provinces over the sample period. Then we examine the entire distribution of provincial labor productivity and analyze the effects of the four growth components on the evolution of the distribution over the 1978-2000 period. In addition, we apply nonparametric kernel methods to test formally for statistical significance of the relative contribution of each of the four components to changes in the shape of the distribution.

Our results reveal several findings. First, the distribution of output per worker across Chinese provinces is multimodal with relatively few provinces in the upper modes and the majority of provinces in the larger "poor" mode. However, over the sample period several poor provinces were able to catch-up and move into the "rich" modes. Second, technology change is decidedly nonneutral, with little improvement at very low capital to effective labor ratios and rapid expansion at high capital to effective labor ratios. Third, physical capital accumulation has been the major driving force behind the growth performance of Chinese provinces over the reform period. Fourth, capital deepening helped drive convergence between provinces. This was primarily driven by the initially poor coastal provinces that caught up due to intensive capital deepening coupled with large efficiency improvements. Finally, the initially rich coastal provinces were able to grow faster because of above-average rates of technological progress and human capital accumulation. This allowed us to identify the lack of technological progress and human capital accumulation as key factors responsible for rising regional disparities in China. These hindered the growth of poor regions despite their increases in efficiency and capital deepening.

The remainder of the paper is organized as follows: the second and third sections describe the methodology and data, respectively. Section 4 summarizes the results and the final section draws conclusions.

2 Methodology

2.1 Data Envelopment Analysis

Following (the nonparametric approach of) Henderson and Russell (2005), we construct China's production-frontier and the associated efficiency levels of individual provincial economies (distances from the frontier) by using Data Envelopment Analysis.[1] The basic idea is to envelop the data in the smallest convex cone, where the

[1] A fully general exposition of this approach, aimed primarily at economists, can be found in Färe et al. (1995); the management science approach to essentially the same methods began with the paper by Charnes et al. (1978), who coined the evocative term "Data Envelopment Analysis".

upper boundary of this set represents the "best practice" production-frontier. One of the major benefits of this approach is that it does not require prior specification of the functional form of the technology. It is a data driven approach, implemented with standard mathematical programming algorithms, which allows the data to tell the form of the production function (see Kneip, Park and Simar 1998 for a proof of consistency for the Data Envelopment Analysis estimator, as well as Kneip, Simar and Wilson 2003 for its limiting distribution).

Our technology contains 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 provinces. 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 province i at time t. The constant returns to scale technology for China in period t is constructed by using all the data up to that point in time as

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

where $z_{i\tau}$ are the activity levels. By using all the previous years data, we preclude implosion of the frontier over time. It is difficult to believe that the technological frontier could implode. Thus, following an approach first suggested by Diewert (1980), we chose to adopt a construction of the technology that precludes such technological degradation.

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

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

This index 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 index is simply the ratio of actual to potential output evaluated at the actual input quantities.

2.2 Quadripartite Decomposition

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, we again follow the approach of Henderson and Russell (2005). We first note that constant returns to scale allows us to 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. By letting b and c stand for the base period and current period respectively, we see, by definition, that potential outputs per efficiency unit of labor in the two periods are given 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 indexes in the respective periods as calculated in (2) above. Accordingly,

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

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 (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 (4) and (5) with (6), we obtain

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

and

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

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

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

2.3 Comparison of Unknown Densities

Our analysis of the change in the productivity distribution exploits nonparametric kernel methods to test formally for 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.[2] 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 the same. The test statistic used to test for the difference between 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, $M(f, g) = \int_x (f(x) - g(x))^2 \, dx$, is

$$J = \frac{Nb^{\frac{1}{2}}M}{\widehat{\sigma}} \sim \text{Normal}(0, 1), \tag{10}$$

where

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

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

K is the standard normal kernel and b is the optimally chosen bandwidth.[3]

3 Data

At the provincial level, China is divided into 33 regions, including 22 provinces, five autonomous regions (ethnic minority areas in West and Southwest China), four metropolises (e.g., Beijing and Shanghai), and two special administrative regions (Hong Kong and Macau – see Figure 1). For simplicity, we will use the terms regions and provinces interchangeably. The data set includes output, labor, capital, and

[2] The explanation that follows assumes that $\{x\}$ and $\{z\}$ are two equally sized samples of size N, taken from f and g respectively. The extension to unequal sample sizes is trivial.

[3] For further details see Fan and Ullah (1999), Li (1996), and Pagan and Ullah (1999).

human capital variables for 28 Chinese provinces over the period 1978-2000.[4] The data is drawn from official publications of the Chinese statistical agency, the National Bureau of Statistics. The two major sources are the *Comprehensive Statistical Data and Materials on 50 Years of New China* and various issues of the *China Statistical Yearbook*.[5]

3.1 Output and Labor

Nominal GDP is deflated by a province-specific price index, with 1952 as the base year.[6] The price index for each province obtained from Wu (2004) is constructed using nominal GDP values and real GDP growth rates, and corresponds approximately to the average of the retail price index and the GDP deflator.

In absence of data on the number of hours worked at the regional level in China, we follow previous studies in using the number of employees in a given year as a proxy for the labor force.

3.2 Capital Stock

The capital stock of each province is estimated using the perpetual inventory method. Data on investment in fixed assets is available for all provinces in our sample for the period 1952-2000. Although investment deflators have been constructed at the national level, the lack of data prevents us from computing their equivalents at the regional level. Therefore, we deflate fixed investment using the same province-specific price index as for GDP with 1952 as the base year.

To construct the capital stock from investment flows we adopt a depreciation rate of 4% as in Chow (2002) and assume that it is constant across provinces.[7] To obtain

[4] Hainan and Tibet were dropped from the data set due to incomplete data. The city of Chongqing which received provincial status in 1997 is still treated as part of Sichuan. Hong Kong and Macau are excluded because they came under Chinese control in 1997 and 1999, respectively.

[5] Due to a lack of alternatives, the majority of empirical studies on China's economy use official statistics. The reliability of Chinese data has often been questioned, however, the extent of data falsification for political purposes in China appears to be limited (Holz 2003). Furthermore, Rawski (2001) and Chow (2002) assert that despite some problems, the official figures represent the most plausible measures of aggregate variables in China and are accurate enough for econometric analysis.

[6] The GDP data can be thought of as being measured in constant 1952 or 1978 prices, since the price level in China changed little between 1952 and the start of market reforms in 1978.

[7] This is the average depreciation rate of fixed assets of state-owned enterprises over the period 1952-1992 (China Statistical Yearbook 1997).

initial values for the capital stock of each province, we use a procedure similar to Nehru and Dhareshwar (1995) and Hall and Jones (1999). Accordingly, the initial value of the 1952 capital stock for province i is constructed as

$$K_{i,1952} = \frac{I_{i,1952}}{(\delta + g_i)}, \tag{11}$$

where I denotes the real value of fixed investment, δ is the depreciation rate and g_i is the average growth rate of real fixed investment between 1952 and 1977 for province i. The capital stock for each province is computed for the 1952-2000 period. The relatively low initial value of capital in 1952 and the high rates of investment ensure that the estimates of the capital stock for our sample period 1978-2000 are not sensitive to the 1952 benchmark value.

3.3 Human Capital

Previous studies on Chinese regional growth that incorporate human capital in the production function use either enrollment rates or the number of graduates at a certain level of education as proxies for the quality of labor.[8] Recently, Wang and Yao (2003) derived a time series of China's human capital stock in terms of the average years of schooling based on the methodology of Barro and Lee (2000). They used the perpetual inventory method with the number of graduates at different schooling levels representing the annual changes in the human capital stock. However, since the initial level of human capital was estimated using comparable data from India, their method is difficult to replicate at the regional level in China.

Instead, we estimate the average years of schooling using data from the three most recent national censuses conducted in 1982, 1990 and 2000. Census data includes the number of graduates by province at every level of education as well as the working-age population in the age group 15-64. The average years of schooling for each of the three years in which a census took place was estimated by

$$\epsilon_{it} = \frac{(6G_{1it} + 9G_{2it} + 12G_{3it} + 15.5G_{4it})}{n_{it}}, \tag{12}$$

[8] For instance, Fleisher and Chen (1997) use the annual flow of university graduates as a proxy for human capital. Alternatively, Chen and Fleisher (1996) and Jones, Li and Owen (2003) employ the number of high school students as a share of all people of high-school age.

where G_{jit} is the number of graduates in year t in province i, 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 province i. The data on the number of graduates at each educational level is thus weighted by the length of the respective schooling cycles and divided by the working-age population to produce the average years of schooling ϵ.[9] The average years of schooling for the remaining periods are obtained by interpolation. However, they correspond closely to the numbers reported by Zhang, Zhao, Park and Song (2006) who rely on data from household surveys conducted in several provinces over the 1988-2001 period.

To construct a human capital index using the average years of schooling, we adopt the approach of Bils and Klenow (2000) and define labor in efficiency units in province i at time t by

$$\hat{L}_{it} = H_{it}L_{it} = h(\epsilon_{it})L_{it} = e^{f(\epsilon_{it})}L_{it}, \tag{13}$$

where

$$f(\epsilon_{it}) = \frac{\theta}{1-\psi}\epsilon_{it}^{1-\psi}. \tag{14}$$

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

$$\frac{d\ln h(\epsilon_{it})}{d\epsilon_{it}} = f'(\epsilon_{it}) = \frac{\theta}{\epsilon_{it}^{\psi}}, \tag{15}$$

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.[10]

[9] The schooling cycles 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. 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.

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

4 Results

4.1 Production-Frontier and Efficiency

China's production-frontier in 1978, 1990, and 2000 along with scatter plots of $\hat{y}$ vs. $\hat{k}$ are presented in Figure 3. The single kink on each curve indicates that there is only one efficient provincial economy, Shanghai, which defines the frontier in each of the three years. Note that the production-frontier shifted up from 1978 to 2000 but not by the same proportion for every value of $\hat{k}$ implying that technological change was non-neutral. It is evident from the graph that, for the majority of provinces with lower ratios of capital to efficient labor, the production-frontier is almost identical in 1978, 1990, and 2000. The largest shifts of the frontier occur for the few regions with a high degree of capitalization, including the three metropolises with provincial status (Beijing, Shanghai and Tianjin).

To assess the efficiency of provincial economies we examine their location relative to the frontier. The efficiency index of each province in 1978 and 2000 is reported in the first two columns of Table 1. On average,[11] China's provincial economies moved closer to the best practice frontier over the 1978-2000 period. This is not surprising given that the transition towards a market economy in China witnessed the emergence of privately-managed firms, export-oriented corporations, and foreign joint-ventures that were more efficient in their use of inputs than state-owned enterprises. The new firms had clearly defined property rights, operated under hard-budget constraints, and responded to market incentives whereas state-owned enterprises were plagued by overproduction, misallocation of resources, and inefficient government subsidies (Shiu 2002).

The results also reveal that the largest efficiency gains were achieved in the second half of the reform period.[12] Tables 2 and 3 show that between 1978 and 1989, efficiency improved by only 3% as opposed to 17% between 1990 and 2000. The reason is that

[11]In addition to the arithmetic average, we also include the weighted average. This method, developed in Färe and Zelenyuk (2003), allows one to weight the efficiency scores by the relative output of the province.

[12]We chose 1990 as a breaking year for two reasons. It is clearly a turning point in the rise of regional inequality in China (Fujita and Hu 2001; Lu and Wang 2002). Moreover, in the aftermath of the Tiananmen Square incident economic growth stumbled, and thus 1990 marks a watershed between two periods of rapid growth.

incremental measures to reform state-owned enterprises were initiated only in the mid-1980s and were soon put on hold or even reversed when serious macroeconomic imbalances coupled with political discontent led to massive protests on Tiananmen Square in 1989. Starting in 1992, a new round of economic liberalization promoted the privatization of state enterprises, the gradual elimination of price controls, the creation of stock exchanges, and an enhanced role for trade and foreign investment, all of which contributed to higher efficiency.

From looking at the province-specific estimates, it is evident that the improvements in efficiency vary widely across regions. Shanghai, the richest regional economy in China, is also the most efficient one. With an efficiency score of 1.00, it is the only province located on the best practice frontier throughout the 1978-2000 period. Whereas the wealthy province of Guangdong was already highly efficient at the start of economic reforms and its efficiency score changed little in the following two decades, other coastal provinces including Jiangsu, Zhejiang and Fujian were able to catch up with large efficiency improvements. By contrast, poor provinces in Southwest China such as Guizhou, Sichuan or Yunnan were far away from the best practice frontier in 1978, and experienced only modest increases in efficiency by 2000.

These results are in line with the findings of several previous works. Wu (1995) and Ao and Fulginiti (2003) report provincial efficiency estimates for the periods 1985-1991 and 1978-1998, respectively. Although both studies use parametric frontier techniques, do not include human capital, and focus on shorter time periods, their estimates are similar to ours, indicating that Shangahai and Guangdong are at the top and Guizhou is at the bottom of the efficiency rankings.

Technological catch-up, represented by movements towards the frontier, could result in convergence in output per worker across regions if poor provinces benefit more from efficiency improvements than rich ones. To examine this issue, we split the sample into rich and poor provinces. Using the distribution of output per worker across provinces in the base period and current period (see Figure 4), we categorize rich provinces as those included in the upper modes in each of the two time periods. The remaining provinces concentrated in the larger lower mode are classified as poor.

The averages of the efficiency indexes for the sub-samples are reported in the first two columns of Table 4. Clearly, wealthy provinces are closer to the frontier than poor ones throughout the sample period. This is echoed by the size of the weighted average of the efficiency scores for all provinces relative to that of the simple average. Given that the weight of the efficiency score is determined by the relative output of the province, it is obvious that the larger economies are more efficient. By 2000, many poor provinces fail to reach even the 1978 efficiency levels of the rich provinces. Furthermore, rich provinces show larger increases in efficiency than poor ones. The efficiency gains of the rich improved by 24% while that of the poor was merely 17%. This suggests that changes in efficiency may be leading to a widening of the regional gap.

We also categorized provinces as rich (poor) if their output per worker was above (below) the median in each year. We obtained two sub-samples with 10 regions each and a middle group consisting of 8 provinces that switched from rich to poor (or vice versa). With this classification, the improvement in efficiency was 16% for the rich and 8% for the poor provinces. However, the group of provinces that crossed the median output per worker saw their efficiency rise (33%) by more than the rich regions.

Lastly, we split the sample into coastal and interior provinces. The efficiency averages displayed in Table 4 indicate that the provinces along China's coast are more efficient and improved their efficiency by larger amounts than the provinces of Central and Western China. This result, supported by previous studies (Wu 1995; Ao and Fulginiti 2003), was to be expected given that the majority of rich provinces are located along the coast. Moreover, the coastal provinces with output per worker below the 1978 median value were also the ones that managed to catch up in terms of efficiency due to their advantageous geographical location that allowed them to benefit most from the opening of China to foreign trade and investment. This corresponds to convergence within the group of coastal provinces reported in the literature (Fujita and Hu 2001).

4.2 Quadripartite Decomposition of Labor Productivity

To gain a more detailed understanding of the factors that contributed to the growth performance of China's provinces, we decompose productivity growth into components attributable to (1) efficiency changes, (2) technological changes, (3) capital deepening, and (4) human capital accumulation. The growth in labor productivity of each province is shown in the third column of Tables 1-3. It is evident that over the entire sample period Chinese provinces experienced stunning increases in productivity. On average, regional output per worker in China quadrupled over a period of 22 years, rivaling the performance of the East Asian “growth miracles”. At one end of the spectrum, the coastal provinces Zhejiang and Jiangsu saw their productivity grow almost tenfold, at the other end, the productivity of the landlocked Western province of Qinghai less than doubled. As can be seen from Table 4, rich and coastal provinces have higher growth rates over the sample period as well as over each of the two sub-periods. The difference between the growth rates of the rich and poor provinces in 1990-2000 is much larger than in 1978-1989, pointing towards increasing divergence between the two groups in the second decade of reforms.

The contributions of changes in efficiency, technological change, capital deepening, and human capital accumulation for the entire sample period 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 spurt in labor productivity at the provincial level in China confirming the findings of previous studies (Wang and Yao 2003; Wu 2003; Arayama and Miyoshi 2004; Miyamoto and Liu 2005). The average contribution of efficiency change is 20% followed by technological change and human capital accumulation, each less than 6%.

Several individual economies deserve special attention. For the two rich metropolises, Beijing and Shanghai, the contribution of efficiency is negligible because their economies were either close to or on the frontier at the start of the sample period. Although physical capital accumulation contributes the most, the percentage increase is below the provincial average. Thus, capital accumulation cannot solely explain their above average change in productivity. Their growth is also strongly driven by technological change and human capital accumulation. The contribution of each of the two components is well above the provincial average. This is most likely the result of a high concentration of top national universities and research institutes in these cities. Moreover, their high level of urbanization ensures that school enrollment rates are higher than in provinces with a predominantly rural population (Heckman 2005).

The provinces Fujian, Zhejiang and Jiangsu were not among the richest regions at the start of the reform period but exhibited phenomenal growth over the following two decades. They are located along the coast between Shanghai and Hong Kong, and across from Taiwan, which made them a magnet for foreign direct investment from abroad. This was facilitated by the creation of special economic zones in these provinces offering tax breaks, relaxed labor regulation and duty-free imports of inputs to foreign firms and joint-ventures. In addition, fiscal decentralization and the preferential policies of the central government allowed coastal provinces to keep large amounts of their fiscal resources which were used to support further industrialization (Tochkov 2006). It is therefore not surprising to see that their growth spurts resulted largely from physical capital accumulation.

Interestingly, technological innovation does not represent any significant contribution to growth for these three provinces. However, the inflow of foreign capital and expertise, and the closure of inefficient state-owned enterprises, seems to have brought above-average improvements in efficiency. In fact, Shiu (2002) shows that the foreign-funded enterprises and state-owned enterprises of the heavy industry sector in the coastal provinces were on average more efficient than their counterparts in Central and Western China. Furthermore, Wu (2000) provides empirical evidence for technological catch-up between Fujian and Guangdong, and the highly efficient neighboring economies of Hong Kong and Taiwan.

A similar story can be told about the wealthy coastal province Guangdong. It is located next to and has the closest economic ties with Hong Kong, has the largest number of special economic zones, and absorbed large amounts of investment from abroad. Guangdong has received preferential treatment from the central government and has always been at the forefront of any economic reforms. Its eightfold increase in labor productivity over the sample period is attributable solely to physical capital accumulation which has the highest contribution to growth of all provinces. Neither technological change, nor human capital accumulation are above average, and given that Guangdong was very close to the frontier at the start of the reforms precludes large increases in efficiency.

Two groups of provinces that showed below-average productivity growth are also noteworthy. Liaoning and Jilin are located in the Northeast, home to the traditional industrial base of socialist China. The large amount of old state-owned enterprises has prevented them from catching up. Their growth comes primarily from above-average efficiency improvements resulting from reforms and privatization of the state sector, and in the case of Liaoning (a coastal province) from foreign investment. The other group includes Gansu, Qinghai and Ningxia, three isolated provinces in the Northwest. Their labor productivity only doubled over a period of 22 years with technological change and physical capital accumulation both contributing well below the provincial average. Growth here was heavily driven by large improvements in efficiency, and in the case of Ningxia and Gansu, by human capital accumulation. The importance of human capital for these provinces is surprising, but has been confirmed in prior studies (Arayama and Miyoshi 2004; Miyamoto and Liu 2005). We can only speculate, but it could be that the introduction of compulsory secondary education in China boosted enrollment rates dramatically in these two provinces.

Table 4 shows the average changes in productivity and the quadripartite decomposition for sub-samples of provinces. Regardless of the categorization method, rich provinces experienced increases in labor productivity due to faster-than-average rates of technological progress as reflected in shifts of the frontier documented above. The contribution of human capital accumulation is also well above average. The picture is very similar for the group of coastal provinces. The weaker growth performance of poor and interior provinces is attributable to the lack of technological progress and below-average human capital accumulation, although in terms of efficiency improvements, they were close to the rich coastal provinces. The middle group of provinces that managed to cross the median output per worker between 1978 and 2000 experienced productivity gains that were above average and close to that of rich provinces. This resulted mostly from improvements in efficiency that were larger than any other group. The quadripartite decomposition for the two sub-periods, 1978-1989 and 1990-2000, indicate that each of the four components of labor productivity increased much faster in the second decade which was due to the intensification of economic liberalization and the further opening to foreign trade and investment (Fujita and Hu 2001; Lu and Wang 2002; Arayama and Miyoshi 2004).

4.3 Regression Analysis

To examine the impact of growth on the regional income distribution in China, we regress the change in labor productivity and its four components on the initial level of output per worker. The estimates are presented in Table 5 and the scatter plots along with fitted regression lines are displayed in Figures 5-7.

Panel A of Figure 5 illustrates the relationship between labor productivity growth over the entire sample period and the initial level of output per worker. Although increases in productivity reflect positive growth for all provinces, there is a wide dispersion of growth rates at lower income levels. In contrast, most of the rich provinces in 1978 recorded above-average growth resulting in a positive slope of the regression line. The slope, while not statistically significant, reflects the view that the market transition in China has led to a more unequal provincial income distribution. In particular, it is well documented that the income gap across provinces has been widening since the late 1980s and early 1990s after an initial period of convergence in the early years of reform (Zhang, Liu, and Yao 2001; Lu and Wang 2002). The results of our regression analysis for the two sub-periods support these findings. The regression line for the 1978-1989 period (Panel A in Figure 6) slopes (insignificantly) downward suggesting that poor provinces were catching up with the rich, whereas the positive (insignificant) slope for the 1990s (Panel A in Figure 7) suggests regional divergence in labor productivity.

Panel B, in Figures 5-7, shows the relationship between the contribution of efficiency to productivity growth and the initial level of output per worker. The scatter plots do not provide a clear pattern due to the wide dispersion of efficiency changes for all levels of income. This suggests that for the entire sample period, technological catch-up did not play a major role in equalizing income levels across Chinese provinces.

The link between productivity growth attributable to technological change and the initial level of output per worker is shown in Panel C. The regression line has a statistically significant positive slope in each case, implying that technological change is associated with income divergence across regions. From the scatter plot it is evident that the majority of provinces did not achieve any technological change and the positive slope is largely driven by a few rich provinces that were able to benefit from new technologies.

The only component of productivity growth that minimized regional disparities appears to be the accumulation of physical capital. As shown in Panel D, the regression line has a statistically significant (at the 10% level) negative slope signaling that provinces with lower levels of income in 1978 recorded higher productivity growth stemming from capital accumulation than did rich provinces. This is equally true in the two sub-periods where the slope coefficients are both statistically significant at the 5% level.

Lastly, Panel E displays the relationship between the contribution of human capital accumulation and the initial level of output per worker. The slope coefficient suggests that human capital accumulation led to a the widening of the provincial income gap. This result also holds in both sub-periods. Significant and growing disparities in educational attainment between coastal and interior provinces have been reported by Zhang and Zhang (2003) and Wang and Yao (2004). A possible explanation is that due to fiscal decentralization during the reform period, interior provinces received smaller amounts of fiscal transfers that were insufficient to support necessary investment in human capital. In addition, Fleisher and Chen (1997) find that the rates of return to investment in higher education in interior provinces are higher than in the coastal region. However, the low rates of return on infrastructure investment create an environment that is not attractive enough to prevent human capital from migrating to the coast, thus exacerbating regional inequality.

In summary, we have seen that although there was some hint of convergence early in the sample, powered by capital deepening, there was a strong divergence in the end of the sample. Although capital accumulation continued to attempt to equate incomes across provinces, the effects of technological change and human capital accumulation led to further distance between the rich and poor. However, some of the initially poor, coastal provinces, were able to capitalize on their location and became rich provinces by attracting large amounts of physical capital. Interestingly, these graphs suggest that efficiency did little, if anything, to equalize incomes.

4.4 Productivity Distributions

Although the regression analysis in the previous section provides important clues about the impact of the four growth components on the regional income gap in China, we reexamine the issue of convergence by comparing the distributions of labor productivity. This is necessary because any conclusions about convergence based on the first moment of the distribution could be misleading, particularly in cases when the distribution is multimodal (Quah 1993, 1996, 1997). The labor productivity distributions (which are nonparametric kernel-based density estimates) appear in Figure 4. The solid and dashed curves represent the distributions of output per worker in the base and current period, respectively, with their corresponding mean values shown as vertical lines.

It is evident that the distribution in each year is in fact multimodal, underlying the importance of conducting a distributional analysis. However, a profound change in the shape of the distribution occurred over the sample period. In 1978, the majority of provinces were concentrated around a relatively low value of output per worker. Close to this "poor" mode we observe several smaller modes at higher income levels. By 2000, the "poor" mode shifted to the right, resulting in a higher mean labor productivity but also an increase in the variance of output per worker. The reason for this increase is that some poor provinces failed to grow as fast, whereas others, such as the middle group of coastal provinces, were able to catch up with regions considered rich in 1978. Furthermore, the relatively small but distinct "rich" modes of 1978 moved far to the right of the "poor" mode as indicated by the long tail of the distribution in 2000. In other words, a few rich provinces achieved higher growth which led to a widening of the income gap between them and the majority of provinces. This is consistent with the positive slope of the regression line in Panel A of Figure 5.

By using the quadripartite decomposition of productivity growth, we can explore the role of each of the four components in the transformation of the productivity distribution over the sample period. For this purpose we adhere to the methodology of Henderson and Russell (2005) and rewrite (9) as follows:

$$y_c = (EFF \times TECH \times KACC \times HACC) \times y_b. \tag{16}$$

Accordingly, 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. To isolate the impact of each component, we create counterfactual distributions by introducing each of the components in sequence. For instance, we assess the shift of the labor productivity distribution due solely to efficiency changes by examining the counterfactual distribution of the variable

$$y^E = EFF \times y_b, \tag{17}$$

assuming no capital deepening, technological change or human capital accumulation. These counterfactual distributions are shown as dotted curves in Panel A of Figures 8-10 along with the actual distributions in the base and current periods. The moderate loss of probability mass at the "poor" mode, for the entire sample period, and the gains in the probability mass at the "rich" modes reflect the fact that some of the poor provinces in 1978 were able to move closer to the production-frontier by 2000. This result is driven by changes in the second sub-period. Panel A of Figure 9 shows that efficiency changes at the beginning of the sample led to an increase in the probability mass of the "poor" mode, while changes in efficiency led to a large decrease in the mass of the "poor" mode towards the end of the sample (Panel A of Figure 10). However, the small shift in the mean labor productivity (the vertical dotted line), in each figure, indicates that improvements in efficiency played a minor role in the increase of the average output per worker.

The counterfactual distribution of the variable

$$y^{EK} = (EFF \times KACC) \times y_b = KACC \times y^E, \tag{18}$$

drawn in Panel B of Figures 8-10, isolates the joint effect of efficiency changes and capital deepening on the base period distribution. The large increase in the mean labor productivity provides strong evidence that capital accumulation is the primary driving force in increasing output per worker. Furthermore, it is obvious that by introducing capital deepening, the counterfactual distribution becomes almost identical to the current period distribution. The prominent "poor" and "rich" modes are replaced by a wide lower mode and a relatively short tail at higher income levels. This reflects the equalizing effect of capital deepening across provinces.

The additional effect of human capital accumulation on the distribution of y^{EK} can be observed by successfully multiplying $HACC$:

$$y^{EKH} = (EFF \times KACC \times HACC) \times y_b = HACC \times y^{EK}. \tag{19}$$

The resulting counterfactual distributions are shown in Panel C of Figures 8-10. Besides a minor increase in the mean productivity, the distribution is almost identical to that in Panel B. The only visible change is the slightly longer upper tail of the distribution indicating that human capital accumulation has more than proportionally benefited rich provinces and has thus contributed to provincial divergence. The effect of the last component, technological change, can be deduced from comparing the counterfactual distribution of y^{EKH} and the actual distribution in 2000. As with human capital accumulation, the only contribution of technological change seems to be an additional extension of the tail of the distribution towards higher levels of income resulting in a higher mean labor productivity and further divergence.[13]

To complement the counterfactual distributions, we perform formal tests for statistical significance of differences between the actual and counterfactual distributions as detailed in the methodology section. The first test in Table 6 indicates that the distributions in 1978 and 2000 are significantly different at the 1% significance level. The next four tests compare the actual distribution in 2000 with the counterfactual distributions, assuming that only one of the four components is introduced each time. The small changes in the test statistics show that efficiency changes, technological changes and changes in human capital did little to shift the base period distribution. However, solely including physical capital decreases the test statistic such that the p-value = 0.7570. In other words, if only physical capital accumulation is added to the 1978 distribution, the resulting counterfactual distribution is not significantly different from the actual 2000 distribution. This confirms our findings above that

[13]We also performed the distribution analysis using different sequencing combinations. The results are not sensitive to changes in the sequencing order. The introduction of capital deepening always leads to a large increase in mean labor productivity, whereas human capital accumulation, technological change and efficiency improvements contribute only modestly to higher output per worker. With respect to the transformation of the distribution, it is again capital deepening that can explain the shift of the probability mass between the base and current periods. Technological change and human capital accumulation lead only to longer tails and divergence whereas efficiency leads to distinct modes and mild divergence. These results are available from the authors upon request.

capital deepening alone can explain the overall change in the distribution from 1978 to 2000. The remaining tests offer further evidence. In fact, regardless of whether we test the combined effect of two or three components on the 1978 distribution, unless physical capital accumulation is included, the test concludes that the actual and counterfactual distributions are significantly different from one another. The results hold for the two sub-periods.

5 Conclusion

In this paper, we attempted to identify the sources of growth for provincial economies in China and to determine their contribution to increasing regional disparities over the reform period. Our results indicate that (1) the distribution of output per worker across Chinese provinces is multimodal with relatively few provinces in the upper modes and the majority of provinces in the larger "poor" mode. Fortuantely, over the 22 year period, several "poor" (predominantly costal) provinces moved to the "rich" modes. (2) Technological change is decidedly nonneutral, with virtually all progress taking place in the highly capital-intensive region of input space. (3) The phenomenal growth of Chinese provinces was mainly driven by physical capital accumulation, thus questioning the sustainability of their growth performance. (4) Capital deepening helped drive convergence between provinces. This was primarily driven by the intially poor costal provinces catching up due to intensive capital deepening along with large efficiency improvements. (5) Minimal technological progress and human capital accumulation are key factors responsible for the regional disparities in China. This appears to have occured because the initially rich coastal provinces were able to grow faster because of above-average rates of technological progress and human capital accumulation. On the other side, poor provinces improved their efficiency and increased their levels of physical capital, however most were unable to catch up with the rich because of a lack of technology advances and human capital accumulation.

References

[1] Ao, X., and L. Fulginiti (2003). "Productivity Growth in China: Evidence from Chinese Provinces," University of Nebraska-Lincoln, *mimeo.*

[2] Arayama, Y., and K. Miyoshi (2004). "Regional Diversity and Sources of Economic Growth," *World Economy* 27, 1583-1607.

[3] Barro, R. J., and J-W. Lee (2000). "International Data on Educational Attainment: Updates and Implications," *Oxford Economic Papers* 53, 541-563.

[4] Bils, M., and P. J. Klenow (2000). "Does Schooling Cause Growth?" *American Economic Review* 90, 1160-1183.

[5] Borensztein, S., and J. D. Ostry (1996). "Accounting for China's Growth Performance," *American Economic Review* 86, 224-228.

[6] Borjas, G. (1992). "Ethnic Capital and Intergenerational Mobility," *Quarterly Journal of Economics* 107, 123-150.

[7] Charnes, A., W. W. Cooper, and E. Rhodes (1978). "Measuring the Efficiency of Decision-Making Units," *European Journal of Operational Research* 3, 429-444.

[8] Chen, J., and B. Fleisher (1996). "Regional Income Inequality and Economic Growth in China," *Journal of Comparative Economics* 22, 141-164.

[9] Chow, G. C. (2002). *China's Economic Transformation*, Blackwell Publishing, Oxford.

[10] Démurger, S. (2001). "Infrastructure Development and Economic Growth: An Explanation for Regional Disparities in China?" *Journal of Comparative Economics* 29, 95-117.

[11] Démurger, S., J. D. Sachs, W. T. Woo, S. Bao, G. Chang, and A. Mellinger (2002). "Geography, Economic Policy, and Regional Development in China," *NBER Working Papers* 8897.

[12] Diewert, W. E. (1980). "Capital and the Theory of Productivity Measurement," *American Economic Review* 70, 260-267.

[13] Ezaki M., and L. Sun (1999). "Growth Accounting in China for National Regional and Provincial Economies," *Asian Economic Journal* 13, 39-71.

[14] Fan, Y., and A. Ullah (1999). "On Goodness-of-fit Tests for Weakly Dependent Processes Using kernel Method," *Journal of Nonparametric Statistics* 11, 337-360.

[15] Färe, R., S. Grosskopf, and C. A. K. Lovell (1995). *Production Frontiers*, Cambridge University Press, Cambridge.

[16] Färe, R., S. Grosskopf, M. Norris, and Z. Zhang (1994). "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries," *American Economic Review* 84, 66-83.

[17] Färe, R., and V. Zelenyuk (2003). "On Aggregate Farrell Efficiency Scores," *European Journal of Operational Research* 146, 615-20.

[18] Fleisher, B., and J. Chen (1997). "The Coast-Noncoast Income Gap, Productivity, and Regional Economic Policy in China," *Journal of Comparative Economics* 25, 220-236.

[19] Fu, X. (2004). "Limited Linkages from Growth Engines and Regional Disparities in China," *Journal of Comparative Economics* 32, 148-164.

[20] Fu, X. (2005). "Exports, Technical Progress and Productivity Growth in a Transition Economy: A Non-Parametric Approach for China," *Applied Economics* 37, 725-739.

[21] Fujita, M., and D. Hu (2001). "Regional Disparity in China 1985-1994: The Effects of Globalization and Economic Liberalization," *Annals of Regional Science* 35, 3-37.

[22] Hall, R. E., and C. I. Jones (1999). "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" *Quarterly Journal of Economics* 114, 83-116.

[23] Heckman, J. J. (2005). "China's Human Capital Investment," *China Economic Review* 16, 50-70.

[24] Henderson, D. J., and R. R. Russell (2005). "Human Capital and Convergence: A Production-Frontier Approach," *International Economic Review* 46, 1167-1205.

[25] Henderson, D.J., and V. Zelenyuk (2007). "Testing for (Efficiency) Catching-up," *Southern Economic Journal*, forthcoming.

[26] Huber, P. J. (1981). *Robust statistics*, John Wiley & Sons, New York.

[27] Holz, C. A. (2003). ""Fast, Clear and Accurate": How Reliable Are Chinese Output and Economic Growth Statistics?" *China Quarterly* 173, 122-63.

[28] Hu, Z., and M. S. Khan (1997). "Why is China growing so fast?" *IMF Staff Papers* 44, 103-31.

[29] Jefferson, G., T. Rawski, and Y. Zhen (1996). "Chinese Industrial Productivity: Trends, Measurement Issues, and Recent Developments," *Journal of Comparative Economics* 23, 146-80.

[30] Jian, T., J. D. Sachs, and A. M. Warner (1996). "Trends in regional inequality in China," *China Economic Review* 7, 1-21.

[31] Jones, D. C., C. Li, and A. L. Owen (2003). "Growth and Regional Inequality in China During the Reform Era," *China Economic Review* 14, 186-200.

[32] Kanbur, R., and X. Zhang (2001). "Fifty Years of Regional Inequality in China: A Journey through Revolution, Reform and Openness," *CEPR Discussion Papers* 2887.

[33] Kneip, A., B. U. Park, and L. Simar (1998). "A Note on the Convergence of Nonparametric DEA Estimators for Production Efficiency Scores," *Econometric Theory* 14, 783-93.

[34] Kneip, A., L. Simar, and P. Wilson (2003). "Asymptotics for DEA Estimators in Non-Parametric Frontier Models," Discussion Paper, Institute de Statistique, Université Catholique de Louvain, Belgium.

[35] Kong, X., E. M. Robert, and G. H. Wan (1999). "Technical Efficiency, Technological Change, and Total Factor Productivity Growth in Chinese State-Owned Enterprises in the Early 1990s," *Asia Economic Journal* 13, 267-281.

[36] Kumar, S., and R. R. Russell (2002). "Technological Change, Technological Catch-up, and Capital Deepening: Relative Contributions to Growth and Convergence," *American Economic Review* 92, 527-48.

[37] Lee, J. (2000). "Changes in the Source of China's Regional Inequality," *China Economic Review*, 11, 232-245.

[38] Li, Q. (1996). "Nonparametric Testing of Closeness between Two Unknown Distribution Functions," *Econometric Reviews* 15, 261-74.

[39] Los, B., and M. P. Timmer (2005). "The 'Appropriate Technology' Explanation of Productivity Growth Differentials: An Empirical Approach," *Journal of Development Economics* 77, 517-531.

[40] Lu, M., and E. Wang (2002). "Forging Ahead and Falling Behind: Changing Regional Inequalities in Post-Reform China," *Growth and Change* 33, 42-71.

[41] Mincer, J. (1974). *Schooling, Experience, and Earnings*, NBER Press, New York.

[42] Miyamoto, K., and H. Liu (2005). "An Analysis of the Determinants of Provincial-Level Performance in China's Economy," *Comparative Economic Studies* 47, 520-542.

[43] National Bureau of Statistics (1997-2000). *China Statistical Yearbook*, China Statistics Press, Beijing.

[44] National Bureau of Statistics (1999). *Comprehensive Statistical Data and Materials on 50 Years of New China*, China Statistics Press, Beijing.

[45] Nehru, V., and A. Dhareshwar (1993). "A New Database on Physical Capital Stock: Sources, Methodology and Results," *Revista de Analisis Economico* 8, 37-59.

[46] Pagan, A., and A. Ullah (1999). *Nonparametric Econometrics*, Cambridge University Press, Cambridge.

[47] Psacharopoulus, G. (1994). "Returns to Investment in Education: A Global Update," *World Development* 22, 1325-43.

[48] Quah, D. (1993). "Empirical Cross-Section Dynamics in Economic Growth," *European Economic Review* 37, 426-34.

[49] Quah, D. (1996). "Twin Peaks: Growth and Convergence in Models of Distribution Dynamics," *Economic Journal* 106, 1045-55.

[50] Quah, D. (1997). "Empirics for Growth and Distribution: Stratification, Polarization,and Convergence Clubs," *Journal of Economic Growth* 2, 27-59.

[51] Rawski, T. G. (2001). "What's Happening to China's GDP Statistics?" *China Economic Review* 12, 347-354.

[52] Tochkov, K. (2006). "Interregional Transfers and the Smoothing of Provincial Expenditure in China," *China Economic Review*, forthcoming.

[53] Sheather, S. J., and M. C. Jones (1991). "A Reliable Data Based Bandwidth Selection Method for Kernel Density Estimation," *Journal of Royal Statistical Society, Series B* 53, 683-90.

[54] Shiu, A. (2002). "Efficiency of Chinese Enterprises," *Journal of Productivity Analysis* 18, 255-267.

[55] Wang, Y. and Y. Yao (2001). "Sources of China's Economic Growth, 1952–99: Incorporating Human Capital Accumulation," *China Economic Review* 14, 32-52.

[56] White, H. (1980). "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica* 48, 817-830.

[57] Wu, Y. (1995). "Productivity Growth, Technological Progress, and Technical Efficiency Change in China: A Three Sector Analysis," *Journal of Comparative Economics* 21, 207-229.

[58] Wu, Y. (2000). "Productivity, Growth, and Economic Integration in the Southern China Region," *Asian Economic Journal* 14, 39-54.

[59] Wu, Y. (2004). *China's Economic Growth: A Miracle with Chinese Characteristics*, RoutledgeCurzon, New York.

[60] Yao, S., and Z. Zhang (2001). "Regional Growth in China under Economic Reforms," *Journal of Development Studies* 38, 167-186.

[61] Ying, L. G. (2000). "Measuring the Spill-Over Effects: Some Chinese Evidence," *Papers in Regional Science* 79, 75-89.

[62] Young, A. (2000). "Gold into Base Metals: Productivity Growth in the People's Republic of China during the Reform Period," *NBER Working Papers* 7856.

[63] Zhang, Z., A. Liu, and S. Yao (2001). "Convergence of China's Regional Incomes, 1952-1997," *China Economic Review* 12, 243-258.

[64] Zhang, X., and K. H. Zhang (2003). "How Does Globalization Affect Regional Inequality within A Developing Country? Evidence from China," *Journal of Development Studies* 39, 47-67.

[65] Zhang, J., Y. Zhao, A. Park, and X. Song (2005). "Economic Returns to Schooling in Urban China, 1988 to 2001," *Journal of Comparative Economics* 33, 730-752.

Table 1: Percentage change of quadripartite decomposition indexes, 1978-2000.

#	Province	TE_b	TE_c	Produtivity Change	$E-1$ $\times$ 100	$T-1$ $\times$ 100	$K-1$ $\times$ 100	$H-1$ $\times$ 100
1	Anhui	0.62	0.57	414.2	-8.4	0.0	460.8	0.1
2	Beijing	0.65	0.69	466.1	5.5	43.4	236.2	11.3
3	Fujian	0.66	0.80	780.1	20.0	1.7	568.4	7.8
4	Gansu	0.30	0.53	259.8	78.5	0.8	81.6	10.1
5	Guangdong	0.81	0.79	802.1	-1.8	1.4	757.0	5.7
6	Guangxi	0.51	0.60	337.8	16.8	0.0	274.8	0.0
7	Guizhou	0.34	0.46	240.7	32.0	0.0	158.1	0.0
8	Hebei	0.57	0.70	457.5	23.6	1.6	315.8	6.7
9	Heilongjiang	0.79	0.71	203.3	-10.4	1.5	221.7	3.6
10	Henan	0.46	0.50	371.3	6.9	0.0	332.3	2.0
11	Hubei	0.52	0.63	589.2	22.3	0.9	419.9	7.5
12	Hunan	0.68	0.60	336.0	-11.3	0.0	391.6	0.0
13	Inner Mongolia	0.49	0.66	396.1	34.6	1.9	244.5	5.0
14	Jiangsu	0.66	0.81	920.6	22.6	2.5	655.6	7.4
15	Jiangxi	0.60	0.56	449.4	-6.8	0.0	457.0	5.8
16	Jilin	0.52	0.72	349.9	39.1	1.8	206.6	3.6
17	Liaoning	0.59	0.94	335.3	58.8	3.0	154.6	4.5
18	Ningxia	0.32	0.50	224.1	66.4	2.7	69.9	11.6
19	Sha'anxi	0.45	0.52	331.7	14.8	0.9	245.0	8.0
20	Shandong	0.55	0.69	627.3	24.6	1.7	432.7	7.8
21	Shanghai	1.00	1.00	675.4	0.0	83.1	285.4	9.9
22	Shanxi	0.44	0.55	330.4	25.8	1.2	220.2	5.6
23	Sichuan	0.39	0.43	334.2	11.2	0.0	281.4	2.4
24	Tianjin	0.57	0.84	553.9	47.6	27.2	213.6	11.0
25	Qinghai	0.35	0.47	181.5	35.8	1.8	94.0	5.0
26	Xinjiang	0.41	0.57	535.0	38.5	2.6	327.6	4.5
27	Yunnan	0.47	0.48	324.2	1.7	0.0	286.8	7.9
28	Zhejiang	0.66	0.80	910.3	20.6	2.2	676.9	5.5
	Average	0.549	0.646	421.3	19.7	5.5	290.4	5.7
	Weighted Average	0.623	0.725					

Table 2: Percentage change of quadripartite decomposition indexes, 1978-1989.

#	Province	TE_b	TE_c	Produtivity Change	$E-1$ $\times$ 100	$T-1$ $\times$ 100	$K-1$ $\times$ 100	$H-1$ $\times$ 100
1	Anhui	0.62	0.63	94.4	1.1	0.0	92.3	0.0
2	Beijing	0.65	0.71	100.6	9.2	23.5	42.1	4.6
3	Fujian	0.66	0.68	143.8	3.1	0.0	136.5	0.0
4	Gansu	0.30	0.42	48.1	42.4	0.0	4.0	0.0
5	Guangdong	0.81	0.72	181.7	-11.4	0.0	217.8	0.0
6	Guangxi	0.51	0.52	53.0	1.5	0.0	50.7	0.0
7	Guizhou	0.34	0.49	85.3	42.3	0.0	30.2	0.0
8	Hebei	0.57	0.56	85.0	-2.4	0.0	89.6	0.0
9	Heilongjiang	0.79	0.52	50.1	-34.0	0.0	124.8	1.2
10	Henan	0.46	0.52	114.2	12.2	0.0	90.9	0.0
11	Hubei	0.52	0.59	120.9	14.3	0.0	93.2	0.0
12	Hunan	0.68	0.66	73.1	-2.0	0.0	76.7	0.0
13	Inner Mongolia	0.49	0.53	104.1	8.5	0.0	88.1	0.0
14	Jiangsu	0.66	0.57	163.9	-14.2	0.0	207.5	0.0
15	Jiangxi	0.60	0.60	96.8	-0.1	0.0	97.0	0.0
16	Jilin	0.52	0.54	52.5	3.9	0.0	46.7	0.0
17	Liaoning	0.59	0.69	69.2	17.6	4.8	33.5	2.9
18	Ningxia	0.32	0.43	85.3	35.3	12.9	9.0	11.2
19	Sha'anxi	0.45	0.47	104.0	4.0	0.0	96.1	0.0
20	Shandong	0.55	0.54	123.9	-2.1	0.0	128.9	0.0
21	Shanghai	1.00	1.00	103.6	0.0	36.7	42.7	4.4
22	Shanxi	0.44	0.42	85.2	-4.5	0.0	93.9	0.0
23	Sichuan	0.39	0.40	85.4	4.2	0.0	77.9	0.0
24	Tianjin	0.57	0.62	80.5	8.3	14.6	39.0	4.7
25	Qinghai	0.35	0.36	47.3	4.1	4.4	30.8	3.5
26	Xinjiang	0.41	0.42	152.2	3.2	0.5	131.5	5.0
27	Yunnan	0.47	0.57	96.1	22.3	0.0	60.4	0.0
28	Zhejiang	0.66	0.63	158.3	-5.5	0.0	173.3	0.0
	Average	0.549	0.565	95.4	4.6	3.2	78.7	1.3
	Weighted Average	0.623	0.618					

Table 3: Percentage change of quadripartite decomposition indexes, 1990-2000.

#	Province	TE_b	TE_c	Produtivity Change	$E-1$ $\times$ 100	$T-1$ $\times$ 100	$K-1$ $\times$ 100	$H-1$ $\times$ 100
1	Anhui	0.59	0.57	165.0	-4.0	0.0	176.1	0.0
2	Beijing	0.68	0.69	182.8	1.2	47.1	74.9	8.6
3	Fujian	0.67	0.80	247.8	18.9	1.7	176.1	4.2
4	Gansu	0.41	0.53	138.6	28.8	0.8	72.3	6.6
5	Guangdong	0.71	0.79	193.3	11.8	1.4	149.9	3.5
6	Guangxi	0.53	0.60	175.7	12.4	0.0	145.2	0.0
7	Guizhou	0.48	0.46	85.4	-5.5	0.0	96.2	0.0
8	Hebei	0.53	0.70	194.4	31.9	1.6	110.8	4.1
9	Heilongjiang	0.52	0.71	96.6	36.7	1.7	36.2	3.9
10	Henan	0.50	0.50	118.2	0.0	0.0	118.1	0.0
11	Hubei	0.57	0.63	202.8	10.8	0.9	158.2	4.9
12	Hunan	0.65	0.60	147.4	-6.9	0.0	165.7	0.0
13	Inner Mongolia	0.52	0.66	129.6	27.4	1.9	71.9	2.9
14	Jiangsu	0.53	0.81	273.3	52.3	2.5	130.4	3.8
15	Jiangxi	0.58	0.56	176.8	-3.3	0.0	178.9	2.6
16	Jilin	0.50	0.72	192.1	44.3	1.8	94.0	2.5
17	Liaoning	0.67	0.94	157.4	40.0	3.9	68.0	5.3
18	Ningxia	0.42	0.50	75.0	18.9	3.6	31.9	7.7
19	Sha'anxi	0.44	0.52	111.0	16.4	0.9	70.5	5.3
20	Shandong	0.51	0.69	216.6	34.8	1.7	121.7	4.1
21	Shanghai	1.00	1.00	269.5	0.0	93.0	79.7	6.5
22	Shanxi	0.41	0.55	125.2	36.0	1.2	57.5	3.8
23	Sichuan	0.39	0.43	128.4	9.1	0.0	108.8	0.3
24	Tianjin	0.62	0.84	243.9	35.0	29.6	81.1	8.5
25	Qinghai	0.36	0.47	89.4	30.1	2.4	32.2	7.5
26	Xinjiang	0.44	0.57	132.3	27.7	2.8	67.3	5.7
27	Yunnan	0.58	0.48	103.4	-17.6	0.0	141.6	2.1
28	Zhejiang	0.60	0.80	281.2	32.5	2.2	172.7	3.3
	Average	0.551	0.646	159.9	17.2	6.0	101.5	3.8
	Weighted Average	0.601	0.725					

Table 4: Percentage change of quadripartite decomposition indexes by classes

Comparison	Category	Statistic	TE_b	TE_c	Product. change	$E-1$ $\times 100$	$T-1$ $\times 100$	$K-1$ $\times 100$	$H-1$ $\times 100$
All									
1978-2000		Average	0.55	0.65	421.3	19.7	5.5	290.4	5.7
		Weighted Average	0.62	0.73					
1978-1989		Average	0.55	0.57	95.4	4.6	3.2	78.7	1.3
		Weighted Average	0.62	0.62					
1990-2000		Average	0.55	0.65	159.9	17.2	6.0	101.5	3.8
		Weighted Average	0.60	0.73					
Wealth Classification: mode is a cut-off									
1978-2000	Rich	Average	0.70	0.87	507.7	28.0	39.2	222.5	9.2
1978-2000	Rich	Weighted Average	0.76	0.90					
1978-1989	Rich	Average	0.70	0.76	88.5	8.8	19.9	39.3	4.2
1978-1989	Rich	Weighted Average	0.76	0.81					
1990-2000	Rich	Average	0.74	0.87	213.4	19.1	43.4	75.9	7.2
1990-2000	Rich	Weighted Average	0.80	0.90					
1978-2000	Poor	Average	0.52	0.61	446.1	20.7	1.1	340.8	5.2
1978-2000	Poor	Weighted Average	0.53	0.65					
1978-1989	Poor	Average	0.52	0.53	100.2	5.3	0.7	93.7	0.9
1978-1989	Poor	Weighted Average	0.53	0.53					
1990-2000	Poor	Average	0.52	0.61	158.3	18.5	1.2	111.8	3.3
1990-2000	Poor	Weighted Average	0.52	0.65					
Wealth Classification: median is a cut-off									
1978-2000	rich	Average	0.67	0.78	535.3	20.7	16.6	346.6	7.1
1978-2000	rich	Weighted Average	0.73	0.85					
1978-1989	rich	Average	0.67	0.65	100.8	-0.9	8.0	93.7	1.8
1978-1989	rich	Weighted Average	0.73	0.74					
1990-2000	rich	Average	0.63	0.78	200.6	26.4	18.4	98.3	5.2
1990-2000	rich	Weighted Average	0.73	0.85					
1978-2000	middle	Average	0.46	0.61	481.1	38.8	1.8	308.9	7.2
1978-2000	middle	Weighted Average	0.43	0.64					
1978-1989	middle	Average	0.46	0.49	105.5	9.5	2.2	88.5	2.5
1978-1989	middle	Weighted Average	0.44	0.49					
1990-2000	middle	Average	0.48	0.61	163.3	28.5	2.1	91.5	5.4
1990-2000	middle	Weighted Average	0.48	0.64					
1978-2000	poor	Average	0.50	0.54	353.6	9.2	0.3	313.2	3.1
1978-2000	poor	Weighted Average	0.50	0.55					
1978-1989	poor	Average	0.50	0.54	90.6	9.4	0.0	76.0	0.0
1978-1989	poor	Weighted Average	0.50	0.54					
1990-2000	poor	Average	0.53	0.54	134.1	2.8	0.3	127.3	1.3
1990-2000	poor	Weighted Average	0.52	0.55					
Geographical Classification									
1978-2000	Coastal	Average	0.66	0.79	624.2	21.7	15.3	415.5	7.1
1978-2000	Coastal	Weighted Average	0.73	0.85					
1978-1989	Coastal	Average	0.66	0.66	114.9	0.4	7.2	105.6	1.5
1978-1989	Coastal	Weighted Average	0.73	0.75					
1990-2000	Coastal	Average	0.64	0.79	221.4	24.6	16.8	119.1	4.7
1990-2000	Coastal	Weighted Average	0.74	0.85					
1978-2000	Interior	Average	0.48	0.56	345.4	21.8	0.9	264.6	4.9
1978-2000	Interior	Weighted Average	0.49	0.58					
1978-1989	Interior	Average	0.48	0.51	87.9	9.2	1.0	73.1	1.2
1978-1989	Interior	Weighted Average	0.49	0.49					
1990-2000	Interior	Average	0.49	0.56	130.4	14.6	1.1	98.7	3.3
1990-2000	Interior	Weighted Average	0.48	0.58					

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)	Regression (B)	Regression (C)	Regression (D)	Regression (E)
	$PROD - 1$ $\times$ 100	$EFF - 1$ $\times$ 100	$TECH - 1$ $\times$ 100	$KACCUM - 1$ $\times$ 100	$HACCUM - 1$ $\times$ 100
Comparison 1978–2000, base period is 1978					
Constant	434.18	21.02	-10.91	376.35	3.95
	0.000	0.002	0.000	0.000	0.000
Slope	2.0E-05	7.2E-07	1.7E-05	-5.1E-05	1.7E-06
	0.511	0.886	0.000	0.086	0.004
Comparison 1978–1989, base period is 1978					
Constant	104.11	7.07	-4.99	104.49	-0.07
	0.000	0.085	0.000	0.000	0.890
Slope	-5.5E-06	-1.3E-06	8.3E-06	-1.8E-05	1.4E-06
	0.310	0.505	0.000	0.008	0.001
Comparison 1990–2000, base period is 1990					
Constant	141.31	18.11	-12.64	123.65	2.26
	0.000	0.003	0.000	0.000	0.005
Slope	1.2E-05	2.2E-07	9.8E-06	-8.3E-06	7.9E-07
	0.511	0.916	0.000	0.032	0.024

Notes: p-values in parentheses, based on “heteroskedasticity-consistent” estimators for the variance (Huber 1981 and White 1980).

Table 6: Distribution Hypotheses Tests

H_0 : Distributions are equal H_1 : Distributions are not equal	Value of statistic	Bootstrap p-value	Conclusion of testing H_0
1978-2000			
$g(y_{2000})$ vs. $f(y_{1978})$	13.5423	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1978} \times EFF)$	10.7953	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1978} \times TECH)$	14.0844	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1978} \times KACC)$	0.2078	0.7570	fail to reject
$g(y_{2000})$ vs. $f(y_{1978} \times HACC)$	13.1475	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1978} \times EFF \times TECH)$	11.0298	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1978} \times EFF \times KACC)$	0.0760	0.9186	fail to reject
$g(y_{2000})$ vs. $f(y_{1978} \times EFF \times HACC)$	10.1118	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1978} \times TECH \times KACC)$	0.1964	0.7640	fail to reject
$g(y_{2000})$ vs. $f(y_{1978} \times TECH \times HACC)$	13.3958	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1978} \times KACC \times HACC)$	0.1109	0.8748	fail to reject
$g(y_{2000})$ vs. $f(y_{1978} \times EFF \times TECH \times KACC)$	0.0080	0.9910	fail to reject
$g(y_{2000})$ vs. $f(y_{1978} \times EFF \times TECH \times HACC)$	9.9615	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1978} \times EFF \times KACC \times HACC)$	0.0695	0.9196	fail to reject
$g(y_{2000})$ vs. $f(y_{1978} \times TECH \times KACC \times HACC)$	0.0598	0.9346	fail to reject
1978-1989			
$g(y_{1989})$ vs. $f(y_{1978})$	5.2432	0.0002	reject
$g(y_{1989})$ vs. $f(y_{1978} \times EFF)$	5.3956	0.0000	reject
$g(y_{1989})$ vs. $f(y_{1978} \times TECH)$	5.1430	0.0004	reject
$g(y_{1989})$ vs. $f(y_{1978} \times KACC)$	-0.1343	0.8454	fail to reject
$g(y_{1989})$ vs. $f(y_{1978} \times HACC)$	5.1089	0.0002	reject
$g(y_{1989})$ vs. $f(y_{1978} \times EFF \times TECH)$	5.4117	0.0002	reject
$g(y_{1989})$ vs. $f(y_{1978} \times EFF \times KACC)$	0.0163	0.9800	fail to reject
$g(y_{1989})$ vs. $f(y_{1978} \times EFF \times HACC)$	5.3659	0.0002	reject
$g(y_{1989})$ vs. $f(y_{1978} \times TECH \times KACC)$	-0.1028	0.8896	fail to reject
$g(y_{1989})$ vs. $f(y_{1978} \times TECH \times HACC)$	4.9277	0.0006	reject
$g(y_{1989})$ vs. $f(y_{1978} \times KACC \times HACC)$	-0.1301	0.8462	fail to reject
$g(y_{1989})$ vs. $f(y_{1978} \times EFF \times TECH \times KACC)$	0.0030	0.9968	fail to reject
$g(y_{1989})$ vs. $f(y_{1978} \times EFF \times TECH \times HACC)$	5.5721	0.0000	reject
$g(y_{1989})$ vs. $f(y_{1978} \times EFF \times KACC \times HACC)$	0.0039	0.9958	fail to reject
$g(y_{1989})$ vs. $f(y_{1978} \times TECH \times KACC \times HACC)$	-0.0869	0.9050	fail to reject
1978-1989			
$g(y_{2000})$ vs. $f(y_{1990})$	6.0909	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1990} \times EFF)$	3.0500	0.0054	reject
$g(y_{2000})$ vs. $f(y_{1990} \times TECH)$	6.1581	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1990} \times KACC)$	1.1952	0.0720	fail to reject
$g(y_{2000})$ vs. $f(y_{1990} \times HACC)$	5.9276	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1990} \times EFF \times TECH)$	3.5532	0.0008	reject
$g(y_{2000})$ vs. $f(y_{1990} \times EFF \times KACC)$	0.0458	0.9506	fail to reject
$g(y_{2000})$ vs. $f(y_{1990} \times EFF \times HACC)$	3.1455	0.0046	reject
$g(y_{2000})$ vs. $f(y_{1990} \times TECH \times KACC)$	1.0664	0.0854	fail to reject
$g(y_{2000})$ vs. $f(y_{1990} \times TECH \times HACC)$	6.0031	0.0000	reject
$g(y_{2000})$ vs. $f(y_{1990} \times KACC \times HACC)$	1.2491	0.0612	fail to reject
$g(y_{2000})$ vs. $f(y_{1990} \times EFF \times TECH \times KACC)$	-0.0011	0.9994	fail to reject
$g(y_{2000})$ vs. $f(y_{1990} \times EFF \times TECH \times HACC)$	3.5104	0.0018	reject
$g(y_{2000})$ vs. $f(y_{1990} \times EFF \times KACC \times HACC)$	0.0707	0.9266	fail to reject
$g(y_{2000})$ vs. $f(y_{1990} \times TECH \times KACC \times HACC)$	1.1133	0.0778	fail to reject

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

Figure 1: China Provinces

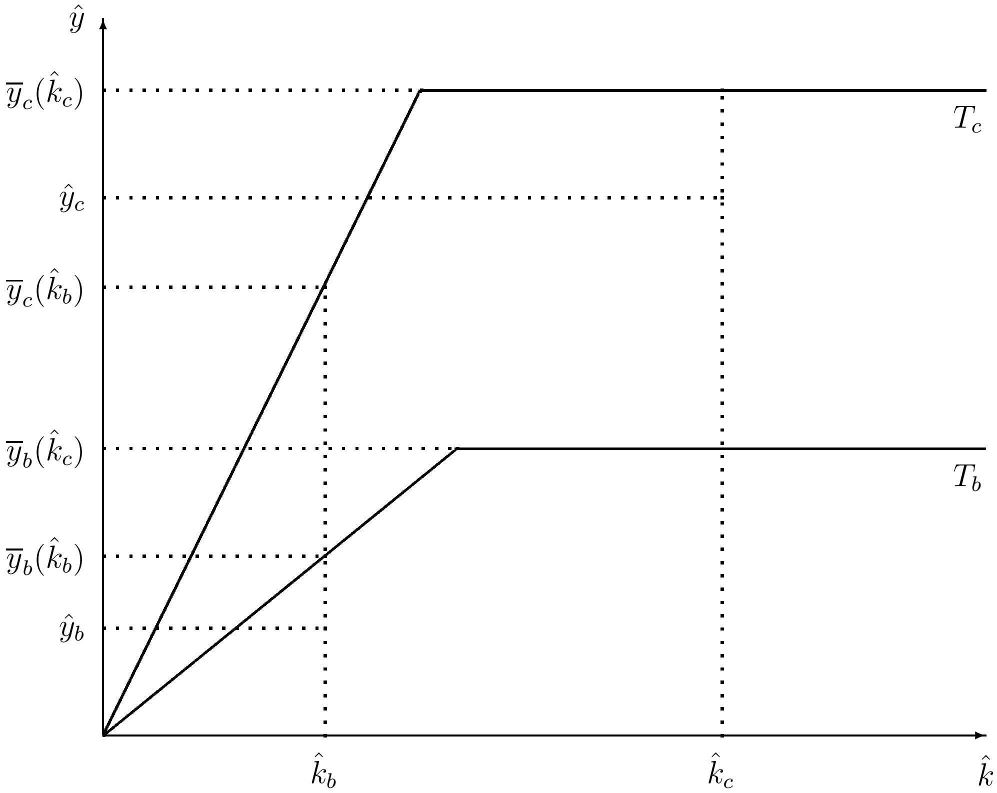

Figure 2: Quadripartite Decomposition

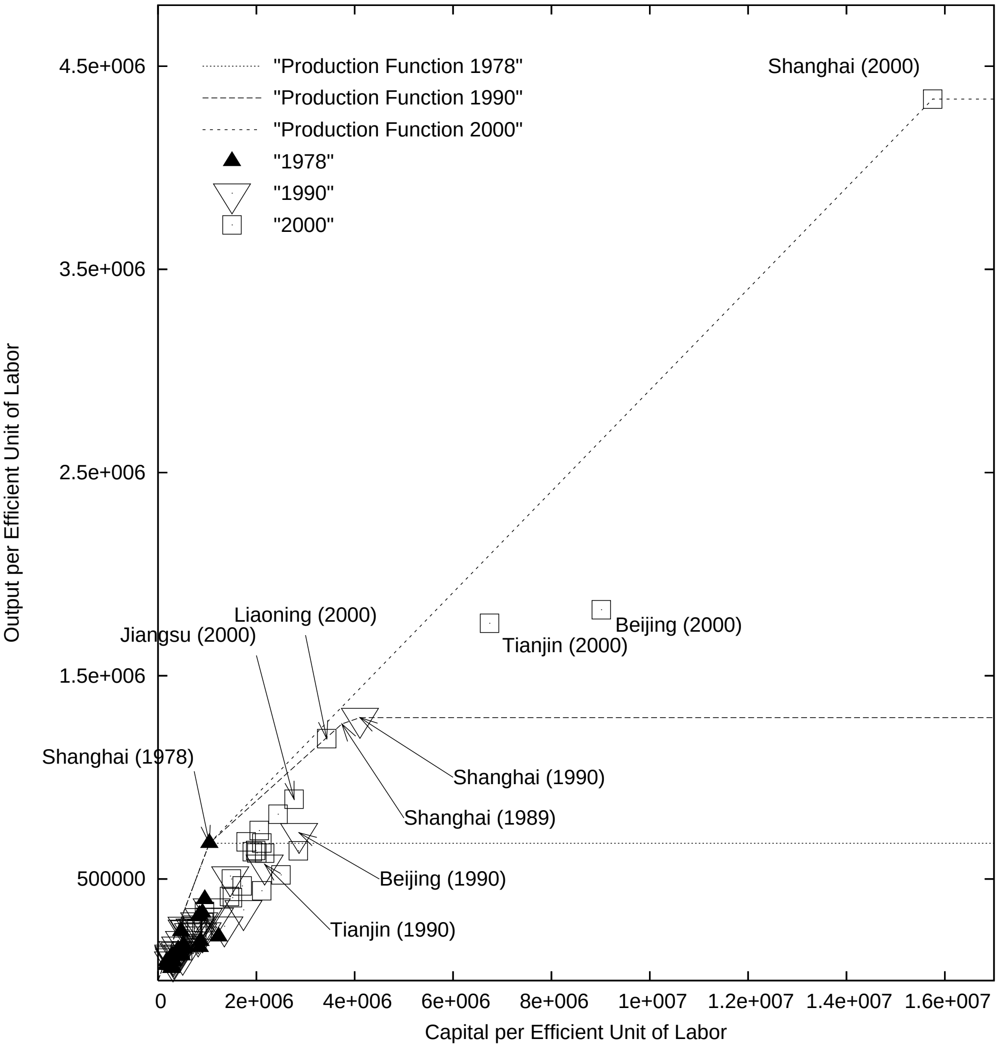

Figure 3: Production Functions and observations in 1978, 1990, and 2000

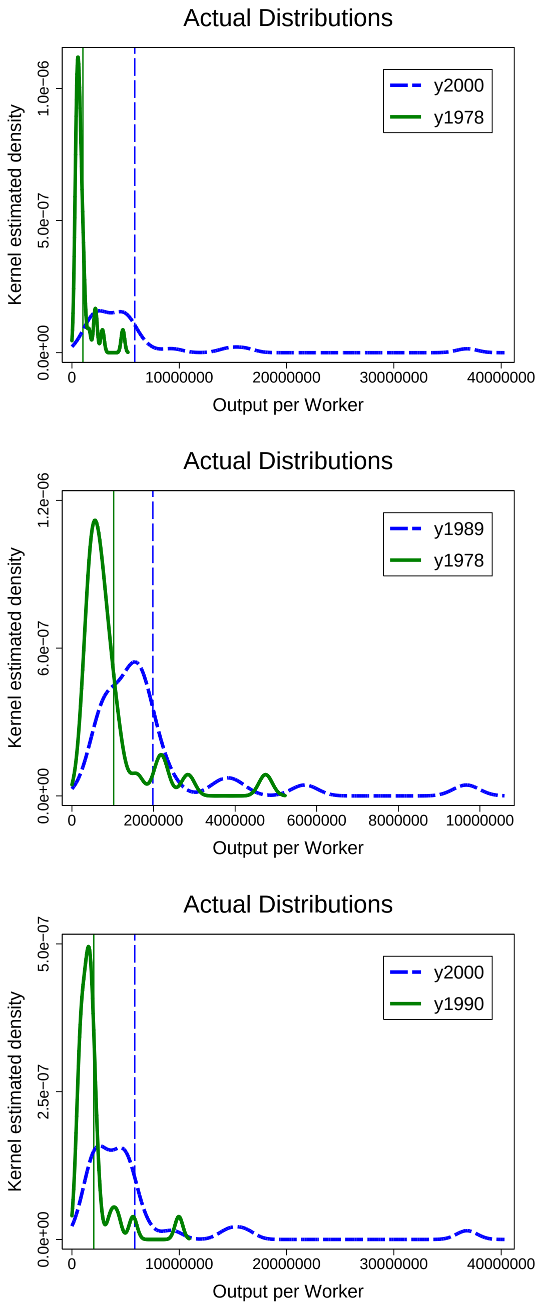

Figure 4: Actual Output per Worker Distributions

Notes: Upper panel presents actual Output per Worker Distributions in 1978 and 2000; middle panel–in 1978 and 1989; the lower panel–in 1990 and 2000. The solid curve is the actual “base” distribution and the solid vertical line represents the “base” mean value. The dashed curve is the actual “current” distribution and the dashed vertical line represents the “current” mean value.

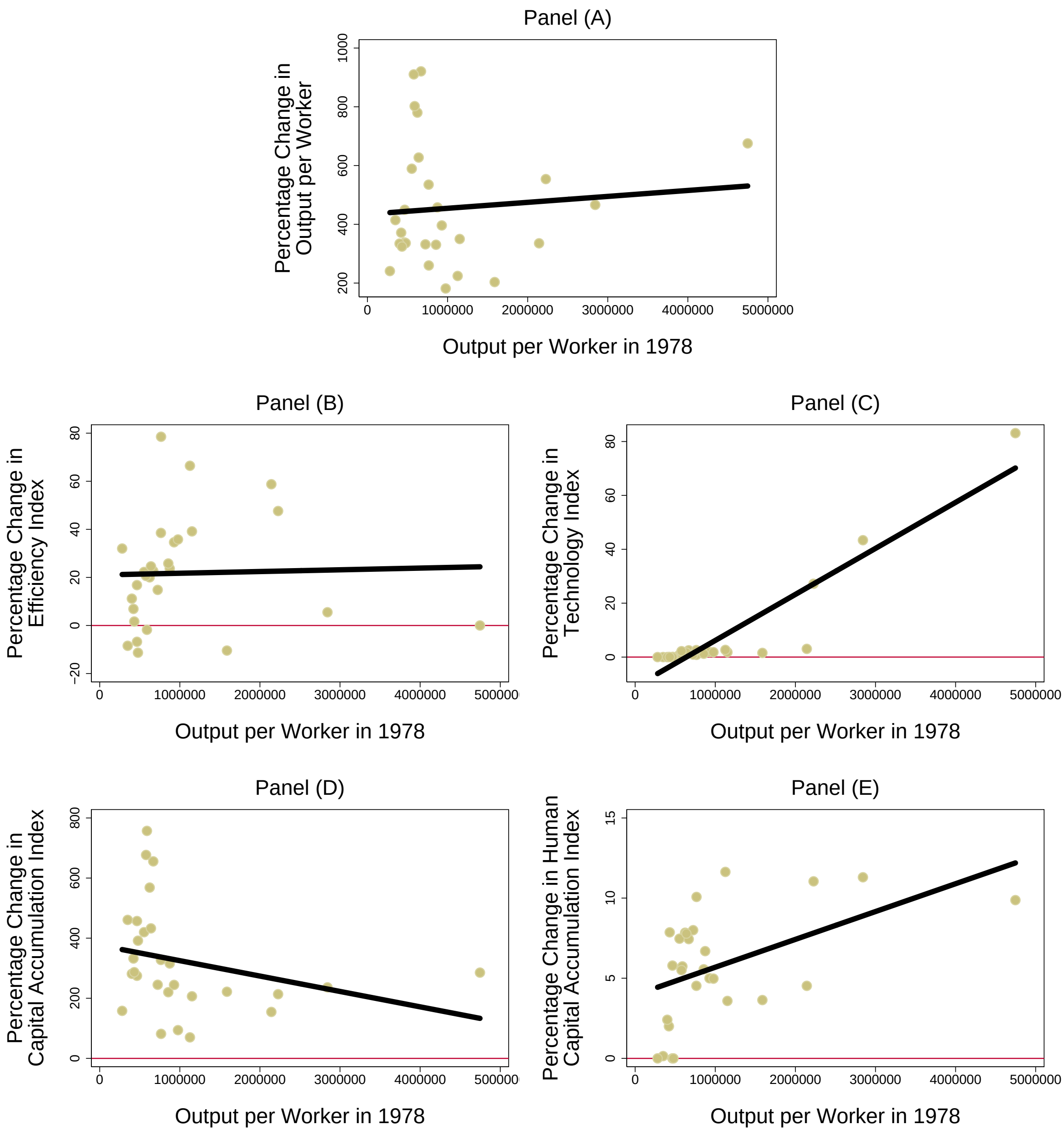

Figure 5: Percentage change (from 1978 to 2000) in output per worker and four decomposition indexes, plotted against output per worker in 1978

Note: Each panel contains a GLS regression line.

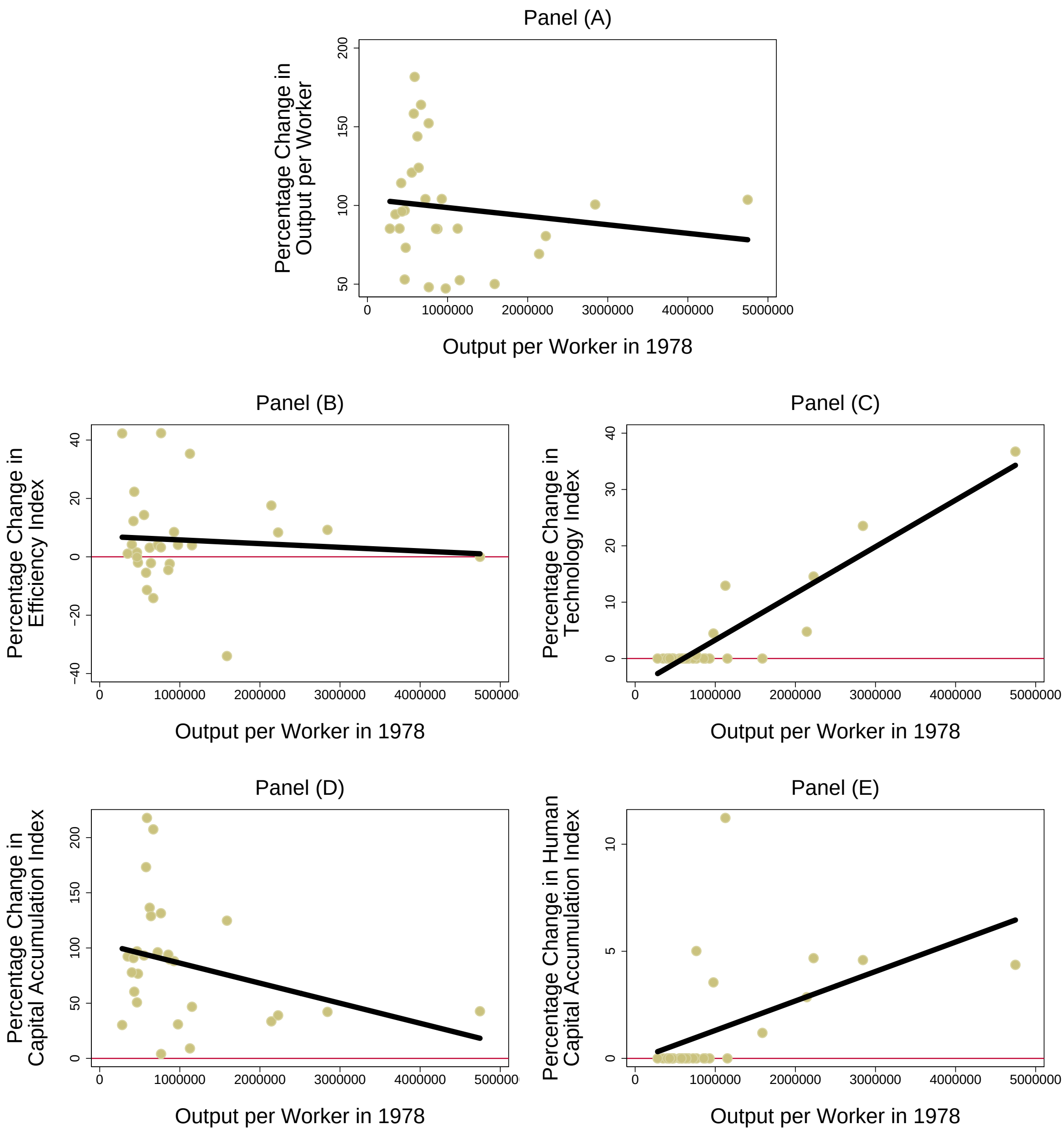

Figure 6: Percentage change (from 1978 to 1989) in output per worker and four decomposition indexes, plotted against output per worker in 1978

Note: Each panel contains a GLS regression line.

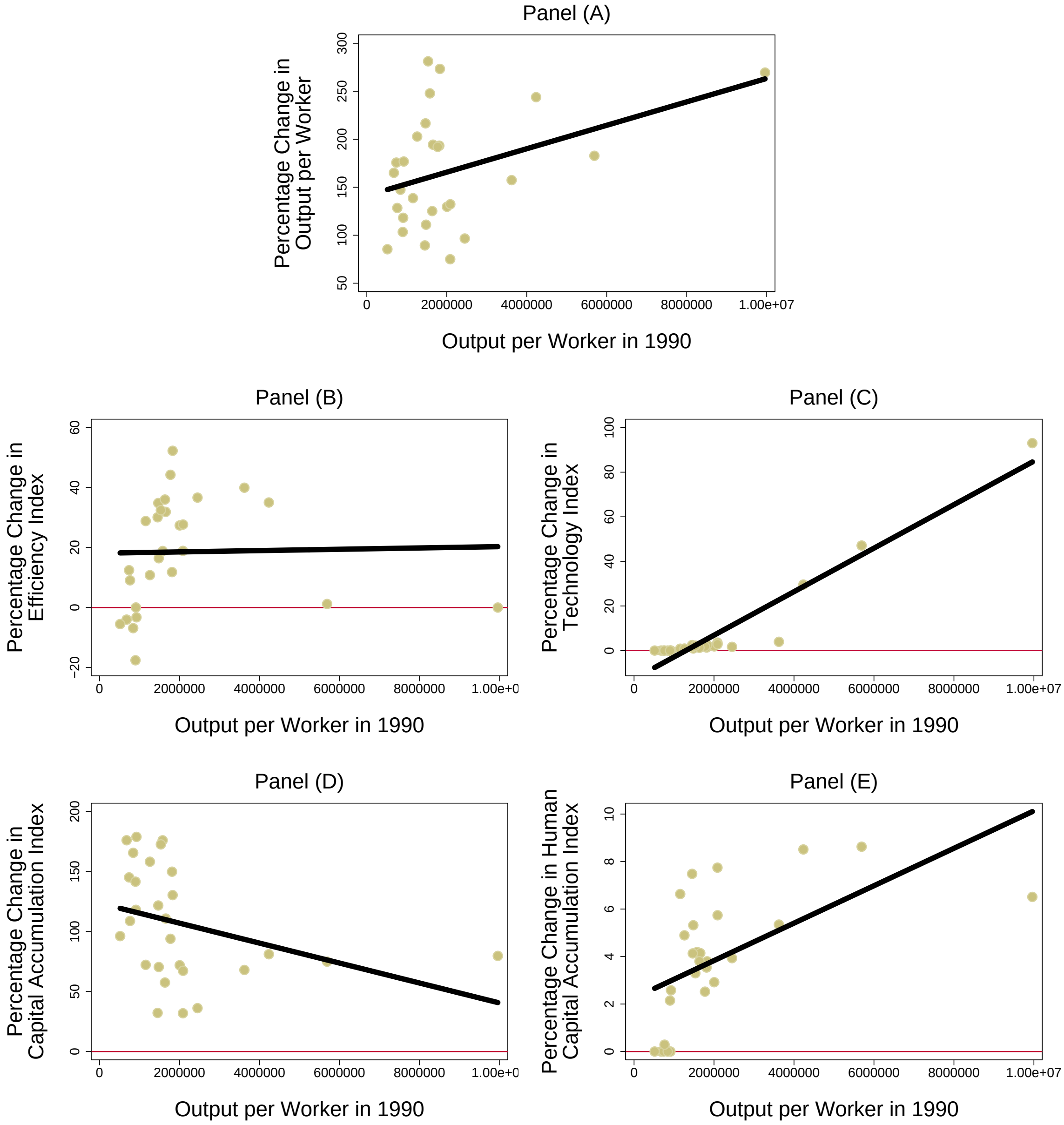

Figure 7: Percentage change (from 1990 to 2000) in output per worker and four decomposition indexes, plotted against output per worker in 1990

Note: Each panel contains a GLS regression line.

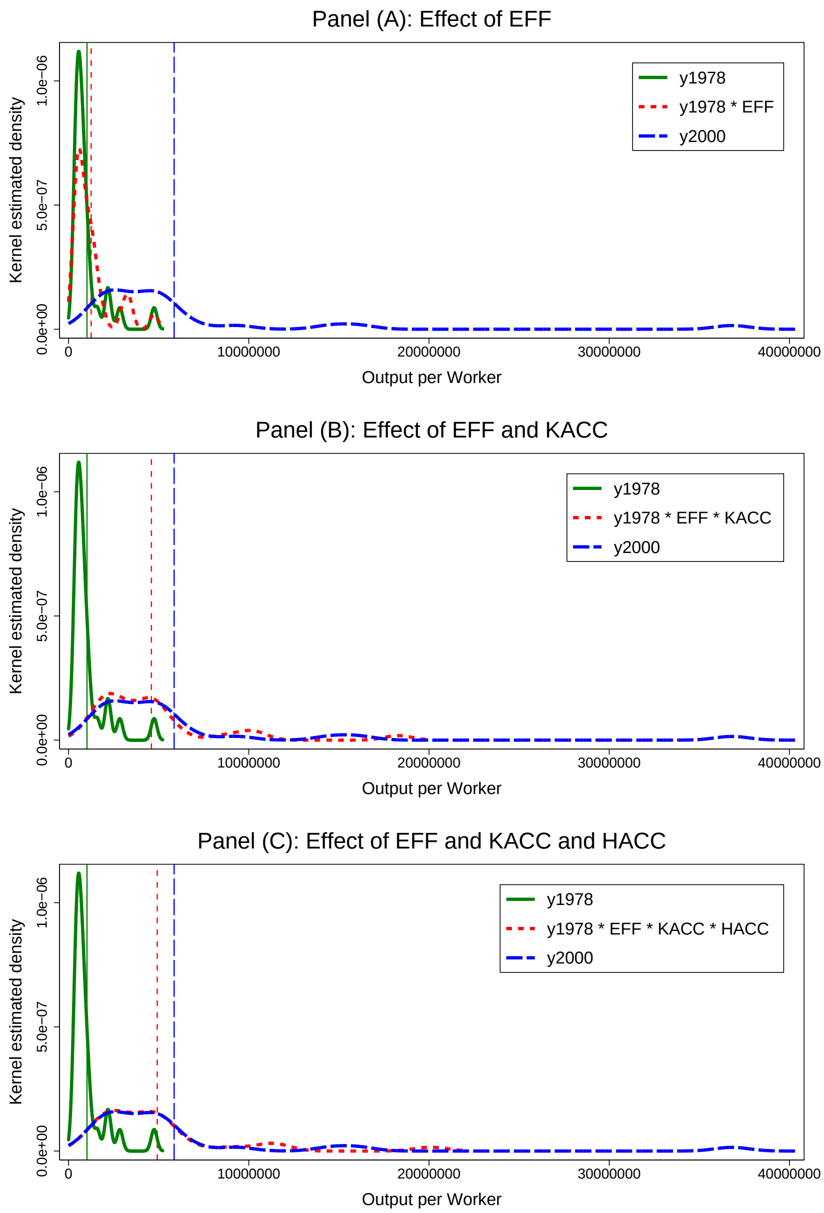

Figure 8: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: EFF, KACC, and HACC

Notes: In each panel, the solid curve is the actual 1978 distribution and the solid vertical line represents the 1978 mean value. The dashed curve is the actual 2000 distribution and the dashed vertical line represents the 2000 mean value. 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 1978 distribution, and the dotted vertical line represents the respective counterfactual mean.

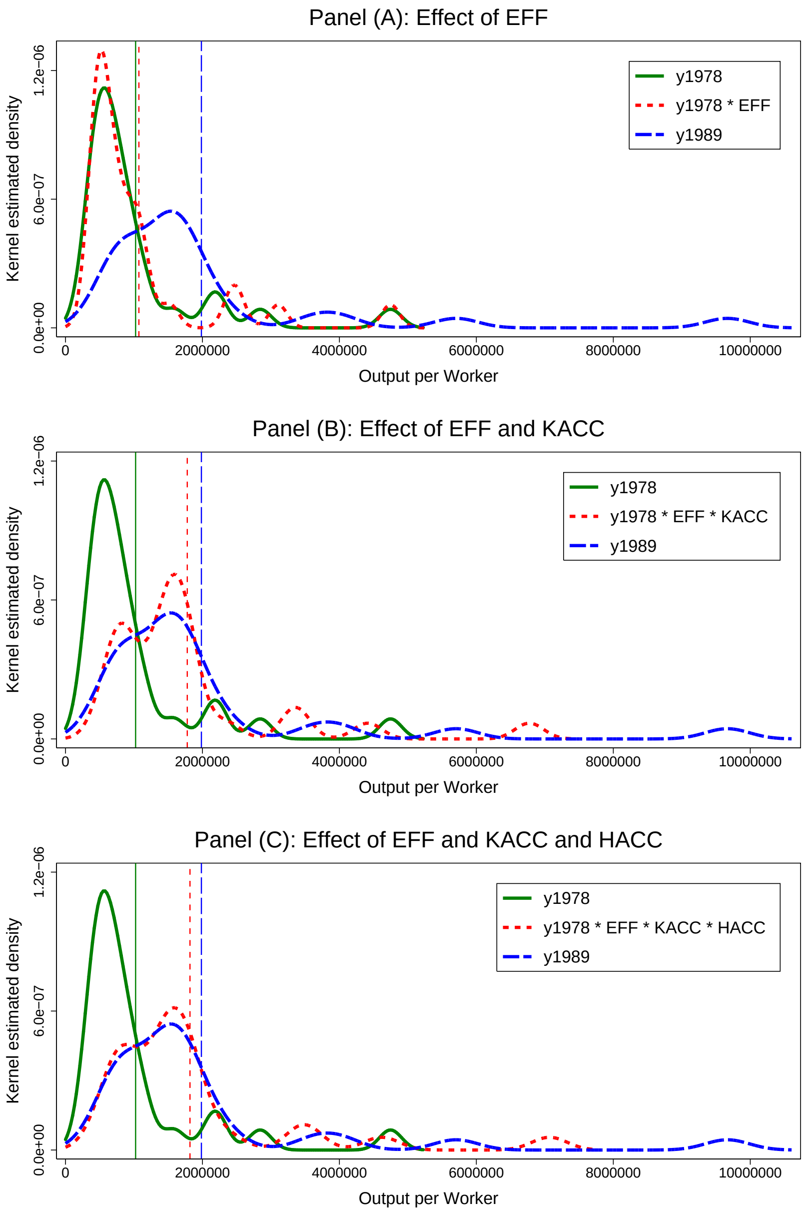

Figure 9: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: EFF, KACC, and HACC

Notes: In each panel, the solid curve is the actual 1978 distribution and the solid vertical line represents the 1978 mean value. The dashed curve is the actual 1989 distribution and the dashed vertical line represents the 1989 mean value. 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 1978 distribution, and the dotted vertical line represents the respective counterfactual mean.

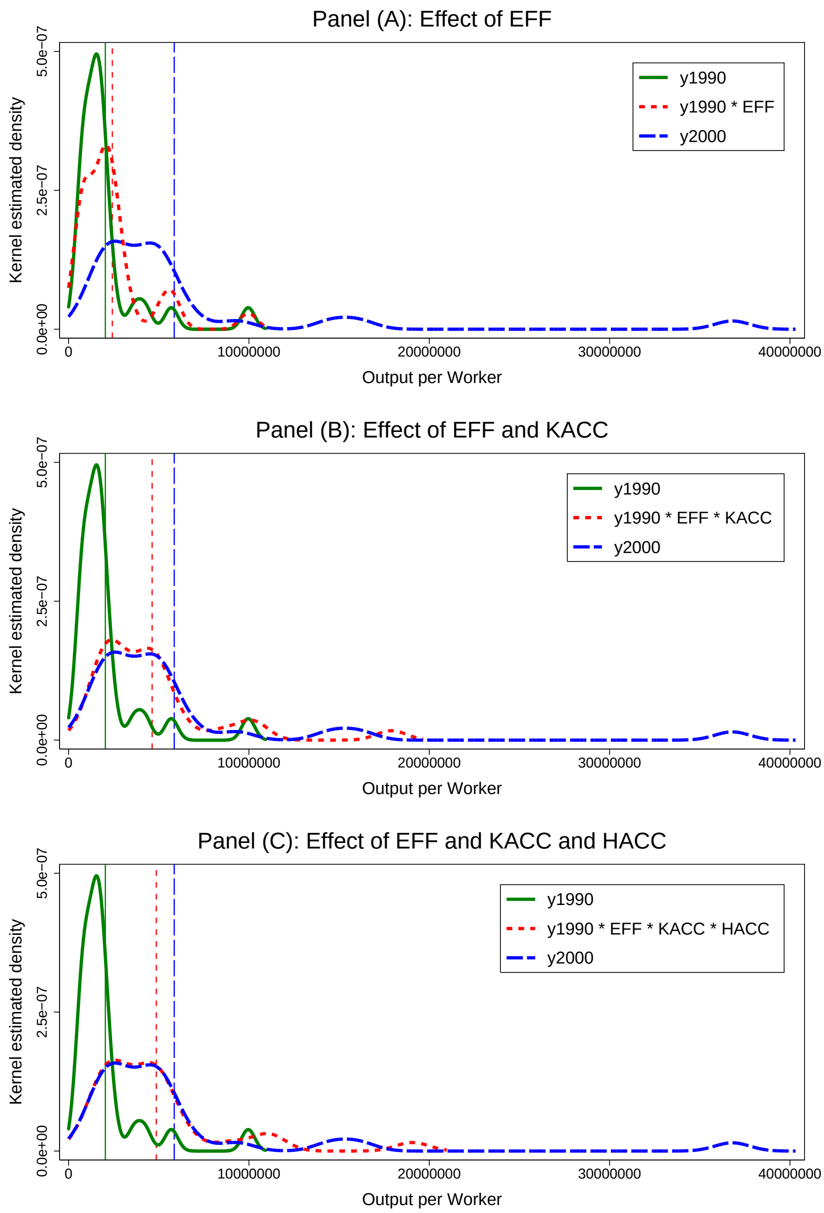

Figure 10: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: EFF, KACC, and HACC

Notes: In each panel, the solid curve is the actual 1990 distribution and the solid vertical line represents the 1990 mean value. The dashed curve is the actual 2000 distribution and the dashed vertical line represents the 2000 mean value. 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 1990 distribution, and the dotted vertical line represents the respective counterfactual mean.