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Technological Change and Transition: Relative Contributions to Worldwide Growth During the 1990's*

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Abstract

In this paper we used the procedures developed in the Kumar and Russell (2002) growth-accounting study to examine cross-country growth during the 1990's. Using a data set comprising developed, newly industrialized, developing and transitional economies, we decomposed the growth of output per worker into components attributable to technological catch-up, technological change and capital accumulation. In contrast to the study by Kumar and Russell (2002), which concluded that capital deepening was the major force of growth and change in the world income per worker distribution over the 1965-1990 period, our analysis showed that, during the 1990's, the major force in the further divergence of the rich and the poor was due to technological change, whereas capital accumulation played a lesser and opposite role. In further contrast, we found that efficiency changes (insignificantly) led (on average) to regress rather than progress. Finally, although on average we found that transitional economies performed similar to the rest of the world, the procedure was able to discover some interesting patterns within the set of transitional countries.

Keywords: Data Envelopment Analysis, Growth, Convergence, Transitional Economies

JEL classification: O47, P27, P52

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1 Introduction

In a recent paper, Kumar and Russell (2002), hereafter K&R, inspired, in part, by Färe, Grosskopf, Norris and Zhang (1994), employed nonparametric production-frontier methods to analyze international macroeconomic convergence. In particular, they decomposed the labor productivity growth[1] of 57 industrial, newly industrialized and developing countries into components attributable to technological catch-up (changes in efficiency), technological change and capital deepening. They found that, although there was substantial evidence of efficiency improvements, with the degree of catch-up directly related to the initial distance from the frontier, this catch-up did not contribute to convergence in income per worker[2] across countries, since the degree of catch-up appeared not to be related to initial productivity. They also found technological change to be non-neutral and that it had only a small effect on the percentage change in output per worker across countries. In fact, they found that capital accumulation was the primary driving force for growth and bimodal international divergence in income per worker across countries in the world during the period 1965–1990.

Indeed, during the period of their study, fast growing countries (*e.g.*, the Asian Tigers) underwent heavy capital accumulation (*cf.*, see Mankiw, Romer and Weil 1992). Further, technological advances (shifts in the production frontier) were only seen at high capital/labor ratios. In addition, Brynjolfsson and Hitt (2000) found the effect of computers on economic growth during that time period to be negligible. However, they also found that the effect of computers on economic growth during the 1990's was quite considerable. Moreover, the OECD (2000) estimated, that in the United States, information technology producing industries contributed, on average, to 35 percent of real economic growth (between 1995 and 1998). That number in Canada (between 1996 and 1997) was nearly 20 percent, while in France the information technology sectors were estimated to have contributed to 15 percent of real economic growth (in 1998).

Not only were the 1990's the time of the high-tech boom, they were also characterized by the collapse of the Soviet empire. Technological

[1] We define labor productivity growth as growth of real GDP per worker.

[2] Following Jones (1997), we will refer to both labor productivity and output per worker as income per worker.

advances and the emergence of transitional economies raises a natural question: Would the results of K&R change if we examined the 1990's?

In fact, the progress of transitional economies has recently become a popular topic in economic research. This has been driven, in part, by the recent availability of data on transitional countries. Generally these studies have focused on individual countries and looked at either firm or industry level data. For example, the range of topics have varied from studies on the effects of foreign direct investment (FDI) and knowledge spillovers in Lithuania (*e.g.*, see Javorcik 2004) to examining the law of one price on food prices in the Ukraine (*e.g.*, see Cushman, MacDonald and Samborsky 2001). However, there is relatively little empirical study on the convergence of transitional economies (on a macro level) versus the rest of the world (*e.g.*, see Blanchard 1997). A major reason for this is that the most popular data set on cross-country differences, the Penn World Tables (Summers and Heston 1991), until recently, included data on only a few transitional economies. However, in October of 2002, the Penn World Tables, Mark 6.1 was released (Heston, Summers and Aten 2002) and this updated data set includes many transitional economies with data up to the year 2000 (some of these countries did not exist before 1991). The incorporation of this updated data set opens the door for comparisons of the performance of transitional countries versus the rest of the world.

In this paper, we used a more recent and updated version of the data set used in the K&R growth-accounting study of international macroeconomic convergence to examine growth and convergence during the 1990's. The purpose for this was two-fold. First, we wanted to compare our results to the previous study to see if the growth pattern changed during the last decade. Second, using this time period allowed us to increase the cross-section studied and enabled us to examine transitional economies and their growth rates as compared to the rest of the world.

Our results confirm the K&R finding regarding the bimodal distribution of income per worker in the world. Specifically, we found evidence of further divergence between the clubs of the rich and poor. We also confirm their finding that technological change was non-neutral, with advances in the higher capital-labor ratios countries and some evidence of technological regress for lower capital-labor ratio countries. However, in contrast to the K&R conclusion that capital accumulation alone accounts for the positive shift in the distribution of output per worker, we found that either capital accumulation or technological change can explain most of the positive shift in the mean of the distribution. Although we found that countries with either high or low capital-labor ratios benefited from capital accumulation, we found that poorer countries benefited more than rich ones, while at the same time rich countries benefited more from technological change than the poor ones. The net result from these two competing effects was further divergence. These advances in technology came at a cost of increased inefficiency for some economies (failure to fully implement new technologies efficiently). Interestingly, on average, OECD economies suffered slightly more from the efficiency changes than did non-OECD countries. Finally, we found that although many transitional economies experienced losses at the beginning of the period studied, they performed (on average) more or less similarly to the rest of the world.

The remainder of our paper is constructed as follows: sections 2 and 3 describe the methodology and data respectively. The fourth section summarizes the results of the experiment whereas section 5 provides a comparison to the literature. Section 6 checks for robustness of the results and the final section concludes.

2 Methodology

2.1 Data Envelopment Analysis

The K&R approach to constructing the worldwide production frontier and associated efficiency levels of individual economies (distances from the frontier) is to use Data Envelopment Analysis (DEA). The basic idea is to envelop the data in the smallest convex cone, and the upper boundary of this set then 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 DEA estimator, as well as Kneip, Simar and Wilson 2003 for its limiting distribution).

Our technology contains three macroeconomic variables: aggregate output and two aggregate inputs – labor and physical capital. Let $\langle Y_{it}, L_{it}, K_{it} \rangle$, $t = 1, 2, \ldots, T$, $i = 1, 2, \ldots, N$, represent T observations on these three variables for each of the N countries. The constant returns to scale (CRS) technology for the world in period t is defined by

$$\mathcal{T}_t = \{\langle Y, L, K\rangle \in \Re^3_+ \mid Y \leq \sum_i z_{it} Y_{it},\ L \geq \sum_i z_i L_{it}, \\ K \geq \sum_i z_i K_{it},\ z_i \geq 0 \ \forall\ i\}, \tag{1}$$

where z_i are the activity levels.

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

$$\mathrm{TE}_{it} \equiv E(Y_{it}, L_{it}, K_{it}) = \min\{\lambda \mid \langle Y_{it}/\lambda, L_{it}, K_{it}\rangle \in \mathcal{T}_t\}. \tag{2}$$

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

2.2 Tripartite Decomposition

To decompose productivity growth into components attributable to changes in efficiency (technological catch-up), technological change and capital accumulation, we follow the approach of K&R. We first note that CRS allows us to construct the production frontiers in $y \times k$ space, where $y = Y/L$ and $k = K/L$. By letting b and c stand for the base period and current period respectively, we see, by definition, that potential outputs per unit of labor in the two periods are given by $\overline{y}_b(k_b) = y_b/e_b$ and $\overline{y}_c(k_c) = y_c/e_c$, where e_b and e_c are the values of the efficiency scores in the respective periods as calculated in (2) above. Therefore,

$$\frac{y_c}{y_b} = \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(k_c)}{\overline{y}_b(k_b)}. \tag{3}$$

By multiplying the numerator and denominator by the potential output per unit of labor at current period capital intensity using base period technology, we obtain

$$\frac{y_c}{y_b} = \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(k_c)}{\overline{y}_b(k_c)} \cdot \frac{\overline{y}_b(k_c)}{\overline{y}_b(k_b)}. \tag{4}$$

Alternatively, by multiplying the numerator and denominator by the potential output per unit of labor at base period capital intensity using current period technology, we obtain

$$\frac{y_c}{y_b} = \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(k_b)}{\overline{y}_b(k_b)} \cdot \frac{\overline{y}_c(k_c)}{\overline{y}_c(k_b)}. \tag{5}$$

These identities decompose the growth of labor productivity in the two periods into changes in efficiency, technology changes and changes in the capital-labor ratio. The decomposition in (4) measures technological change by the shift in the frontier in the output direction at the current period capital-labor ratios, whereas the decomposition in (5) measures technological change by the shift in the frontier in the output direction at base period capital-labor ratios. Similarly (4) measures the effect of capital accumulation along the base period frontier, whereas (5) measures the effect of 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. We resolve this ambiguity, as did K&R, by adopting the "Fisher Ideal" decomposition, based on geometric averages of the two measures of the effects of technological change and physical capital accumulation and obtained mechanically by multiplying the numerator and denominator of (3) by $(y_b(k_c)y_c(k_b))^{1/2}$:

$$\begin{aligned} \frac{y_c}{y_b} &= \frac{e_c}{e_b} \cdot \left(\frac{\overline{y}_c(k_c)}{\overline{y}_b(k_c)} \cdot \frac{\overline{y}_c(k_b)}{\overline{y}_b(k_b)}\right)^{1/2} \cdot \left(\frac{\overline{y}_b(k_c)}{\overline{y}_b(k_b)} \cdot \frac{\overline{y}_c(k_c)}{\overline{y}_c(k_b)}\right)^{1/2} \\ &\equiv EFF \times TECH \times KACC. \end{aligned} \tag{6}$$

2.3 Comparison of Unknown Densities

Our analysis of the change in the productivity distribution exploits recent developments in nonparametric methods to test formally for the statistical significance of differences between (estimated and counterfactual) distributions. Specifically, we follow K&R 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 the same. The test statistic used to test for the difference between the two unknown distributions (which Fan and Ullah 1999 show goes asymptotically to the standard normal), 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

$$T = \frac{Nb^{\frac{1}{2}} I}{\widehat{\sigma}} \sim N(0,1), \tag{7}$$

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.[3]

3 Data

The data used in the study comes from the PWT, Version 6.1 (Heston, Summers, and Aten 2002). The number of workers is obtained as $RGDPCH * POP / RGDPWOK$, where $RGDPCH$ is per capita GDP computed via the chain method, POP is the population and $RGDPWOK$ is real GDP per worker. The measure of output is calculated as $RGDPWOK$ multiplied by the number of workers; the resulting output is in international dollars. Real aggregate investment in international dollars is computed as $RGDPL * POP * KI$, where $RDGPL$ is the real GDP computed via the Laspeyres index, and KI is the investment share of real GDP. We use the real investment series to estimate the capital stock via the perpetual inventory method. The perpetual inventory method assumes that the level of capital stock in any given period is the accumulation of investments

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

made in previous years as in the following generalized equation

$$K_t = \delta_t I_t + \delta_{t-1} I_{t-1} + \ldots + \delta_{t-T} I_{t-T}, \tag{8}$$

where δ_t is a proportionality constant which essentially shows the efficiency of using investment in period t. In the PWT, Version 5.6 (Summers and Heston 1991), used in K&R, investment was disaggregated into five different types of assets: machinery, transportation equipment, residential construction, business construction, and other construction. With this disaggregation in mind, the level of capital stock is calculated using the following formula:

$$K_{l,T} = \sum_{t=0}^{T} I_{l,t} (1 - \delta_l)^{T-t}, \tag{9}$$

where l is the type of investment. Accordingly, the depreciation (decay) rate is estimated separately for each type of investment, which allows measuring the capital stock for a given level of accuracy. In Version 6.1 of the PWT, investment is aggregated and a single decay rate (0.06) is used. Following the most recent methodology, we calculate the initial capital stock level K_0 as follows: first, we compute the growth rate in the first three years of the available investment data and then annualize it by applying the formula $r = (1 + R)^{\frac{1}{3}} - 1$. We then use the growth rate r to extrapolate the investment series back beyond the years for which the data is available. The perpetual inventory method is then applied to the extrapolated investment series as in equation (9).[4] The perpetual inventory method is generally agreed upon to be sufficient for calculation of the capital stock. However, one should take these methods of calculating capital stock levels cautiously, especially when examining transitional economies due to the limited data used to calculate the initial capital stock. That being said, Caselli (2005) has shown that differences in the method used to estimate the capital stock do not appear to make major differences in empirical results.

Although the estimation procedures (discussed above) and their properties do not change, there are two main differences between our sample and that of K&R. First, we consider a more recent time period, 1992–2000. Although it is considerably shorter, this is the longest time period attainable (at this point) if one wants to consider transitional countries, since many of them did not exist as sovereign nations before the end of 1991. Another reason we want to focus on this period is that this is the period of

[4] We thank Alan Heston for valuable discussion on capital stock estimation.

the high-tech boom. It is worth noting that the relatively short period we consider is unlikely to represent the long-run convergence/divergence path, if one exists, but it still can show some interesting dynamics and tendencies, as we will see in our results.

The second difference is that we have about a 50 percent wider sample that includes 22 transitional countries. The question that arises is whether or not it is justifiable to consider them under the same frontier with developed countries (*e.g.*, because they have different institutions). In our opinion, it is arguably as reasonable as considering developing countries under the same frontier as developed countries, as K&R did in their original work. Indeed, one of the points of this exercise is to compare all economies relative to the best practice frontier. Further, the gap from the input-output allocation of each country to this frontier represents the relative inefficiency of this country associated with differences in institutions and the like.

For completeness, a lengthy section on robustness includes a check to see if the results of the paper are driven by the inclusion of the additional countries. To do so, we take the countries included in the K&R analysis and examine them over the 1992-2000 period. We find that the conclusions of the paper do not change. We also take the K&R countries and examine them over the 1965-2000 period. The main departure from K&R shows a larger emphasis for technological change. This is as expected given the results for the 1990's. We also examine the sensitivty of the results to changes in the returns to scale assumption, implosion of the frontier, the presence of possible measurement error and data quality as well as the inclusion of a 'problematic country'. The results show that the conclusions of the paper are not sensitive to the robutsness checks, and if anything, actually emphasize the technological change arguement presented in the paper.

4 Results

4.1 Tripartite Decomposition

Figure 1 superimposes the estimated production frontiers for 1992 and 2000. One fact that emerges immediately from these graphs is the non-neutrality of technological change. Up to a capital/labor ratio of approximately 6000, the 1992 and 2000 frontiers are virtually coincident, but for higher levels of capitalization, the 2000 frontier shifts upwards dramatically. This is basically the same result found in K&R, indicating, not surprisingly, that almost all technological change occurs at high levels of capitalization.

Table 1 shows country specific estimates of efficiency and each of the components of the decomposition of the growth rate of output per worker from 1992 to 2000. The first two columns of numbers show the estimated efficiency in both the base period (1992) and the current period (2000) for each country. We observed that Hong Kong, Paraguay, Sierra Leone, Taiwan and the United States appeared on the best practice frontier in 1992, whereas Guatemala, Ireland, Mauritius, and Sierra Leone are all on the best practice frontier in 2000 (of those countries, Hong Kong, Paraguay, Sierra Leone and the United States also formed portions of the best practice frontiers in K&R).[5] For Hong Kong, the key financial center of Asia, its fall from the technological frontier by 20 percentage points was not surprising considering the political takeover by China and subsequent instability. The fall from the frontier by the United States by about 1 percentage point can be explained by the 'explosion' of productivity in Ireland[6].

It should be noted that on average there was a decrease in the average efficiency level across countries. Table 2 shows that the biggest drops are in East Asian economies (probably due to the Asian currency crisis) and in former USSR republics (due perhaps to disorganization and instability). These results are intuitive. However, it may appear puzzling to some why African countries improved their efficiency in the 1990s by almost 5% while it fell by almost 5% in OECD countries. One explanation for this phenomenon is technical. Figure 1 shows some implosion at lower capital-labor ratios and a dramatic increase in the technology at higher capital-labor ratios. Consider the case where a country makes no changes in its capital-labor ratio or output over time. If a country sits at a lower-capital ratio, its efficiency score will rise given the implo-

[5] Although the data is available, we have chosen to remove Luxembourg from the analysis of this paper. This is important because, with Luxembourg in the data set, it defines the production frontier for high capital-labor ratios in each period. One reason we have chosen to drop this country is because Luxembourg's high productivity is partly created by residents of nearby countries (*e.g.*, Belgium) commuting to work in Luxembourg who are not included in the labor variable. We further discuss this issue in Section 6.

[6] Margaritis, Färe, and Grosskopf (2007) argue that it is Ireland's superb performance in the high-tech manufacturing sector that mainly pushes its enormous productivity growth.

sion of the frontier. On the other hand, if the country was at a higher capital-labor ratio, its efficiency score would fall due to the shift up in the frontier. While no country had fixed levels of inputs and output over the sample, it should be obvious that changes in countries input and output levels relative to countries similar to it can affect the efficiency score of that particular economy. Specifically, during the 1990's, Ireland moved the technological frontier up so dramatically that even some of the most developed countries were not able to catch-up with it to maintain their 1992 efficiency level. This led to efficiency decreases for many OECD economies. Further, minimal shifts and/or technological degradation at lower capital-labor ratios only required small changes in output levels for lower capital-ratios economies to increase their efficiency levels.

The next column of numbers in Table 1 shows each country's productivity growth ($(PROD-1)\times 100$) and subsequent columns show the contributions to productivity growth of the three factors: efficiency change ($(EFF-1)\times 100$), technological change ($(TECH-1)\times 100$) and physical capital accumulation ($(KACCUM-1)\times 100$). Ordering of the average contributions are similar to what was found in K&R. The table suggests that capital accumulation, on average, was again the principal driving force in the *mean* growth of worldwide productivity. The second largest source, on average, was technological change, followed by efficiency change. However, here we found the average contribution of technological change was nearly 80 percent that of capital accumulation, whereas in K&R it was less than 11 percent. Further, we found the average contribution of efficiency change to be negative, suggesting that (on average) changes in efficiency during the 1990's actually lead to regress.

Table 2 reports mean changes in productivity and the three components of productivity change for several groups of countries. OECD countries experienced productivity gains above the world average primarily because of faster rates of technological progress.[7] The strong growth rates

[7]The rates of labor productivity growth of course differ. The "average" growth was primarily driven by scandinavian economies (Denmark, Finland, Norway) and Ireland. This is probably because of fewer labor market rigidities in these economies, which allows lower costs of either adopting or development of a new technology (Scarpetta, Hemmings, Tressel, and Woo 2002). Note that for some OECD economies (France, Germany, Greece, Italy, Japan, the Netherlands, Spain and Switzerland), labor productivity growth was much weaker. One possible explanation for this difference comes from the paradox of thrift argument (*The Economist*, 2005). Other possible explanations include (1) changes in the composition of an economy (for example, in the case of Germany, there was a significant change in the industry composition of the manufacturing sector in the aftermath of the reunification), and (2) the growth of the service sector, which

of the Asian Tigers were attributable primarily to well-above-average contributions of capital accumulation, while technological change played a lesser role. Transitional economies performed more or less similarly to the rest of the world on average, their slightly above average growth was due mostly to capital accumulation and to a lesser extent technological progress. The poor Latin America performance was attributable to efficiency losses, and the abysmal African performance was attributable to negative technological progress and minimal capital accumulation.

Similar to K&R, we found that technological change was non-neutral and that the largest contribution from technological change to increase labor productivity growth came with developed countries. This result appears to be driven by a shift up in the best practice frontier by Ireland at mid and high capital-labor ratios (e.g. see Daveri 2002). Also similar to the previous study, we found that technology change was actually negative for many developing countries. This can partly be explained by the modest implosion of the frontier at lower capital-labor ratios, caused by decreases in productivity of the best-practice frontier defining countries Paraguay and Sierra Leone, over the sample period.

Finally, the largest labor productivity changes due to capital accumulation were observed in developing countries. The Asian Tigers continued their high capitalization over this time period, but they were also accompanied by nearby China, India, Indonesia, Malaysia and Sri Lanka. Further, Mauritius, Turkey and a number of Latin American countries followed suit with similar increases in labor productivity changes due to capital deepening. At the same time, developed economies experienced relatively minor percentage increases in labor productivity due to changes in capital per worker.

4.2 Regression Analysis

Figure 2 contains plots of the four growth rates (labor productivity and the three components) against output per worker in the base period (1992), along with fitted regression lines.[8] Panel A suggests that relatively richer countries have grown significantly faster than relatively poorer ones. This

seems to be less productive. This feature closely corresponds to what the study by Färe, Grosskopf and Margaritis (2006) finds.

[8]Specifically, the lines are OLS fitted lines with "heteroskedasticity-consistent" estimators for the variance (Huber 1981 and White 1980). See Table 3 for further details.

supports the view of the absence of absolute convergence in income per worker in the world (*e.g.*, see Quah 1996 and DeLong 1998). In contrast, K&R found statistically insignificant evidence (for a smaller number of countries) of world-wide labor productivity convergence. Although unconditional convergence is subject to Barro's (1991) critique, we concentrate on Quah's criticism of absolute convergence and leave conditional convergence during the 1990's to future research.

Panel B shows that there has been a disproportionate amount of decrease in efficiency in our sample. As was shown in Table 1, we noticed that some of the relatively rich economies have become less efficient, whereas many relatively poorer countries experienced efficiency improvements. This was different from K&R who noted that in their sample that efficiency did little, if anything, to lower income inequality across countries. countries. This panel suggests that efficiency changes led towards convergence. A major explanation for this contrast is that during the 1990's Ireland moved the technological frontier up so dramatically that even some of the most developed countries were not able to catch-up with it to maintain their 1992 efficiency level (*e.g.*, Belgium, France, Germany, Italy, Portugal and Spain). This finding goes hand in hand with the general purpose technology argument, emphasizing that it takes time before newly implemented technology can be utilized 100 percent efficiently (see Helpman and Rangel 1999).

Panel C suggests that technological change contributed to productivity growth positively for many countries. Moreover, richer countries (in the base period) benefitted more from this technological change than poorer countries (the estimated coefficient is significant at any conventional level). This finding is the same as that of K&R. However, more so than in K&R, world technological progress hindered economical development in some relatively poor countries. This suggests that the technological change contributed to further divergence in income per worker amongst countries in the world in the 1990's.

Finally, panel D reveals that capital deepening was positive for most countries, and it appeared to have a significant relationship with base level income per worker. In other words, capital deepening was the major source in the *average* increase of labor productivity from 1992-2000, and it seems to have contributed to convergence of income per worker across our sample. This finding repeats that of K&R for the 1965-1990 period. Of course, each of these interpretations are based on first-moment characterizations of the productivity distribution and are therefore vulnerable to the Quah's (1993a,b, 1996, 1997) critique.

4.3 Analysis of World Income per Worker Distributions

Given this critique, we now turn to an analysis of the distribution dynamics of labor productivity. A plot of the distributions of output per worker across the 84 countries in our sample in 1992 and 2000 appears in Figure 3. The solid (dashed) curve is the estimated 1992 (2000) distribution of output per worker and the solid (dashed) line represents the mean value of output per worker.[9] The first thing to note is that the distribution in both periods is bimodal. This was found to be the case in 1990 in K&R and holds true for the distribution of labor productivity through the end of 2000. It also should be noted that the 'poor mode' remained relatively stagnant while the 'rich mode' moved further away. This is consistent with the positive and significant slope in panel A of Figure 2. In other words, the richer the country, the higher the rate of growth. Both these findings give support to the hypothesis of divergence in income per worker in the world, emphasizing the increased distance between the 'peak of the rich' and the 'peak of the poor'.

We again follow the work of K&R by re-writing the tripartite decomposition of labor productivity in (6) as

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

Thus, the labor productivity distribution in the current period (2000) can be constructed by successively multiplying labor productivity in the base period (1992) by each of the three factors. This in turn allowed us to construct counterfactual distributions by sequential introduction of each of these three factors in parentheses. We estimated the actual and counterfactual distributions by employing nonparametric kernel methods and applied the Li-test to test formally for statistical significance of differences between the corresponding distributions.

In Figures 4-6, in each panel, again the solid (dashed) curve is the estimated 1992 (2000) distribution of output per worker and the solid (dashed) vertical line represents the 1992 (2000) mean value of output per worker, whereas the dotted curve is the counterfactual distribution

[9]For the estimated distributions we use a Gaussian kernel and use the Sheather and Jones (1991) method for choice of the optimal bandwidth.

(and the corresponding dotted line represents the counterfactual mean) isolating, sequentially, the effects of efficiency change, technology change and capital accumulation on the 1992 distribution of output per worker.

In contrast to K&R, the major source of divergence (during the nine-year period) between the rich and the poor appeared to be technological change. This is inferred by comparing panel A in Figure 5 with Figure 4. One can see that the technological change effect alone appeared to have constituted most of the shift of the 1992 distribution of output per worker closer to that of the 2000 distribution. This story is backed by the Li-tests in Tables 4 and 5. These tables compare the counterfactual distributions to the distribution in the current and base periods, respectively.[10] Here we see that technological change alone could describe the significant shift in the distribution from 1992 towards that in 2000 (at the 5% level), and appears to be the only effect (among three under consideration) to do so. Correspondingly, the Li-test was able to show that the counterfactual distribution incorporating technical change is significantly different from the 1992 distribution.

Again, in contrast to K&R, according to Table 4, it appears that capital accumulation alone cannot statistically explain the shift from 1992 to 2000 (see panel A of Figure 5). Only in combination with technological change does capital accumulation have an effect on the shape of the distribution of output per worker in 1992. This is clearly seen from panel B of Figure 5. Mixed with efficiency change, the effect of capital accumulation is negligible: opposite effects cancel each other out (see panel B of Figure 6). The Li-tests confirm this conjecture.

Further, Table 4 suggests that efficiency alone cannot explain the shift in the base period distribution towards that in 2000. However, efficiency changes did have an impact. Unfortunately, the direction of this change was not towards the 2000 distribution. As noted previously, efficiency changes actually caused regress on average. This result corresponds to the increase in the test statistic of $f(y1992 \times EFF)$, relative to $f(y1992)$, in Table 4, and in the shifting of the counterfactual distribution in panel A of Figure 6.

Overall, we found that all three effects were important in the evolution of the distribution of income per worker in the world. We found that both

[10] Here we use the Gaussian kernel and the Silverman (1986) adaptive (robust) rule of thumb choice for optimal bandwidth partially to avoid the large computational burden involved with the Sheather and Jones (1991) method when bootstrapping is employed.

capital accumulation and technological change had similar influences on the *average* increase in output per worker, but only technological change brought about a significant positive effect itself to the 1992 distribution of output per worker. Further, we identified technological change as the major source of additional divergence in the *distribution* of output per worker. Finally, efficiency change insignificantly shifted the distribution, but on average the effect introduced regress rather than progress.

4.4 What Can We Learn from Transitional Economies

As noted in Table 2, the group of transitional countries performed on par with the average country in the sample. However, we can still learn much about them from the procedures used in this paper.

Although many of the transitional countries experienced sudden efficiency drops before and during the 1990's (especially starting with Soviet 'Perestroyka'), those who started their transitions earlier (*e.g.*, Hungary, Poland, and Slovenia) or successfully passed key economic and political reforms (*e.g.*, China, Estonia, and Latvia) managed to recover and actually increased their efficiency score over the sample. On the other hand, some countries that started their transition later or were slow on reforms (*e.g.*, Bulgaria, Russia, and Ukraine) experienced a deterioration in efficiency. These findings are consistent with past evidence and theoretical explanations given in the transitional economics literature (*e.g.*, see Blanchard 1997). However, we were somewhat surprised to see countries like Albania, Armenia and Tajikistan improve in terms of efficiency. One possible explanation was that among these countries, Albania and Armenia were improving their economic freedom, as suggested by the 'economic freedom index' during the 1990's.[11]

It is interesting to note that the Baltic countries (see Table 2) performed differently from the rest of the world as well as from the rest of the transitional economies. Their labor productivity growth was twice as large as the average growth rate and they actually possessed a positive efficiency change on average. However, the latter phenomenon was mainly driven by Estonia. The remarkable achievement of Estonia can be explained by the impressive progress of liberal economic reforms–not only relative to other former USSR countries, but also relative to most countries in the Central Europe. Indeed, various cross-country economic reports and in-

[11]See http://www.heritage.org/research/features/index/countries.cfm for details.

dexes (*e.g.*, by the Heritage Foundation) have been ranking Estonia above most other transitional countries for the speed, progress and success of pro-market economic reforms.

On the other extreme, we have the countries from the former USSR (excluding the Baltic states). During the nine years under consideration, they were only able (on average) to return to their initial level of labor productivity after plummeting during the beginning and mid 1990's. Further, during this period of transition, they lost nearly eleven percent in terms of efficiency.

Central and Eastern European economies performed, on average, similar to the rest of the world. Thus, together with the fact that former USSR and Baltic countries compensated each others labor productivity and efficiency indices, transitional countries together performed on the same level as the rest of the world.

An alternative explanation for these highs and lows is somewhat more technical rather than intuitive. During the sample, it was found that some transitional economies experienced sudden decreases in their total output while their stocks of capital did not fall as much (*e.g.*, Azerbaijan, Bulgaria, Moldova, Russia, and Ukraine). This would show up as a decrease in efficiency, *ceteris paribus*. A theoretical explanation for this phenomenon is given via the disorganization argument of Blanchard and Kremer (1997). Also, some transitional economies that experienced major efficiency improvements (*e.g.*, Armenia, Estonia, Macedonia, and Poland) looked as if they made huge strides partly due to low efficiency levels in the base period.

The inclusion of transitional countries does not necessarily help us learn something new about the pattern of economic growth of the entire world, but it definitely sheds light on the pattern of various transitional countries relative to the general pattern. We have found evidence to suggest that the sources of growth associated with transitional economies was heterogeneous. Countries of Central and Eastern Europe (except for Albania, Bulgaria, Macedonia and Romania, but certainly those that later entered the European Union) had patterns very similar to OECD countries (the largest source of growth being due to technological change). The countries of the former Soviet Union experienced a different pattern. Estonia was the leader, having a positive contribution from all three sources, with the largest being due to capital accumulation, as was the case for Lithuania. For Latvia, the largest source was technological change. The three Slavic countries of the former Soviet Union (Belarus, Russia and Ukraine) experienced a pattern similar to OECD countries: high contribution from (positive) technological change with a similarly high but negative efficiency change. The former Soviet Union countries of Central Asia were quite heterogeneous in their pattern of growth: for Kazakhstan, technological change was the largest source (with minimal effects from the other two components), while for Kyrgyzstan and Tadjikistan the largest sources were capital accumulation and efficiency change, respectively.

As compared to the former Soviet economies, the transition of China is unique and deserves separate attention.[12] In fact, China's growth over the nine year period was quite impressive. Its percentage increase in labor productivity was second only to Ireland. In addition, its contribution to productivity growth from capital accumulation was the largest in the entire sample. Further, it showed a large percentage increase in efficiency. All of these results suggest that China's growth over the 1992-2000 period was far different from that of the other transitional economies.

Although it was shown that both efficiency change and capital accumulation brought about positive increases in labor productivity, the primary driving force for China was capital deepening. It is well known that FDI into China was extremely high during this time period. The China Statistical Yearbook 1999 (SSB 1999) reported that FDI flows from 1992 to 1999 increased by nearly 400 percent. In fact, China became the largest recipient of FDI in the developing world and second globally only to the United States (since 1993). In 1997, FDI flows into China constituted 31 percent of total FDI in all developing and transitional countries (UNCTAD 1998).

These increases in FDI can also partly explain the increases in efficiency over the sample period (*e.g.*, see Cheung and Lin 2004). FDI in China not only brought much needed capital, it also brought advanced machines, better production and human resource management, new products, and marketing techniques (*e.g.*, see Zhiqiang 2000). In addition to better practices, labor has been moving from the less efficient state-owned enterprises to the more efficient non-state-owned enterprises (*e.g.*, see Jefferson, Rawski and Zhen 1996). Specifically, the China Statistical Yearbook 1999 (SBB 1999) reported that while the percentage of urban

[12]The reliability of Chinese economic statistics has been questioned in the literature due to falsifications of data (Rawski, 2001; Rawski and Xiao, 2001). Despite these shortcomings, official Chinese statistics generally seem to be fairly accurate for econometric analysis (Chow, 2002; Marton, 2000).

employment in state-owned enterprises was over 62 percent in 1990, it dropped to less than 44 percent in 1998. Capital moved in a similar fashion. The percent of capital employed in state-owned enterprises was over 66 percent in 1990, but fell to 55 percent in 1998.

Overall we found such heterogeneity in the sources of economic growth across countries to be quite intriguing. It was likely to have been caused by differences in economic policies, stages of development, success rates of transitional reforms, and the comparative advantages of each country. Here we suggest that future research should emphasize on more micro level data as well as additionally focus on country and regional case studies.

5 A Comparison to the Literature

Although our principal interest is in the shift over time of the cross-country distribution of productivity levels, the tripartite decomposition of productivity change in Table 1 plays an important role in that analysis. Thus, some assessment and comparisons to other decompositions in the literature are informative.

The standard approach to growth accounting (using time-series or panel data) or productivity-level accounting (using cross-country data at a point in time) is to posit a CRS Cobb-Douglas production function that is identical over time and/or across countries, apart from a (Solow residual) shift factor. This structure is

$$y = Ak^{\alpha}, \tag{11}$$

and A is the country-specific and/or time-specific technology coefficient. The assumption is that each country at each point in time operates on its own production frontier, uniquely determined by A. This standard approach, in addition, restricts technological change or technological dispersion to be neutral. Another assumption of this model is that all workers are perfect substitutes in production, regardless of skill level. There is little reason to believe, in a cross-country study, that the elasticity of substitution between say, skilled and unskilled workers, is close to infinity.

In a paper closely related to ours, Caselli and Coleman (2006)[13] relax the assumption of perfect substitutability of different types of labor, as well as the assumption of neutral technological change. They are able to do this by generalizing the production function in (11) to incorporate skilled and unskilled labor as

$$y = k^{\alpha}\left[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}\right]^{(1-\sigma)/\sigma}, \tag{12}$$

where u and s, stand for unskilled and skilled, respectively, and $1/(1-\sigma)$ is the elasticity of substitution between skilled and unskilled labor. The choice of the constant elasticity of substitution (CES) production function allows for increased flexibility relative to the Cobb-Douglas functional form (a special case when $\sigma = 1$).

Not only is the model more flexible, but the division of labor allows the authors to determine if skill-biased cross-country technology differences exist. They find skill biases and suggest that poor countries use certain factors more efficiently than rich ones. Specifically, by using this model, they discover that poor countries use unskilled labor more effectively, while rich countries use skilled labor more effectively. This disputes the view that all that is needed is to give poor countries the technologies observed in rich countries. Their approach allows each country in each time period to have access to many different feasible technologies. Thus, those countries that are poor can choose to exploit their abundant factor, unskilled labor.

Although the model appears to differ from ours, the thought process is similar. Neither approach requires technological change to be neutral. Further, each economy need not be compared to a single economy. Caselli and Coleman (2006) suggest that each country has a separate technology and that the outer envelope of the country-specific frontiers generates the world technology frontier. In our approach, there is a single technology available to all countries and the upper envelope of the input-output sets defines the world technology frontier. The main difference appears to be in the definitions. In the Caselli and Coleman (2006) framework, the distance between a particular countries input-output set and the world frontier is called a difference in technology. In our framework, the distance between a particular countries input-output set and the world frontier is called inefficiency. Alternatively, we define changes in technology as shifts in the frontier over time. Essentially, we can loosely think of our

[13]Other interesting papers related to this study include Caselli (2005), Caselli and Coleman (2002) and Caselli and Teneryo (2004).

approach as decomposing the Solow residual coefficient into changes in efficiency and changes in technology.

Although the CES production function is a nice device for a theoretical framework, a nonparametric approach may be more appropriate for an empirical problem. An advantage of our approach is that we do not need to make restrictive assumptions that are necessary in a parametric model. First, there is no need to assume a functional form for the technology. The DEA approach is data driven and allows the data to tell the form of the production function. Although the CES production function is an improvement over the Cobb-Douglas form, there is little evidence to show that all countries over all time periods follow this model (even with the country specific shifting parameters). Further, there is no need for assumptions about market structure or the absence of market imperfections (e.g., taking rental rates on labor and capital as given). Indeed, market imperfections, as well as technical inefficiencies, are possible reasons for countries falling below the worldwide production frontier. Finally, there is no need to calibrate parameters (α and σ) or obtain data on wages (specifically the skilled/unskilled wage ratio).

The advantages of their approach over ours are also noteworthy. In their setup, they are able to examine several phenomenon which we are unable to uncover. First, as noted, they are able to relax the assumption of perfect substitutability of different types of labor. Second, they are able to determine whether technological change is skilled-labor or unskilled-labor augmenting. A third benefit, not available in the baseline specification (12), is the ability to allow for capital-skill complementarity. All these are achieved by incorporating data on human capital. Perhaps a worthy research project would be to attempt these types of approaches on the DEA human capital model of Henderson and Russell (2005).[14]

[14]Another related paper is the recent study by Sala-i-Martin (2006) regarding divergence or convergence of the world income distribution. His paper estimates the evolution of the world income distribution using data across and within countries, and comes to some different conclusions. However, the major argument in his paper regards the convergence of incomes of individuals, rather than GDP per capita. The upper panel of Sala-i-Martin's Figure 1 (unweighted GDP per capita) does not contradict our results.

6 Robustness of the Results

6.1 K&R Sample

Finally, we wanted to check our results for robustness. For example, one may think that the reason our results for the 1992-2000 period are different from those of the 1965–1990 period used in K&R is because our sample includes transitional countries. Admittedly we had the same concern. Therefore, we re-ran the analysis only using countries from K&R (of which we had data for all but two of the countries–with the omitted countries being the Ivory Coast, Luxembourg[15] and Yugoslavia) for the period 1992–2000. Appendix A gives the results of this exercise. A brief examination of the tables and figures show that the results for most countries changed minimally. Further, the conclusions of the paper do not change because none of the transition economies defines the frontier.

Instead of limiting this paper to the 1992 to 2000 period, we also investigate what components of productivity were responsible for the difference in the results from the K&R (sample) years (1965–1990) and the sample from 1992-2000. In doing so we are able to raise the question: are the conclusions reached by K&R robust to extending their sample of countries from 1990 to 2000? This is necessary because the results in the first robustness check do not address this question. If the results are not robust, then what factors have changed in the 1965–2000 period?

The full set of results, using the K&R sample of countries, for the tripartite decomposition spanning 1965–2000 appear in Appendix B. The efficiency scores differ slightly from those in K&R. However, the same major conclusion can be inferred, namely that capital deepening drove the average productivity growth (approximately 89 percent). However, the results conceptually differ from K&R in that the average efficiency across the sample fell and the technology component is larger. If we generically "subtract" the K&R 1965–1990 results from the 1965–2000 results, we can infer that the major fall in efficiency and rise in technology components happened during the final decade. The major contribution of capital deepening came during the 1965–1990 period. This further shows the importance of researching the 1990's.

[15]The addition of Luxembourg in this example did not significantly change the results. These are also available upon request.

6.2 Returns to Scale

Although the tripartite decomposition requires CRS, the estimation of technical efficiency does not. To see what role returns to scale play in the decomposition, it makes sense to see what happens to the efficiency scores when the assumption of CRS is relaxed. We consider the efficiency scores under three different assumptions: CRS, non-increasing returns to scale (NIRS), and variable returns to scale (VRS). Mathematically, the difference of CRS from NIRS and VRS is that the NIRS model adds the constraint $\sum_{i=1}^{n} z_i \leq 1$ to (1), whereas the VRS technology adds the constraint to $\sum_{i=1}^{n} z_i = 1$ to (1).[16] Intuitively, the relationship is as follows: the VRS technology is a subset of the NIRS technology, which is itself a subset of the CRS technology. Therefore, it is obvious, for a given input-output pair, that technical efficiency under CRS is less than or equal to technical efficiency under NIRS, which is less than or equal to technical efficiency under VRS.

Appendix C reports the efficiency scores for the entire sample, as well as for particular groups of countries, under the three different assumptions. As expected, the scores do not differ where all three technologies overlap. However, the subadditivity and restricted subadditivity constraints of the NIRS and VRS assumptions, respectively, make the efficiency scores of the low- and rich-endowed economies larger in our exercise. For example, on the low side, India becomes efficient in the VRS and NIRS 'world'. On the other side, the efficiency of the United States slightly increases in 2000, putting it on the VRS and NIRS frontiers. Although the efficiency scores increase for several countries, they do not appear to differ enough to substantially change the conclusions of the study. These results suggest that the CRS assumption is justifiable and that we can have faith in the tripartite decomposition, which requires this premise.

6.3 Implosion of the Frontier

In construction of the world-wide frontier, we find evidence of negative technological progress among a set of very poor countries for the 1992 to 2000 sample period. Given the relatively short sample, a careful analysis of such instances of technological recess might be useful. As a robustness check, we perform the tripartite decomposition of labor productiv-

[16] A more formal description is given in Appendix C.

ity change with the assumption that the technology is not allowed to implode (*e.g.*, see Diewert 1980 and Henderson and Russell 2005). Appendix D replicates the results of the study, but assumes that the technology cannot implode. The economies that form the frontier in 1992 do not change. However, the results for 2000 are different. The 1992 observations of Paraguay, Sierra Leone and Taiwan define the frontier in 2000, along with Ireland in 2000.

The impact of the restriction on the tripartite decomposition is as expected. Because the technology component for each country is now assumed to be non-negative, several relatively poorer countries now show technology components that are either zero or slightly positive. These results show that this component changed primarily for non-OECD countries, in particular for transitional, Latin American, and especially African economies. However, we do notice that the capital deepening component is robust with regard to the "non-implosion" assumption. The fall in efficiency is necessarily larger since the frontier now envelops a larger input-output space. The major conclusion, though, remains unaffected. It is technological change which plays the major role in changing the distribution of labor productivity during the 1990's. If anything, not allowing the frontier to implode only emphasizes the technological change argument.

6.4 Measurement Error and Data Quality

Given the emphasis of the paper on extending the data, a detailed discussion of data quality and measurement issues seems to be appropriate. One of the most common critiques of the DEA approach is that it assumes away any measurement error and so could potentially suffer from outliers. For example, Koop, Osiewalski, and Steel (1999) state that "the sensitivity of DEA to outliers is no doubt one of the weaknesses of the DEA approach. In particular, it is difficult to present some measure of uncertainty (*e.g.*, confidence intervals) using DEA methods." To combat comments such as these, Simar and Wilson (1998, 2000) and others have introduced bootstrapping into the DEA framework. Their methods, based on statistically well-defined models, allow for consistent estimation of the production frontier, corresponding efficiency scores, as well as standard errors and confidence intervals.

The technology in the equation (2) is necessarily *estimated* and since DEA does not allow a measurement error, the estimated $\widehat{\mathcal{T}}_t$ is a subset of some unknown true technology in period t, $\mathcal{T}_t$. The efficiencies *estimated* relative to $\widehat{\mathcal{T}}_t$ are too optimistic. The bootstrap procedures (Wilson (1998, 2000), Kneip, Simar and Wilson, 2003) are proposed to correct the bias. The bootstrap method uses the idea that the known distribution of the difference between estimated and bootstrapped efficiency scores mimics the unknown distribution of the difference between the true and the estimated efficiency scores. Such relationship facilitates estimation of the bias and confidence intervals for the individual estimated efficiency scores.

In practice, the bootstrap distribution is obtained by calculating B (B should be rather large) efficiency scores relative to bootstrap technology $\mathcal{T}_t^*$,

$$\begin{aligned}\mathcal{T}_t^* = \{\langle Y, L, K\rangle \in \Re^3_+ \mid Y \leq \sum_i z_{it} Y^*_{it},\ L \geq \sum_i z_i L_{it},\\ K \geq \sum_i z_i K_{it},\ z_i \geq 0\ \forall\ i\},\end{aligned} \tag{13}$$

where B samples $\langle Y^*_{it}, K_{it}, L_{it}\rangle$ are obtained by bootstrapping from the data generating process, from which the original $\langle Y_{it}, K_{it}, L_{it}\rangle$ are coming. The bias and confidence intervals are obtained from this bootstrap distribution.[17]

Although advances were made to DEA, these have not been included in many recent papers that examine macroeconomic growth. One exception is the study by Henderson and Zelenyuk (2007). Specifically, they use recently developed techniques in the statistical analysis of DEA estimates to check for robustness of efficiency estimates for a sample of 52 developed and developing countries. In addition, they also investigate the issue of convergence/divergence in terms of efficiency across countries.

In Appendix E, we give the results for the bias-corrected efficiency scores for each country in 1992 and 2000. Although most of the results change slightly, the relative ranking of the countries changes little. As in Henderson and Zelenyuk (2007), each of the countries initially considered efficient now fall below the upper boundary of the output set. Most notable of these frontier defining countries is the case of Sierra Leone. The bootstrap procedure gives a bias corrected efficiency score of 0.79 in 1992 with similar results in 2000. This result is important since many view Sierra Leone being on the frontier as a serious case of measurement error (the Penn World Table grades the accuracy of data of each country on an A to F scale, to which Sierra Leone received a D). That being said, the bias

[17] A more formal description is included in Appendix E.

correction virtually did not change the ranking of the countries in terms of efficiency. The Spearman rank correlation coefficient is approximately 0.99 (similar results are found for the Kendall correlation coefficient). This is a good indication for robustness of results.

6.5 Luxembourg

As noted earlier, we decided to remove Luxembourg from the data set. One of the main criticisms of the DEA estimator is that a single decision making unit can drastically alter the shape of the frontier. When Luxembourg was included in the data set, it defined the best practice frontier for high capital/labor ratio countries in both 1992 and 2000. Further, it had a dramatic increase in productivity over that time period (thus shifting up the best practice frontier). We feared that some may believe that this observation may have driven the technological change argument of the paper. Therefore, we decided to present the results without Luxembourg in the sample. In fact, when Luxembourg was included in the data set (Appendix F), we found that technological change played a similar role, but efficiency decreases brought about a significant negative shift in the counterfactual distribution of labor productivity. In fact, the group of OECD countries were found to suffer the greatest from efficiency loses, even more so than the former republics of the USSR. These results did not seem intuitive to the authors, nor did it make sense for such a specialized (in financial services) and small (in terms of population) country to determine the best-practice technological frontier for the world. Luxembourg is a very special case, and in this sense, possibly an outlier country. A large amount of business related to banking and finance for other countries in the European Union and the rest of the world is carried out there. Moreover, many employees in Luxembourg are living and commuting from Belgium, France, Germany, and the Netherlands. These individuals create part of the GDP of Luxembourg, but are not counted as part of its population. However, for those who disagree and believe that Luxembourg should be included, this only adds to our story that technological change was the driving force of bimodal divergence and growth in the 1990's.

We also attempted to play with the results by assuming that Luxembourg had no changes over the nine year period. Here we artificially restricted Luxembourg's GDP and capital per worker to be fixed at its 1992 level (Appendix G). Interestingly enough, Luxembourg (1992 values) remained on the 2000 best practice frontier. However, more importantly, this experiment did not significantly change the conclusions of the paper.

Although these checks have brought about some minor differences, we suggest that the results of this paper are robust and leave it to others to experiment with other tests for robustness.

7 Conclusion

As was stated in the conclusion of K&R, it must be noted that this approach has several limitations. First, the techniques used in this paper do not provide reasons for the phenomena that are measured. This approach was only able to tell us what happened. It is left to the authors and readers to give stories as to why these phenomenon occur. Also, this paper only examines three macroeconomic variables commonly used in empirical studies of convergence: potentially important variables (*e.g.*, natural resources) are omitted. As our goal was to compare our results to those of K&R, we chose to use the variables employed in their paper and leave the remaining variables to future research. Lastly, although we used a more recent and updated version of the data available from the Penn World Tables, we still must admit that the increased sample of countries was arbitrary and that the data may be measured with considerable error. All of this information should be taken into account when assessing our results.

In spite of the above mentioned caveats, our approach was able to uncover many important findings. Specifically, using a more recent and updated version of the data set used in the K&R growth-accounting analysis of international macroeconomic convergence enabled us to increase the cross-section studied and thus to include many transitional economies. In summary, our principal conclusions are as follows:

- We confirmed the K&R conclusion that the distribution of income per worker persisted to be bimodal, with evidence for further divergence between the club of the rich and the club of the poor. We also confirmed their finding that technological change appears to be non-neutral.

- In contradistinction to the K&R conclusion that capital accumulation primarily accounts for the shift in the distribution and the mean productivity increase, we found that technological change constituted the major (significant) source of change in the labor productivity *distribution* towards further divergence. Capital accumulation did not bring a significant shift in the base period distribution of output per worker. However, we found some evidence to suggest that capital accumulation did contribute significantly to beta-type convergence in income per worker amongst the countries.

- We found the effect of efficiency change contributed to regress rather than progress. Further, efficiency deterioration contributed to convergence between the rich and poor.

- Although on average transitional countries performed on par with the rest of the world, the procedure was able to discover patterns within the set of transitional economies: from some stagnating countries of the former USSR to booming China.

Overall, our results have shed additional and sometimes unexpected light onto world development during the era of the 1990's–a time of major structural change in the world–shaped by the collapse of the Soviet empire and the high-tech boom.

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Tables and Figures

Table 1: Efficiency scores and percentage change of tripartite decomposition indexes, 1992−2003

Country	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100
Albania	0.62	0.75	46.06	20.90	-3.96	25.80
Argentina	0.58	0.54	9.57	-6.52	16.08	0.98
Armenia	0.23	0.29	32.89	24.78	-6.45	13.83
Australia	0.79	0.79	22.74	0.79	22.19	-0.34
Austria	0.82	0.78	16.14	-5.43	22.49	0.26
Azerbaijan	0.31	0.30	-0.31	-2.39	-7.37	10.26
Belarus	0.28	0.25	17.39	-13.51	28.54	5.59
Belgium	0.92	0.87	16.63	-5.22	22.64	0.34
Bolivia	0.57	0.62	9.22	8.07	-4.09	5.37
Brazil	0.53	0.55	16.34	3.87	3.40	8.33
Bulgaria	0.68	0.57	-12.21	-16.48	-7.33	13.42
Canada	0.81	0.81	23.72	-0.81	23.37	1.10
Chile	0.65	0.70	31.71	8.39	1.62	19.57
China	0.67	0.74	69.40	11.11	-6.14	62.43
Colombia	0.81	0.74	-6.55	-9.56	-5.22	9.01
Costa Rica	0.67	0.70	8.23	4.90	-7.54	11.59
Croatia	0.43	0.41	13.81	-3.29	12.52	4.59
Czech Republic	0.41	0.37	9.48	-10.07	21.90	-0.14
Denmark	0.74	0.78	28.29	5.47	21.69	-0.04
Dominican Republic	0.75	0.97	55.25	29.13	-5.07	26.65
Ecuador	0.47	0.43	-13.46	-7.76	-8.95	3.04
Estonia	0.33	0.38	57.91	14.77	9.58	25.56
Finland	0.68	0.75	34.30	9.70	22.35	0.06
France	0.82	0.75	12.38	-8.27	22.07	0.36
Germany	0.79	0.71	11.07	-9.29	22.29	0.13
Greece	0.64	0.54	13.25	-15.68	29.41	3.78
Guatemala	0.97	1.00	5.76	3.00	-3.40	6.30
Honduras	0.74	0.58	-10.35	-21.39	-4.15	18.98
Hong Kong	1.00	0.80	28.98	-20.00	22.26	31.87
Hungary	0.45	0.40	37.39	-10.76	26.25	21.94
Iceland	0.70	0.69	21.86	-1.39	22.99	0.48
India	0.74	0.88	42.00	18.42	-5.84	27.34

(*continued on next page*)

Table 1 (*Continued*)

Country	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100
Indonesia	0.96	0.74	9.87	-22.96	-4.19	48.86
Ireland	0.91	1.00	71.44	10.00	27.34	22.39
Israel	0.80	0.67	16.25	-16.11	28.56	7.79
Italy	0.92	0.83	10.68	-9.17	21.61	0.19
Jamaica	0.34	0.31	-5.64	-8.64	-8.12	12.42
Japan	0.75	0.60	6.98	-20.24	27.88	4.88
Kazakhstan	0.32	0.32	11.45	-1.27	14.42	-1.35
Kenya	0.54	0.56	-5.06	3.37	-8.20	0.05
Korea, Republic of	0.77	0.65	36.56	-15.58	17.49	37.68
Kyrgyzstan	0.83	0.81	13.36	-2.44	-5.24	22.62
Latvia	0.24	0.23	44.23	-3.65	24.21	20.52
Lithuania	0.38	0.37	16.49	-3.69	5.11	15.08
Macedonia	0.34	0.37	13.79	10.00	0.75	2.68
Madagascar	0.58	0.68	-3.51	16.33	-11.54	-6.23
Malawi	0.37	0.55	33.83	47.25	-10.17	1.18
Malaysia	0.75	0.76	33.92	2.29	-1.53	32.96
Mauritius	0.83	1.00	55.90	20.00	-3.82	35.08
Mexico	0.68	0.64	12.80	-5.13	6.20	11.96
Moldova	0.36	0.28	-16.85	-19.94	-3.96	8.15
Morocco	0.65	0.65	3.30	0.00	-5.68	9.53
Netherlands	0.85	0.80	15.21	-5.60	22.29	-0.20
New Zealand	0.63	0.61	18.19	-4.24	22.82	0.50
Nigeria	0.65	0.46	-28.70	-29.49	-11.23	13.92
Norway	0.80	0.83	27.04	4.17	22.02	-0.05
Panama	0.57	0.51	5.14	-10.71	-4.19	22.91
Paraguay	1.00	0.78	-34.43	-22.48	-4.01	-11.88
Peru	0.32	0.36	4.47	13.00	-2.42	-5.25
Philippines	0.55	0.57	11.72	5.17	-3.84	10.47
Poland	0.27	0.31	53.35	16.77	26.70	3.65
Portugal	0.76	0.61	20.13	-20.12	19.91	25.42
Romania	0.28	0.28	4.56	0.00	-3.27	8.10
Russia	0.33	0.25	-9.26	-26.54	22.82	0.57
Sierra Leone	1.00	1.00	-4.83	0.00	-17.81	15.80
Singapore	0.76	0.82	49.94	8.20	26.81	9.28
Slovak Republic	0.36	0.36	22.70	0.72	22.03	-0.18
Slovenia	0.46	0.51	39.58	11.73	23.42	1.22
Spain	0.78	0.68	13.81	-12.24	25.78	3.11

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Table 1 (*Continued*)

Country	TE_b	TE_c	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100
Sri Lanka	0.83	0.81	18.03	-2.42	-5.20	27.59
Sweden	0.71	0.70	20.00	-1.40	21.75	-0.04
Switzerland	0.85	0.73	4.32	-14.60	22.27	-0.09
Syria	0.79	0.95	15.52	20.95	-5.46	1.02
Taiwan	1.00	0.99	45.28	-0.99	1.06	45.20
Tajikistan	0.28	0.36	27.09	28.67	-4.29	3.20
Thailand	0.53	0.46	22.83	-14.16	-5.79	51.88
Turkey	0.77	0.67	11.65	-12.75	-7.38	38.16
Ukraine	0.29	0.14	-41.99	-52.45	22.11	-0.09
United Kingdom	0.78	0.69	23.41	-11.03	27.63	8.69
Uruguay	0.58	0.58	10.78	0.00	5.70	4.81
USA	1.00	0.99	21.08	-0.99	21.84	0.36
Venezuela	0.58	0.44	-17.13	-23.56	10.38	-1.79
Zambia	0.26	0.27	-10.16	2.41	-4.01	-8.61
Zimbabwe	0.36	0.36	-5.33	0.36	-3.90	-1.84
Average			14.17	-3.30	7.34	9.98

Table 2: Mean Percentage Changes of the Tripartite Decomposition Indices (Country Groupings)

Country Group	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100
OECD[1]	20.25	-4.88	22.33	3.34
Non OECD	12.17	-2.41	2.10	12.57
Asian Tigers[2]	32.63	-10.41	18.68	24.75
Latin America	2.98	-2.98	-1.61	7.88
Africa	1.46	4.91	-8.60	5.81
Transition (all)[3]	16.52	-3.06	8.41	10.87
Non-Transition	13.29	-3.38	6.94	9.65
Baltic Countries[4]	38.44	2.12	12.68	20.31
Central and Eastern Europe[5]	21.23	1.26	11.10	7.76
Republics of Former USSR[6]	0.99	-10.59	5.83	6.74
All countries	14.56	-3.30	7.34	9.98

[1] OECD countries by UNESCO classification as of 2004; excluding Czech Republic, Hungary, Korea, Poland and Slovak Republic, *and* Luxembourg.
[2] Hong Kong, Japan, Singapore, South Korea and Taiwan.
[3] Albania, Armenia, Azerbaijan, Belarus, Bulgaria, China, Croatia, Czech Republic, Estonia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russia, Slovak Republic, Slovenia, Tajikistan, Ukraine.
[4] Estonia, Latvia, Lithuania.
[5] Albania, Bulgaria, Croatia, Czech Republic, Hungary, Macedonia, Poland, Romania, Slovak Republic, Slovenia.
[6] Excluding Baltic Countries.

Table 3: Growth Regressions of the Percentage Change in Output per Worker and the Three Decomposition Indices on Output per Worker in Base (1992) Period

Regression	(A)	(B)	(C)	(D)
	Productivity change	(EFF−1) ×100	(TECH−1) ×100	(KACC−1) ×100
Constant	10.51	2.83	−7.54	16.01
	(0.018)	(0.376)	(0.000)	(0.000)
Slope	0.00028	−0.00024	0.00078	−0.00025
	(0.048)	(0.018)	(0.000)	(0.008)

Notes: p-values in parentheses, based on robust standard errors (see footnote 8).

Table 4: Testing for Changes in the Distribution of Labor Productivity due to Different Sources (Comparison Year, 2000)

H_0 : Distributions are equal H_1 : Distributions are not equal	Value of statistic	Bootstrap p-value	Conclusion of testing H_0
$g(y2000)$ vs. $f(y1992)$	1.1146	0.0824	reject
$g(y2000)$ vs. $f(y1992 \times EFF)$	1.3659	0.0504	reject
$g(y2000)$ vs. $f(y1992 \times TECH)$	–0.0187	0.9786	fail to reject
$g(y2000)$ vs. $f(y1992 \times KACCUM)$	1.0716	0.0754	reject
$g(y2000)$ vs. $f(y1992 \times EFF \times TECH)$	0.0267	0.9722	fail to reject
$g(y2000)$ vs. $f(y1992 \times EFF \times KACCUM)$	1.3698	0.0576	reject
$g(y2000)$ vs. $f(y1992 \times TECH \times KACCUM)$	0.1275	0.8600	fail to reject

Notes: We used the bootstrapped Li (1996) Tests with 5000 bootstrap replications and the Silverman's (1986) rule-of-thumb bandwidth.

Table 5: Testing for Changes in the Distribution of Labor Productivity due to Different Sources (Comparison Year, 1992)

H_0 : Distributions are equal H_1 : Distributions are not equal	Value of statistic	Bootstrap p-value	Conclusion of testing H_0
$g(y1992)$ vs. $f(y2000)$	1.1146	0.0762	reject
$g(y1992)$ vs. $f(y1992 \times EFF)$	–0.0183	0.9774	fail to reject
$g(y1992)$ vs. $f(y1992 \times TECH)$	1.8620	0.0240	reject
$g(y1992)$ vs. $f(y1992 \times KACCUM)$	0.0979	0.8948	fail to reject
$g(y1992)$ vs. $f(y1992 \times EFF \times TECH)$	1.1508	0.0778	reject
$g(y1992)$ vs. $f(y1992 \times EFF \times KACCUM)$	–0.0816	0.9134	fail to reject
$g(y1992)$ vs. $f(y1992 \times TECH \times KACCUM)$	2.3893	0.0116	reject

Notes: We used the bootstrapped Li (1996) Tests with 5000 bootstrap replications and the Silverman's (1986) rule-of-thumb bandwidth.

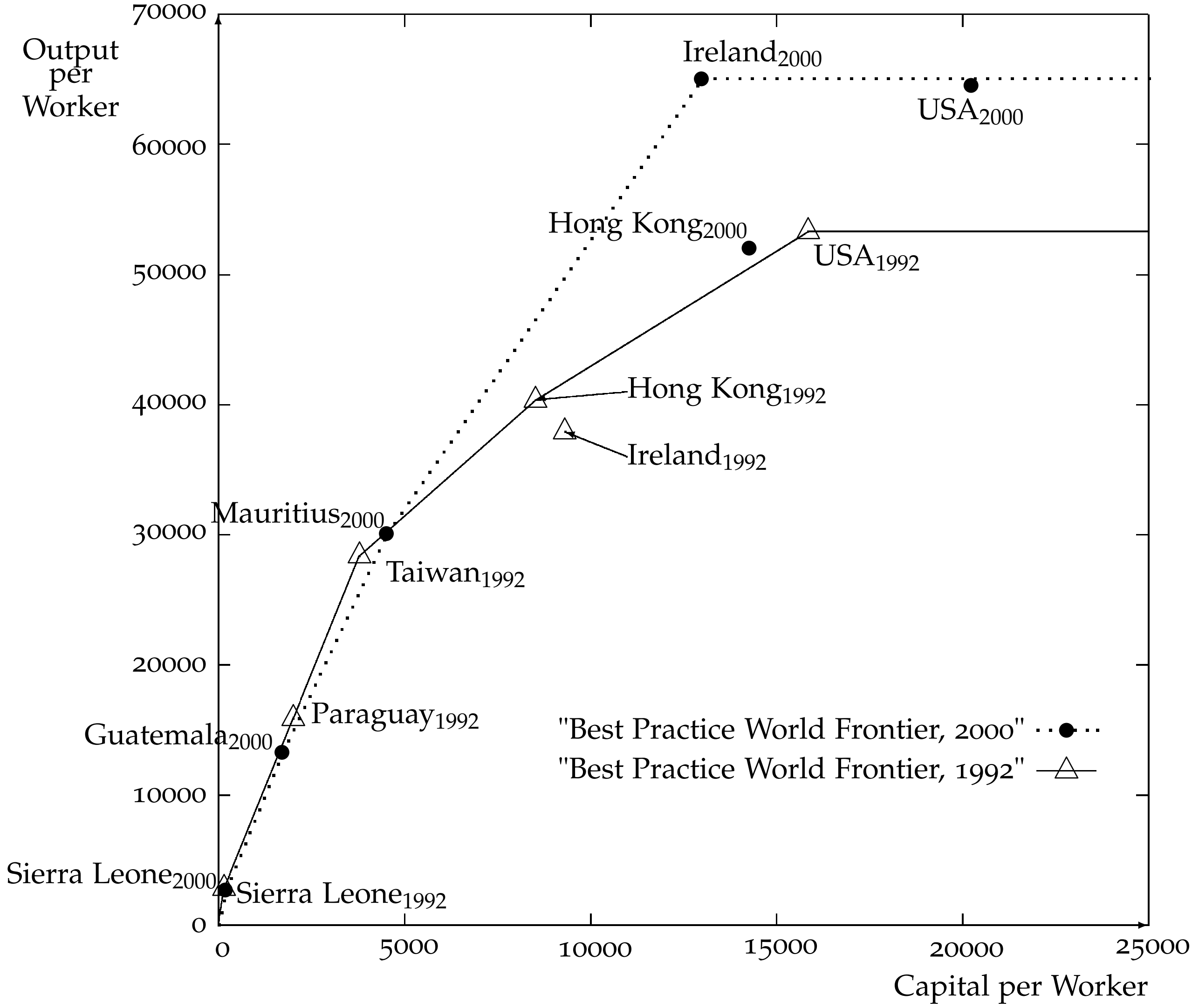

Figure 1: Estimated Best-Practice World Production Frontiers in 1992 and in 2000

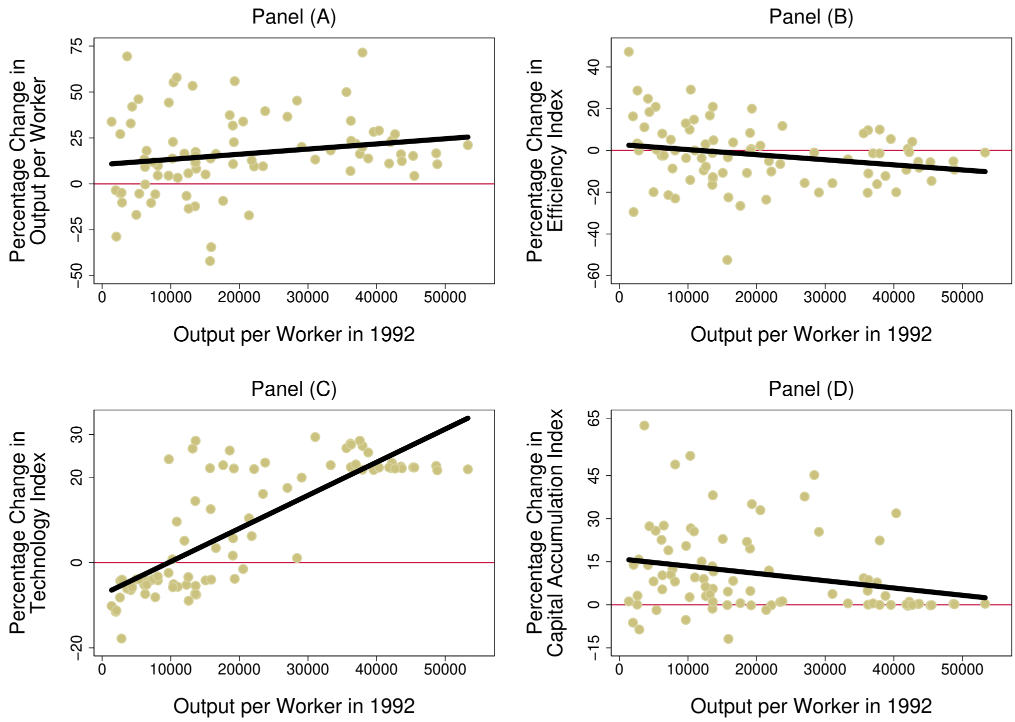

Figure 2: Percentage Change in Output per Worker and Three Decomposition Indexes, Plotted Against Output per Worker in 1992

Note: Each panel contains a GLS regression line.

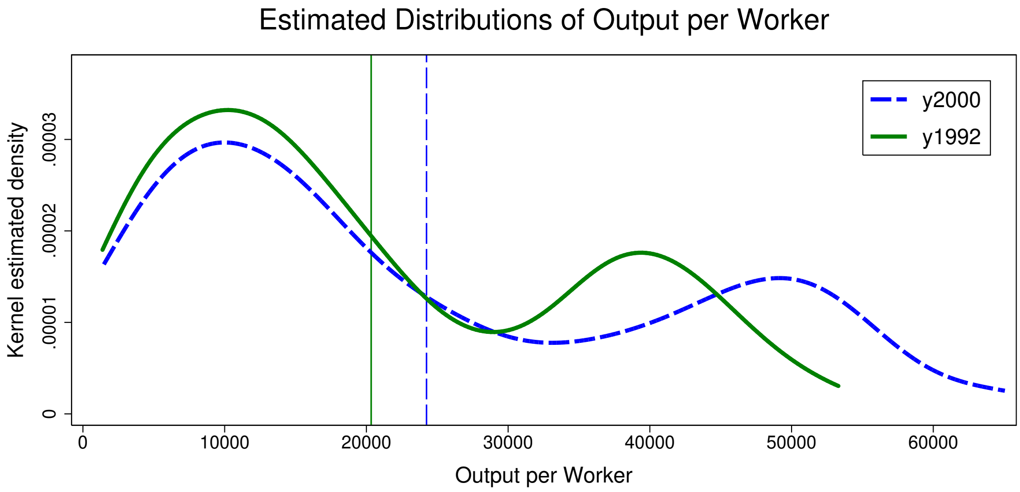

Figure 3: Estimated 1992 and 2000 Output per Worker Distributions

Notes: In the panel, the solid curve is the estimated 1992 distribution and the solid vertical line represents the 1992 mean value. The dashed curve is the estimated 2000 distribution and the dashed vertical line represents the 2000 mean value.

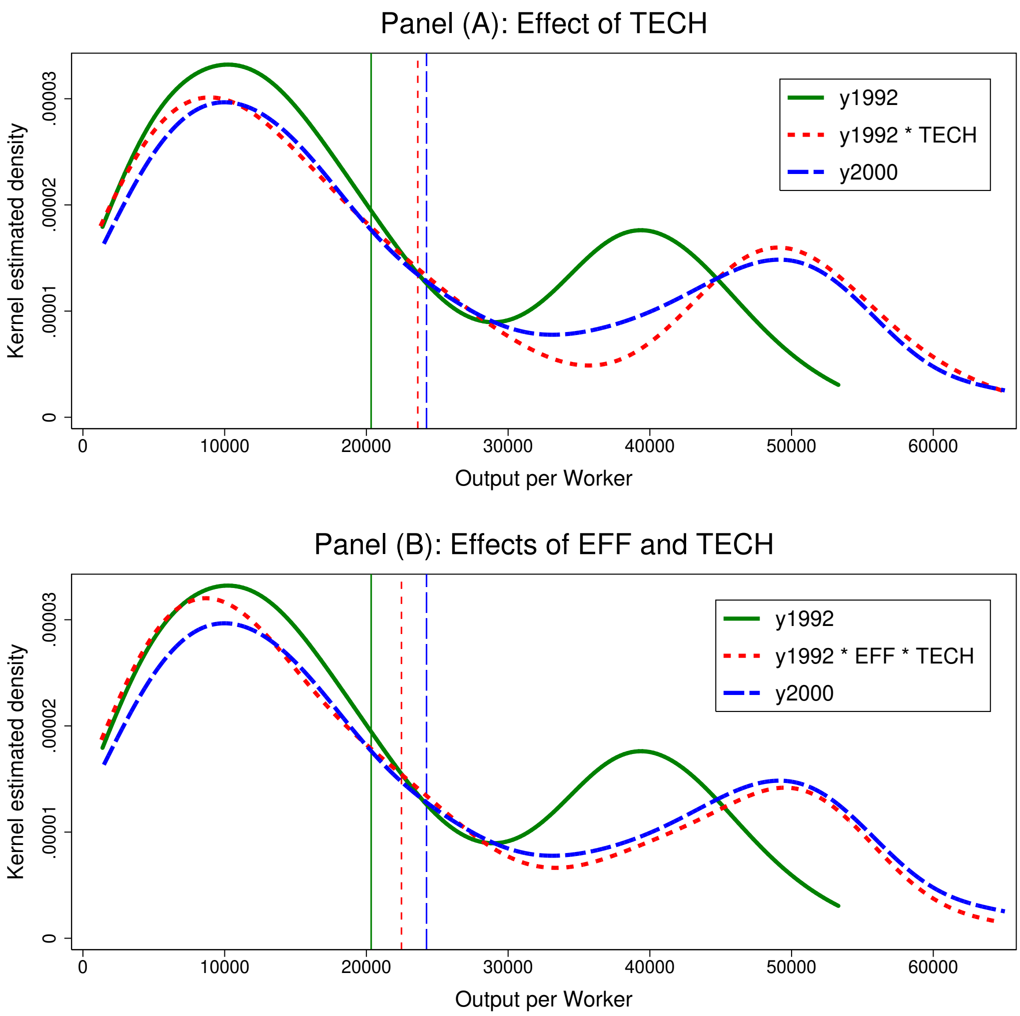

Figure 4: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: TECH, EFF

Notes: In each panel, the solid curve is the estimated 1992 distribution and the solid vertical line represents the 1992 mean value. The dashed curve is the estimated 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 technological change and efficiency change on the 1992 distribution, and the dotted vertical line represents the respective counterfactual mean.

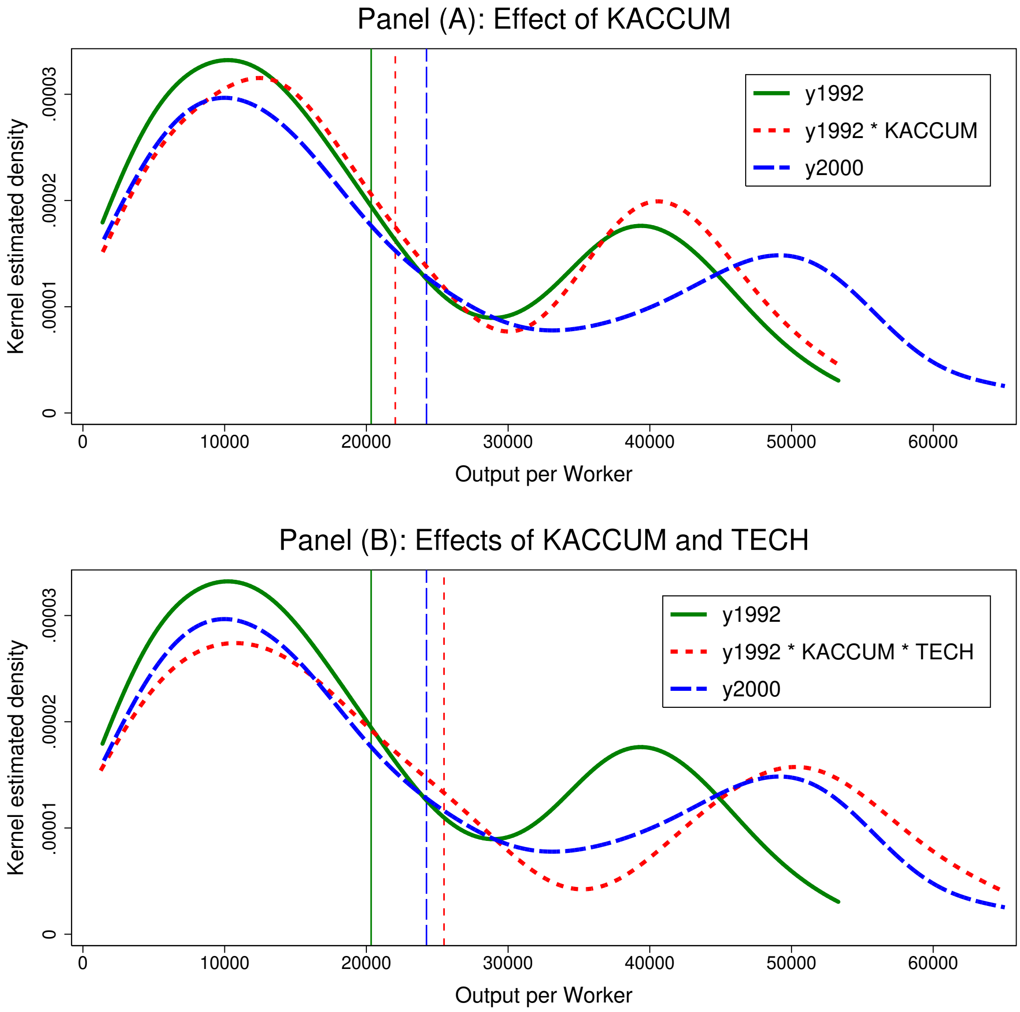

Figure 5: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: KACCUM, TECH

Notes: In each panel, the solid curve is the estimated 1992 distribution and the solid vertical line represents the 1992 mean value. The dashed curve is the estimated 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 capital accumulation and technological change on the 1992 distribution, and the dotted vertical line represents the respective counterfactual mean.

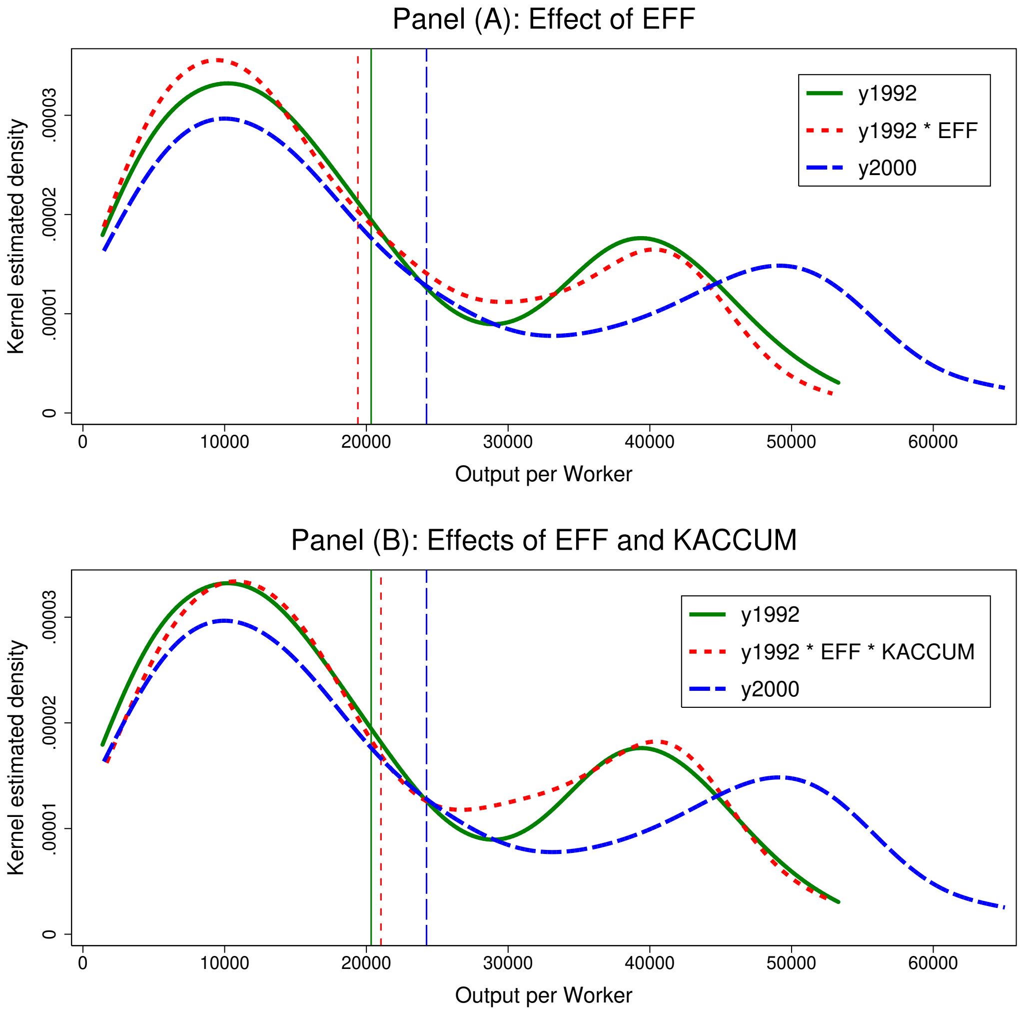

Figure 6: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: EFF, KACCUM

Notes: In each panel, the solid curve is the estimated 1992 distribution and the solid vertical line represents the 1992 mean value. The dashed curve is the estimated 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 and capital accumulation on the 1992 distribution, and the dotted vertical line represents the respective counterfactual mean.