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HUMAN CAPITAL AND CONVERGENCE: A PRODUCTION-FRONTIER APPROACH♣

Daniel J. Henderson and R. Robert Russell*

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Abstract

We decompose labor-productivity growth into components attributable to (1) technological change (shifts in the world production frontier), (2) technological catch-up (movements toward or away from the frontier), (3) human capital accumulation (changes in the efficiency of labor), and (4) capital accumulation (movement along the frontier). The world production frontier is constructed using deterministic methods requiring no specification of functional form for the technology nor any assumption about market structure or the absence of market imperfections. We find that technological change is decidedly non-neutral. We also analyze the evolution of the cross-country distribution of labor productivity in terms of the quadripartite decomposition, finding that (1) productivity growth and the increased dispersion of the distribution is driven primarily, and roughly equally, by physical and human capital accumulation and (2) international bipolarization (the shift from a unimodal to a bimodal distribution) is brought about primarily by efficiency changes.

Key words: international convergence, productivity, human capital, production frontiers, DEA.

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1. Introduction.

In the last 15 years, we have seen a striking resurgence of interest in empirical analysis of economic growth, powered in part by the early theoretical inquiries of Romer [1986] and Lucas [1988], which in turn built upon and extended the classic papers of Solow [1956] and others. We see two basic (intersecting) strands in this recent empirical research. One, building on the early cross-sectional regressions of Baumol [1986], seeks to determine whether there is a tendency for the world's economies to converge over time—for the poor to catch up with the rich. The other, harking back to the Solow [1957] decomposition of U.S.A. growth into two components attributable to capital deepening and technological progress, seeks to determine the sources of economic growth. These convergence and growth-accounting studies, summarized in Barro and Sali-i-Martin [1995] and Temple [1999],[1] have been facilitated by the ambitious development of a comprehensive system of internationally comparable real national income accounts: the Penn World Table (see Summers and Heston [1991] and Heston and Summers [1999]).

These empirical growth studies have not led to many definitive conclusions. Indeed the approaches to both strands of research have met with cogent criticism from Quah [1993, 1996a, 1997]. He has argued compellingly that analyses based on standard regression methods focusing on first moments of the distribution cannot adequately address the convergence issue. These arguments are butressed by the empirical analyses of Quah [1993, 1996b, 1997] and others (*e.g.*, Jones [1997]) posing a robust stylized fact about the international growth pattern that begs for explanation. Over the last few decades, the distribution of labor productivity has been transformed from a unimodal into a bimodal distribution with a higher mean. This transformation in turn means that the world is becoming divided, as a stylized fact, into two categories: the rich and the poor. Quah refers to this phenomenon as "two-club," or "twin-peak," convergence. Perhaps "bipolar divergence" would be another evocative characterization.

Most of the literature outlined above, especially the growth-accounting research, is heavily model-driven, relying on particular assumptions about the technology, market structure, technological change, and other aspects of the growth process. In a recent paper, Kumar and Russell [2001] (hereafter KR) employ (deterministic) production-frontier methods[2] to analyze international macroeconomic convergence. In particular, they decompose the labor-productivity growth of 57 industrial, newly industralized, and developing countries

[1] See, also, the 1996 *Economic Journal* symposium (Bernard and Jones [1996], Durlauf [1996], Galor [1996], Quah [1996b], and Sali-i-Martin [1996]).

[2] See Section 2 below for a brief description of this technique.

into components attributable to (1) technological change (shifts in the world production frontier), (2) technological catch-up (movements toward or away from the frontier), and (3) capital accumulation (movement along the frontier). These calculations amount to standard growth accounting with a twist—without the need for specification of a functional form for the technology, for the assumption that technological change is neutral, or for assumptions about market structure or the absence of market imperfections. Indeed, market imperfections, as well as technical inefficiencies, are possible reasons for countries falling below the world-wide production frontier. Taking a cue from the Quah critique, KR go on to analyze the evolution of the entire distribution of these three growth factors.

> Although the analysis of KR is quite simple, it yields somewhat striking results: (1) While there is substantial evidence of technological catch-up (movements toward the production frontier), with the degree of catch-up directly related to initial distance from the frontier, this factor apparently has not contributed to convergence, since the degree of catch-up appears not to be related to initial productivity. (2) Technological change is decidedly non-neutral, with no improvement—indeed, possibly some implosion—at very low capital/labor ratios, modest expansion at relatively low capital/labor ratios, and rapid expansion at high capital/labor ratios. (3) Both growth and bipolar international divergence are driven primarily by capital deepening. [KR, p. 4.]

A major drawback of the KR study is the absence of human capital in their modeling. Inspired in part by the early theoretical work on endogenous growth models (Lucas [1988] and Romer [1990]), many empirical growth researchers have focused on the important role played by human capital in the growth process. Extensive research on the development of educational data for a large number of countries[3] and on the returns to education,[4] has greatly facilitated the modeling of human capital and the growth process. The literature over the past decade indicates, not surprisingly, that various measures of mean years of schooling are correlated with productivity growth rates.[5] In addition, growth-accounting studies have indicated that the human-capital accumulation accounts for a large proportion of productivity growth or of cross-country differences of productivity levels, possibly even all of it.[6]

[3] See, especially, Barro and Lee [1993, 1996, 2000].

[4] See Psacharopoulos [1994, 1995], who in turn built on the classic research of Schultz [1961], Becker [1964/1993], and Mincer [1974].

[5] See, *e.g.*, Barro [1991, 1999, 2001], Barro and Sali-i-Martin [1995], Benhabib and Spiegal [1994], O'Neil [1995], and Sali-i-Martin [1997].

[6] See, *e.g.*, Bils and Klenow [2000], Hall and Jones [1999], and Wöβmann [2000]. These studies are in the tradition of Solow neoclassical (exogenous) growth theory, since human capital is treated as a (typically labor augmenting) input. In some endogenous growth theory models, the level of human capital is not simply an input into the production process, but is a catalyst for innovation

Ignoring the growth of human capital could generate a bias in the KR results, especially to the extent that the growth of human capital is correlated with any of the other components of their decomposition. In this paper, we incorporate human capital into the KR analysis. We use the human capital measure of Hall and Jones [1999], which is based on the summary of returns-to-education regressions by Psacharopoulos [1994]. Introduction of human capital into the KR framework results in a quadripartite decomposition of productivity growth into the contributions of technological change, efficiency changes, physical-capital accumulation, and human-capital accumulation. We analyze the contribution of these four components to the growth of productivity and to the shift in the worldwide distribution of productivity.

We introduce two additional changes in the KR framework. First, the KR approach admits the possibility of an implosion of the technological frontier over time. In fact, their calculations indicate a modest implosion in the mid-level of the capital-labor ratio and a substantial implosion at low levels of capitalization. It is difficult to believe that the technological frontier could implode. Moreover, the large implosion at low levels of capitalization appears to be generated entirely by the economic collapse of one (problematic) frontier country (Sierra Leone), and Summers and Heston [1991] stress that measurement error tends to be greatest for the poorest countries. Thus, following an approach first suggested by Tulkens and Vanden Eeckaut [1995], we adopt a construction of the worldwide technology that precludes such technological degradation. Second, we analyze separately the effects of the components of the quadripartite decomposition on (a) the change in mean productivity and (b) the mean-preserving shift of the productivity distribution. The KR analysis of productivity distribution shifts confounds these two phenomena.

Our results confirm the KR finding that technological change is palpably non-neutral but contradict the KR finding that capital accumulation accounts for most of increase in productivity and for the shift in the productivity distribution over 1965–90 period. In particular, we find that about half of the productivity growth can be attributed to the accumulation of human capital and that the qualitative shift from a unimodal to a bimodal distribution is accounted for by efficiency changes, whereas the increased dispersion of productivity is accounted for primarily by the accumulation of human and physical capital.

Section 2 constructs the worldwide technology frontiers in 1965 and 1990 and measures the efficiency of 52 economies. Section 3 decomposes the productivity changes in the four

and technological growth. An interesting application in this spirit, using production-frontier methods and Malmquist productivity indexes, can be found in the recent paper by Grosskopf and Self [2001].

components and Section 4 analyzes the mean-preserving shift in the world productivity distribution. Section 5 concludes.

2. Technology Frontiers and Efficiency Measurement (Technological Catch-Up).

2.1. Data Envelopment Analysis.

The KR approach to constructing the worldwide production frontier and associated efficiency levels of individual economies (distances from the frontier), motivated in part by the first such effort in this direction by Färe, Grosskopf, Norris, and Zhang [1994], is based on the pioneering work of Farrell [1956] and Afriat [1972].[7] The basic idea is to envelop the data in the "smallest," or "tightest fitting," convex cone, and the (upper) boundary of this set then represents the "best practice" production frontier. Although this data-driven approach, implemented with standard mathematical programming algorithms, requires no specification of functional form, it does require an assumption about returns to scale of the technology (as well as free input and output disposability).

Our technology contains four macroeconomic variables: aggregate output and three aggregate inputs—labor, physical capital, and human capital. Let $\langle Y_t^j, L_t^j, K_t^j, H_t^j \rangle$, $t = 1, \ldots, T,\ j = 1, \ldots J$, represent T observations on these four variables for each of the J countries. Following the macroeconomic literature, we assume that human capital enters the technology as a multiplicative augmentation of physical labor input, so that our JT observations are $\langle Y_t^j, \hat{L}_t^j, K_t^j \rangle,\ t = 1, \ldots, T,\ j = 1, \ldots J$, where $\hat{L}_t^j := H_t^j L_t^j$ is the amount of labor input measured in *efficiency* units in country j at time t.

As noted in the Introduction, our approach to constructing the frontier uses the "sequential production set" formulation of Tulkens and Vanden Eeckaut [1995] to preclude implosion

[7] A fully general exposition of this approach, aimed primarily at economists, can be found in Färe, Grosskopf, and Lovell [1995]; the management-science approach to essentially the same methods began with the paper by Charnes, Cooper and Rhodes [1978], who coined the evocative term "data envelopment analysis" (DEA), and is comprehensively treated in Charnes, Cooper, Lewin, and Seiford [1994].

of the frontier over time. In particular, we construct the constant-returns-to-scale, period-t technology using (in principle[8]) all data up to that point in time:

$$\mathcal{T}_t = \Big\{ \langle Y, \hat{L}, K \rangle \in \mathcal{R}^3_+ \;\Big|\; Y \leq \sum_{\tau \leq t} \sum_j z^j_\tau Y^j_\tau \;\wedge \\ \hat{L} \geq \sum_{\tau \leq t} \sum_j z^j_\tau \hat{L}^j_\tau \;\wedge\;\; K \geq \sum_{\tau \leq t} \sum_j z^j_\tau K^j_\tau,\; z^j \geq 0 \;\;\forall\, j \Big\}. \tag{2.1}$$

This technology is the Farrell cone; other assumptions about returns to scale would incorporate an additional constraint on the activity levels, $z^j_t,\ t = 1, \ldots, T,\ j = 1, \ldots J$ (see, *e.g.*, Färe, Grosskopf, and Lovell [1995]). For later reference, note that the assumption of constant returns to scale allows us to represent the technology in a two-dimensional subspace, scaling output and capital by effective labor:

$$\hat{\mathcal{T}}_t = \Big\{ \langle \hat{y}, \hat{k} \rangle \in \mathcal{R}^2_+ \;\Big|\; \hat{y} \leq \sum_{\tau \leq t} \sum_j z^j_\tau \hat{y}^j_\tau \;\wedge \\ 1 \geq \sum_{\tau \leq t} \sum_j z^j_\tau \;\wedge\;\; \hat{k} \geq \sum_{\tau \leq t} \sum_j z^j_\tau \hat{k}^j_\tau,\; z^j \geq 0 \;\;\forall\, j \Big\}, \tag{2.2}$$

where $\hat{y} = Y/\hat{L}$ and $\hat{k} = K/\hat{L}$ are the ratios of output and capital to effective labor, respectively.

The Farrell (output based) efficiency index for country j at time t is defined by

$$E(Y^j_t, \hat{L}^j_t, K^j_t) = \min \big\{ \lambda \mid \langle Y^j_t/\lambda, \hat{L}^j_t, K^j_t \rangle \in \mathcal{T}_t \big\} \tag{2.3}$$

or, equivalently,

$$\hat{E}(\hat{y}^j_t, \hat{k}^j_t) = \min \big\{ \lambda \mid \langle \hat{y}^j_t/\lambda, \hat{k}^j_t \rangle \in \hat{\mathcal{T}}_t \big\}. \tag{2.4}$$

This index is the inverse of the maximal proportional amount that output Y^j_t can be expanded while remaining technologically feasible, given the technology $\mathcal{T}_t$ and the input quantities $\hat{L}^j_t$ and K^l_t, or, equivalently, the inverse of the maximal proportional amount that output per efficiency unit of labor $\hat{y}^j_t$ can be expanded while remaining technologically feasible, given the technology $\hat{\mathcal{T}}_t$ and the capital per efficiency unit of labor $\hat{k}^j_t$; it is less than or equal to 1 and takes the value of 1 if and only if the jt observation is on the period-t production frontier. In this 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,

[8] Because of data limitations, we focus on two time periods, 1965 and 1990, and changes over that 25-year interval.

but in multiple-output technologies the index is a radial measure of the (proportional) distance of the actual output vector from the production frontier.[9]

2.2. Data.

For aggregate output, physical capital, and labor, we use the same Penn World Table data as KR, focusing on the first and last years for which data are available, 1965 and 1990, and the changes over that 25-year period.[10] For human capital, we adopt the Hall and Jones [1999] construction, which in turn is based on the Barro and Lee [1993, 1996, 2000] education data and the Psacharopoulos [1994] survey of wage equations evaluating the returns to education. In particular, let ϵ_t^j represent the average number of years of education of the adult population in country j at time t and define labor in efficiency units in country j at time t by

$$\hat{L}_t^j = H_t^j L_t^j = h(\epsilon_t^j) L_t^j = e^{\phi(\epsilon_t^j)} L_t^j, \tag{2.5}$$

where ϕ is a piecewise linear function, with a zero intercept and a slope of .134 through the fourth year of education, .101 for the next four years, and .068 for education beyond the eighth year. Clearly, the rate of return to education (where ϕ is differentiable) is

$$\frac{d \ln h(\epsilon_t^j)}{d\epsilon_t^j} = \phi'(\epsilon_t^j), \tag{2.6}$$

and $h(0) = 1$.

Because of a lack of data on human capital for some countries, our data set includes 52 countries, five fewer than the KR data set.[11] The countries included in our data base, along with the values of the augmentation factors, $H_t^j = e^{\phi(\epsilon_t^j)}$, for 1965 and 1990, are listed in Table 1.

[9] The Farrell efficiency index can be calculated by solving a linear program for each observation. See, *e.g.*, Färe, Grosskopf, and Lovell [1995].

[10] These are the countries for which complete data sets on output, labor, and capital are available, though, as is common in the convergence literature, KR exclude two major oil-producing countries, Iran and Venezuela. Including these two countries has no significant effect on their results, though it is worth noting that when they are included both are on the KR production frontier in 1965.

[11] Unfortunately, four of the five omitted countries (Ivory Coast, Madagascar, Morocco, and Nigeria) are African, leaving us with just six countries from that continent. The other omitted country is Luxembourg.

2.3 Efficiency and Technological Catch-Up.

Table 2 lists the efficiency levels of each of the 52 countries for the beginning and end years of our sample, 1965 and 1990.[12] For comparison purposes, we calculate these efficiency indexes both with and without human capital. The technology and efficiency index without human capital are constructed by replacing $\hat{L}_t^j$ with L_t^j in (2.1) and (2.3). The efficiency figures for 1965 without human capital are identical (up to rounding error) to those in KR, since the 1965 production frontiers are identical, being determined by the same (frontier) countries: those with efficiency scores of 1.00 (Argentina, Paraguay, Sierra Leone, and the U.S.A.).[13] The 1990 efficiency indexes without human capital, however, are different from those in KR, because our calculations preclude implosion of the frontier, thus knocking Sierra Leone off the 1990 frontier, and because Luxembourg, a 1990 frontier economy in KR, is not in our data set.

We are primarily interested in comparisons of efficiency measurement with and without the inclusion of human capital in the technology. Assuming that human capital is reasonably well measured, an improvement in the efficiency score when human capital is incorporated into the measurement of efficiency indicates that some of the measured inefficiency in the simpler model should, in fact, have been attributed to a relative paucity of the quantity of human capital, or, equivalently, to a mismeasurement of labor input. A similar interpretation applies to a decrease in efficiency scores.

Note first, from Table 2, that the mean efficiency score in 1965 is increased from .64 to .68 by the incorporation of human capital. This suggests that a good deal of the dispersion of 1965 efficiency in KR is attributable to mismeasurement of labor input: adjusting for the efficiency of the labor force moves economies toward the frontier, closing the gap by about 11 percent on average. Curiously, the biggest efficiency improvements emanating from the incorporation of human capital in 1965 occur in highly capitalized economies—Finland, the Netherlands, Norway, and Switzerland—as well as in some developing countries—most notably, Syria, Guatemala, and Mexico. Also notable, though, is the movement to the 1965 frontier of Mauritius, the Netherlands, and Spain, countries that, even without considerations of human capital, are not far from the frontier.

The effect of incorporating human capital into the 1990 calculations is less pronounced; some countries move substantially toward the frontier while others move farther away. Those helped most by the consideration of human capital are a few OECD countries

[12] Our efficiency calculations were carried out using the software *OnFront*, available from Economic Measurement and Quality i Lund AB (Box 2134, S-220 02 Lund, Sweden [www.emq.se]).

[13] The (two-dimensional) frontiers, discussed below, appear in Figures 1–3.

(especially Italy, Portugal, and Spain) and some developing countries (notably again, Syria and Guatemala), while those whose scores suffer are some of the most highly capitalized countries (notably, Norway, Canada, Switzerland, and the U.S.A.). The case of Italy is especially interesting, because taking account of human capital moves that country to the frontier, replacing the United States at high capital/effiency-labor ratios.

Over time, the mean efficiency index increases slightly when human capital accumulation is not taken into account but declines slightly when human capital is included in the calculations. Figure 4 shows plots of the distributions in 1965 and 1990.[14] This picture suggests that some mass in the middle of the distribution was shifted toward the frontier and some away from the frontier.

Constant returns to scale and labor-augmention of human capital allow us to construct the production frontiers in $\hat{y} - \hat{k}$ space, as elucidated by the constructions in (2.2) and (2.4). Figures 1 and 2 contain the production frontiers and scatter plots of the data for 1965 and 1990, respectively, while Figure 3 superimposes the two frontiers.[15] The construction in (2.1) (alternatively (2.2)) does not allow implosion of the frontier. One fact that emerges immediately from these graphs is the non-neutrality of technological change. Up to a capital/efficiency-labor ratio of 6000, the 1965 and 1990 frontiers are virtually coincident, but for higher levels of capitalization the frontier shifts upwards dramatically. This is basically the same result as found in the KR analysis without human capital, indicating, perhaps not surprisingly, that almost all technological change occurs at high levels of capitalization.

3. Quadripartite Decomposition of the Factors Affecting Labor Productivity.

3.1. Conceptual Decomposition.

The tripartite decomposition of productivity growth in KR can be applied straightforwardly to the growth of output per efficiency unit of labor as follows. Letting b and c stand for the base period and the current period, respectively, we see, by definition, that

[14] This distribution and the others we employ below are nonparametric kernel-based density estimates, essentially “smoothed” histograms of productivity levels. See the Appendix for the particulars.

[15] West Germany and, especially, Switzerland (with a capital/efficiency-labor ratio 69 percent greater than Italy) are off the horizontal scale in 1990. (Neither is on the frontier.)

potential (frontier) outputs per efficiency unit of labor in the two periods are given by $\hat{\hat{y}}_b(k_b) = \hat{y}_b/e_b$ and $\hat{\hat{y}}_c(k_c) = \hat{y}_c/e_c$, where e_b and e_c are the values of the efficiency indexes in the respective periods. Thus,

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c \cdot \hat{\hat{y}}_c(\hat{k}_c)}{e_b \cdot \hat{\hat{y}}_b(\hat{k}_b)}. \tag{3.1}$$

Now denote potential output per unit of efficiency unit of labor at *current*-period capital intensity using the *base*-period technology by $\hat{\hat{y}}_b(k_c)$. Similarly, potential output per unit of efficiency labor at *base*-period capital intensity using the *current*-period technology is denoted $\hat{\hat{y}}_c(k_b)$. Multiplying top and bottom of (3.1) alternatively by $\hat{\hat{y}}_b(k_c)$ and $\hat{\hat{y}}_c(k_b)$ yields two alternative decompositions of the growth of $\hat{y}$:

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c}{e_b} \cdot \frac{\hat{\hat{y}}_c(k_c)}{\hat{\hat{y}}_b(k_c)} \cdot \frac{\hat{\hat{y}}_b(k_c)}{\hat{\hat{y}}_b(k_b)} \tag{3.2}$$

and

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c}{e_b} \cdot \frac{\hat{\hat{y}}_c(k_b)}{\hat{\hat{y}}_b(k_b)} \cdot \frac{\hat{\hat{y}}_c(k_c)}{\hat{\hat{y}}_c(k_b)}. \tag{3.3}$$

The decomposition in (3.2) measures technological change by the shift in the frontier in the output direction at the *current*-period capital/efficiency-labor ratio and measures the effect of capital accumulation along the *base*-period frontier. The decomposition in (3.3) measures technological change at the *base*-period capital/labor ratio and capital accumulation by movements along the *current*-period frontier. These two decompositions do not yield the same results; that is, the decomposition is path dependent. In fact, in the absence of neutrality of technological change (as assumed by Solow [1957] and the many studies building on his pioneering paper), this ambiguity is endemic to growth accounting exercises. In the tradition of Caves, Christensen, and Diewert [1982] and Färe, Grosskopf, Lindgren, and Roos [1994], we resolve this ambiguity, as did KR, by adopting the "Fisher ideal" decomposition, based on geometric averages of the two measures of the effects of technological change and capital accumulation, obtained by multiplying top and bottom of (3.1) by $\left(\hat{\hat{y}}_b(k_c)\hat{\hat{y}}_c(k_b)\right)^{1/2}$:

$$\begin{aligned}\frac{\hat{y}_c}{\hat{y}_b} &= \frac{e_c}{e_b}\left(\frac{\hat{\hat{y}}_c(k_c)}{\hat{\hat{y}}_b(k_c)} \cdot \frac{\hat{\hat{y}}_c(k_b)}{\hat{\hat{y}}_b(k_b)}\right)^{1/2}\left(\frac{\hat{\hat{y}}_b(k_c)}{\hat{\hat{y}}_b(k_b)} \cdot \frac{\hat{\hat{y}}_c(k_c)}{\hat{\hat{y}}_c(k_b)}\right)^{1/2} \\ &=: EFF \times TECH \times KACC.\end{aligned} \tag{3.4}$$

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:

$$\frac{y_c}{y_b} = \frac{H_c}{H_b} \cdot \frac{\hat{y}_c}{\hat{y}_b}. \tag{3.5}$$

Combining (3.4) and (3.5), we obtain the quadripartite decomposition:

$$\begin{aligned} \frac{y_c}{y_b} &= \frac{e_c}{e_b}\left(\frac{\hat{\bar{y}}_c(k_c)}{\hat{\bar{y}}_b(k_c)}\cdot\frac{\hat{\bar{y}}_c(k_b)}{\hat{\bar{y}}_b(k_b)}\right)^{1/2}\left(\frac{\hat{\bar{y}}_b(k_c)}{\hat{\bar{y}}_b(k_b)}\cdot\frac{\hat{\bar{y}}_c(k_c)}{\hat{\bar{y}}_c(k_b)}\right)^{1/2}\frac{H_c}{H_b} \\ &=: EFF \times TECH \times KACC \times HACC. \end{aligned} \tag{3.6}$$

3.2. Empirical Results.

Table 3 shows each of the components of the (relevant) decomposition of productivity growth from 1965 to 1990, both without and without human capital. The first row for each country shows the country's productivity growth and 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 ($[KACC - 1] \times 100$), ignoring the role of human capital in the production process. The second row for each country shows the contributions to productivity growth of human capital accumulation ($[HACC - 1] \times 100$) as well as each of the other three components of the quadripartite decomposition.

The figures without human capital are little different from those in KR for most countries. The differences in the means of the efficiency and technological-change components of growth are not substantially changed by the incorporation of human capital, but the mean contribution of capital accumulation is sliced from 58 percent to 30 percent. The difference is made up by a 26-percent mean contribution from the accumulation of human capital. It appears that roughly half of the growth of productivity attributed to physical-capital accumulation by KR is, in fact, attributable to human-capital accumulation. This result accords closely with the standard (model driven) growth-accounting exercise of Wöβmann [2000], who incorporates notions of quality of education into the calculation of human capital. On the other hand, Wöβmann finds that human capital explaind *all* of the disparity of productivity levels of OECD countries in 1988.

Observations about several interesting individual cases by KR hold up fairly well when human capital is introduced into the analysis. Consider the four Asian "growth miracles," with output per worker more than tripling in Hong Kong and Japan, quadrupling in Taiwan, and more than quintupling in South Korea over this 25-year span (Singapore is not in our data set). Although human-capital accumulation is well above average for Hong Kong, Korea, and Taiwan (and somewhat below average for Japan), it remains the case that the Japan, South Korea, and Taiwan growth spurts were driven primarily by capital accumulation, whereas that of Hong Kong resulted primarily from efficiency improvements. In fact, the Hong Kong experience is even more sharply focused by including human capital, since this has little effect in lowering the contribution of efficiency improvements to the growth process, while substantially lowering the contribution of capital accumulation. We should add Thailand to the “Asian Tiger” group, since its productivity almost tripled over our 25-year period. It appears that the largest contribution to the Thai growth spurt is physical capital accumulation, with human capital accumulation accounting for no more than the improvement in efficiency.

The story of Argentina’s stagnation is also little changed by the incorporation of human capital. It remains the case that the cause seems to be a collapse in efficiency; the accumulation of both human and physical capital are about average over this period. On the other hand, the disastrous 34-percent collapse of productivity in Zambia looks a little different: while the large (roughly 30 percent) contribution of the deterioration in efficiency is unaffected by the introduction of human capital, the negative contribution of physical capital accumulation is worsened to about 30 percentage points and compensated for by an above-average accumulation of human capital.

Figure 5 summarizes these calculations by plotting the four productivity-component growth rates against output per worker in 1965. GLS regression lines are also plotted. Panel (a), showing the relationship between the contribution of efficiency to productivity growth and the initial level of productivity, evinces no clear pattern, with many negative as well as positive changes. The regression slope coefficient is not statistically significant, suggesting that technological catch-up has done little, if anything, to lower income inequality across countries. Apparently, technology transfer has benefited relatively rich countries about as much as relatively poor countries. Panel (b) indicates that relatively wealthy countries have benefited much more from technological progress than have less-developed countries, as is evident from Figure 3. Clearly, the positive regression slope coefficient is highly statistically significant. Panel (c) indicates a wide dispersion of contributions of capital contribution. The negative slope is statistically insignificant at the 5-percent level but significant at the 10-percent level, suggesting that poorer countries might have benefited more from capital accumulation, on average, over the sample period. Finally, Panel (d) evinces a highly significant inverse relationship between the intitial productivity level and the contribution of human capital accumulation to productivity growth; apparently, human capital accumulation has contributed to the convergence of productivity levels.

4. Analysis of Productivity Distributions.

We now turn to an analysis of the distribution dynamics of labor productivity. A plot of the distributions of output per worker across the 52 countries in our sample in 1965 and

1990 appears in Figure 6. Over this 25-year period, the distribution of labor productivity was transformed from a unimodal into a bimodal distribution with a higher mean. Here we extend the analysis of KR by attempting to explain this bipolarization of the distribution of output per worker in terms of our quadripartite decomposition. Since the effect of the four factors on the mean change in productivity has already been analyzed in the context of Table 3, however, we focus in this paper on *mean-preserving* shifts in the distribution when we sequentially introduce the four components. Figure 7 shows the 1965 and 1990 distributions of departures from the productivity mean, $y_t - \tilde{y}$, where $\tilde{y}$ is the productivity mean in year t; that is, each distribution has zero mean. The salient features of the shift are the switch from unimodal to bimodal and an increased dispersion, perhaps more evident in this mean-preserving comparison than in that of Figure 6. We aim to explain these features of the change in the productivity distribution from 1965 to 1990 in terms of the four components of the decomposition of productivity changes.

Re-write the tripartite decomposition of labor productivity changes in (3.6) as follows:

$$y_c = (EFF \times TECH \times KACC \times HACC) \cdot y_b. \tag{4.1}$$

Thus, the labor productivity distribution in 1990 can be constructed by successively multiplying labor productivity in 1965 by each of the four factors. This in turn allows us to construct counterfactual distributions by sequential introduction of each of these factors (where $b = 1965$ and $c = 1990$). For example, the counterfactual 1990 labor-productivity distribution of the variable,

$$y^E = EFF \cdot y_b, \tag{4.2}$$

with its mean extracted, isolates the (mean preserving) effect on the distribution of changes in efficiency only, assuming a stationary world production frontier, no capital deepening, and no accumulation of human capital, and the counterfactual 1990 labor-productivity distribution of the variable,

$$y^E = (EFF \times TECH) \cdot y_b, \tag{4.3}$$

with its mean extracted, isolates the (mean preserving) effect on the distribution of changes in efficiency and the technology, assuming no capital deepening, and no accumulation of human capital.

We can then exploit recent developments in nonparametric methods to test formally for the statistical significance of differences between (actual and counterfactual) distributions—to test indirectly, that is, for the statistical significance of the relative contributions of the four components of the decomposition of productivity changes to (mean preserving) changes in the distribution of labor productivity. In particular, Fan and Ullah [1999], building on earlier work of Li [1996], have proposed a nonparametric, time-series test for the comparison of two unknown distributions, say f and g—that is, a test of 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.[16] Since this test is likely to have low power, given the relatively small number of observations in our data set, we believe that a 5-percent, or even a 10-percent significance level is more appropriate than a 1-percent significance level.

Table 4 contains the test results for all possible combinations, and Figures 8–11 contain a selection of counterfactual distributions generated by sequential introduction of components of the quadripartite decomposition. The first test (first row of Table 4) easily rejects the hypothesis that the actual 1965 and 1990 distributions in Figure 7 are identical, indicating that the increase in the mean is not the only statistically significant change in the productivity distribution over the 1965–90 period. The next four tests (rows 2–5) each introduce just one of the four components, and it is apparent that the null hypothesis is rejected in each case at the (preferred) 5-percent level, though identity of the two distributions is barely rejected when physical capital accumulation alone is used to construct the counterfactual distribution. This result contrasts with that of KR, suggesting that their result that capital accumulation alone can explain the shift in the distribution, even at the 10-percent significance level, is essentially attributable to the effect on the shift in the mean rather than the shift from a unimodal to a bimodal distribution with increased dispersion.

Let us now examine what happens when we introduce more than one component, first following the sequence in (4.1). This sequence is illustrated in Figure 8. Panel (a) in this figure, as in those that follow, is identical to Figure 7, displaying the actual distributions of deviations from the mean in 1965 and 1990, to facilitate comparisons to the counterfactual distributions for 1990 that follow. Each of the succeeding panels contains the actual 1990 distribution and a counterfactual distribution. Thus, Panel (b) compares the actual 1990 distribution to the counterfactual 1990 distribution corresponding to equation (4.2); it shows what the 1990 distribution would have looked like if only efficiency had changed for each country in our sample. A striking aspect of this comparison is that the bimodalism emerges in this counterfactual distribution, but the dispersion seems to be substantially unaffected. Thus, it seems that efficiency changes alone can account for the qualitative change from unimodalism to bimodalism. Although we do not report the result here, it should be noted that the bimodalism does not arise in the mean-preserving comparison of the actual 1990 distribution to the counterfactual 1990 distribution corresponding to equation (4.2) when human capital accumulation is not included in the analysis; thus, it

[16] See the Appendix for an exact description of the test statistic, which is also described in Pagan and Ullah [1999].

appears that this contrast to the KR results is attributable to the incorporation of human capital accumulation into the analysis, not to the abstraction from shifts in the mean.

Panel (c) of Figure 8 contains the counterfactual distribution under the assumption that only efficiency and the technology changed. This factor seems to dampen the bimodalism a bit but also spreads the distribution somewhat. As shown in Table 4 (row 6), this counterfactual distribution is statistically significantly different from the actual 1990 distribution at the most-stringent significance level. Thus, it appears that efficiency changes and technological change together cannot explain the mean-preserving shift of the productivity distribution. Panel (d) adds capital accumulation to the mix. This seems to restore the bimodalism and enhance the dispersion. As revealed in Table 4 (row 12), this counterfactual distribution is statistically insignificantly different from the actual 1990 distribution at the most-stringent significance level. Thus, it appears that the change in human capital is not needed to explain the (mean preserving) shift in the distribution from 1965 to 1990.

Let us see, however, what happens if we reverse the order of introduction of the physical and human capital accumulation components of the decomposition. The first three panels of Figure 9 are identical to those in Figure 8, but panel (d) introduces human instead of physical capital accumulation. Here, too, the resulting distribution is statistically identical to the actual 1990 distribution at the most stringent significance level (row 13). Thus, it appears that neither physical nor human capital accumulation needs to be taken into account to explain the mean-preserving shift in the productivity distribution from 1965 to 1990, but either suffices when added to changes in efficiency and technological change.

Figure 10 introduces capital accumulation first, and the resultant counterfactual 1990 distribution in panel (b) is slighty bimodal and more dispersed, but, as noted above, still statistically significantly different from the actual 1990 distribution at the 5-percent level. When technological change is added in panel (c), however, the bimodalism becomes a little more prominent, the spread is enhanced, and the resultant counterfactual distribution is not statistically significantly different from the actual one at any significance level. Thus, capital accumulation, along with technological change suffices to explain statistically the distribution shift, without the help of efficiency changes.

Figure 11 introduces human capital accumulation first and then technological change, and the resultant counterfactual distribution in panel (c) is not bimodal, although the spread is considerably enhanced. The resultant distribution is not statistically significantly different from the actual distribution at the 10-percent level and is right on the boundary of significance at the 5-percent level. Thus, human capital accumulation and technological change are not quite sufficient to explain the shift at the 5-percent level.

To summarize, inspection of the various counterfactual distributions in Figures 8–11 and the statistical tests in Table 4, leaves us with the gestalt impression that (a) efficiency changes are the principal driving force behind the qualitative change in the productivity distribution from unimodal to bimodal, with some help from physical capital accumulation, and (b) physical and human capital are the principal driving forces behind the increased dispersion of productivity levels, with some help from technological change. With help from technological change, physical capital accumulation can explain statistically, at all significance levels, the mean-preserving shift in the distribution from 1965 to 1990. Human capital accumulation can account for the shift statistically at the 5-percent level with help from technological change, but not at the 10-percent level.

5. Conclusion.

In this paper, we have introduced human capital into the KR growth-accounting analysis of international macroeconomic convergence. Along the way, we have also amended the KR methodology by (1) adopting the Tulkens and Vanden Eeckaut [1995] approach to dynamic frontier analysis, thus precluding implosion of the worldwide production frontier over time and (2) separating the analysis of changes in the productivity distribution to analyses of (a) changes in the mean and (b) mean-preserving shifts in the distribution of productivity. Our principal conclusions are as follows:

- Well over half of the increase in mean productivity attributed by KR to the accumulation of physical capital was, in fact, the result of the accumulation of human capital.

- In contradistinction to the KR conclusion that capital accumulation also accounts for the shift in the distribution, primarily from unimodal to bimodal, our analysis indicates that efficiency changes account for the qualitative shift from unimodal to bimodal, whereas the accumulation of physical *and* human capital account for the increased worldwide dispersion of productivity.

- The KR conclusion that technological change is decidedly non-neutral, with virtually all progress taking place in the highly capital-intensive region of input space, is confirmed by our analysis incorporating human capital accumulation.

Of course, these conclusions rely heavily on the conceptual measurement of human capital, and the underlying measurement of years of education. As Wöβmann [2000] points out, these measurements are problematic and controversial. Nevertheless, theoretical and empirical research, as well as simple intuition, suggests that human capital is an element of the growth process that is too important to ignore.

Appendix

Each of the distributions in Figures 4 and 6–11 is a kernel-based estimate of a density function, $f(\cdot)$, of a random variable x, based on the standard normal kernel function and optimal bandwidth:

$$\hat{f}(x) = \frac{1}{nh} \sum_{j=1}^{J} k\left(\frac{x_j - x}{h} \right),$$

where $\int_{-\infty}^{\infty} k(\psi) d\psi = 1$ and $\psi = (x_j - x)/h$. In this construction, h is the optimal window width, which is a function of the sample size n and goes to zero as $n \to \infty$. We assume that k is a symmetric standard normal density function, with non-negative images. See Pagan and Ullah (1999) for details.

The statistic used to test for the difference between two distributions, predicated on the integrated-square-error metric on a space of density functions, $I(f,g) = \int_x \big(f(x) - g(x)\big)^2 dx$, is

$$T = \frac{nh^{1/2}}{\hat{\sigma}} \;\sim\; N(0,1),$$

where

$$= \frac{1}{n^2 h} \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \left[k\left(\frac{x_i - x_j}{h} \right) + k\left(\frac{y_i - y_j}{h} \right) - k\left(\frac{y_i - x_j}{h} \right) - k\left(\frac{x_i - y_j}{h} \right) \right]$$

and

$$\hat{\sigma}^2 = \frac{1}{n^2 h \pi^{1/2}} \sum_{i=1}^{n} \sum_{j=1}^{n} \left[k\left(\frac{x_i - x_j}{h} \right) + k\left(\frac{y_i - y_j}{h} \right) + 2k\left(\frac{x_i - y_j}{h} \right) \right].$$

As shown by Fan and Ullah [1999], the test statistic asymptotically goes to the standard normal. Our sample in our study contains only 52 observations, but the KR bootstrapping exercise for a similar number of observations shows that the critical values, at 5 percent and 1 percent are very near the standard normal critical values; hence, we use the standard normal critical values in our significance tests.

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Table 1: Human-Capital Augmentation Factors

Country	1965	1990	Country	1965	1990
Argentina	1.93	2.50	Korea, Rep.	1.78	2.79
Australia	2.80	2.96	Malawi	1.25	1.41
Austria	2.29	2.60	Mauritius	1.47	1.92
Belgium	2.48	2.64	Mexico	1.40	2.07
Bolivia	1.68	1.84	Netherlands	2.00	2.67
Canada	2.57	3.04	New Zealand	2.82	3.18
Chile	1.85	2.35	Norway	2.13	3.11
Columbia	1.45	1.77	Panama	1.74	2.39
Denmark	2.71	2.96	Paraguay	1.56	2.05
Dominican Rep.	1.36	1.7	Peru	1.52	2.08
Equador	1.50	2.08	Philippines	1.72	2.33
Finland	2.05	2.83	Portugal	1.35	1.77
France	2.06	2.45	Sierra Leone	1.07	1.19
Germany, West	2.60	2.75	Spain	1.65	2.11
Greece	1.88	2.47	Sri Lanka	1.62	1.94
Guatemala	1.21	1.42	Sweden	2.47	2.85
Honduras	1.25	1.64	Switzerland	2.39	2.92
Hong Kong	1.87	2.62	Syria	1.20	1.77
Iceland	2.07	2.55	Taiwan	1.66	2.42
India	1.22	1.64	Thailand	1.52	1.96
Ireland	2.19	2.65	Turkey	1.32	1.70
Israel	2.26	2.75	U. K.	2.35	2.69
Italy	1.85	2.13	U.S.A.	2.79	3.36
Jamaica	1.41	1.81	Yugoslavia	1.88	2.43
Japan	2.37	2.78	Zambia	1.27	1.73
Kenya	1.17	1.49	Zimbabwe	1.26	1.72
			Mean	**1.84**	**2.29**

Table 2: Efficiency Indexes.

	Without Human Capital		With Human Capital	
Country	1965	1990	1965	1990
Argentina	1.00	.65	1.00	.64
Australia	.76	.82	.74	.76
Austria	.85	.73	.80	.75
Belgium	.70	.86	.72	.86
Bolivia	.50	.41	.50	.42
Canada	.79	.93	.84	.80
Chile	.85	.65	.86	.63
Columbia	.41	.45	.48	.54
Denmark	.76	.69	.73	.67
Dominican Republic	.72	.51	.80	.54
Equador	.38	.34	.42	.40
Finland	.51	.74	.66	.67
France	.80	.83	.85	.87
Germany, West	.69	.80	.69	.74
Greece	.55	.57	.56	.61
Guatemala	.81	.73	.96	.85
Honduras	.45	.41	.52	.44
Hong Kong	.45	1.00	.46	.996
Iceland	.96	.83	.94	.87
India	.37	.41	.44	.47
Ireland	.71	.80	.67	.82
Israel	.60	.79	.61	.80
Italy	.67	.87	.76	1.00
Jamaica	.56	.52	.62	.54
Japan	.59	.62	.54	.60
Kenya	.26	.29	.31	.37
Korea, Republic of	.43	.57	.41	.57

Table 2: Efficiency Indexes (Continued).

	Without Human Capital		With Human Capital	
Country	1965	1990	1965	1990
Malawi	.28	.26	.27	.30
Mauritius	.94	.98	1.00	.99
Mexico	.85	.74	.996	.82
Netherlands	.84	.88	1.00	.90
New Zealand	.84	.71	.83	.66
Norway	.61	.80	.79	.65
Panama	.44	.32	.46	.33
Paraguay	1.00	1.00	.98	1.00
Peru	.58	.40	.66	.40
Philippines	.42	.47	.42	.43
Portugal	.67	.77	.75	.92
Sierra Leone	.94	.63	1.00	.78
Spain	1.00	.80	1.00	.93
Sri Lanka	.32	.33	.33	.35
Sweden	.81	.77	.84	.71
Switzerland	.84	.89	.96	.78
Syria	.42	.63	.62	.80
Taiwan	.52	.57	.52	.62
Thailand	.44	.57	.45	.56
Turkey	.50	.55	.57	.61
United Kingdom	.99	.89	.92	.91
U.S.A.	1.00	1.00	1.00	.90
Yugoslavia	.70	.59	.65	.55
Zambia	.42	.29	.48	.33
Zimbabwe	.17	.23	.21	.25
Mean	**.64**	**.65**	**.68**	**.67**

Table 3: Percentage Change of Quadripartite Decomposition Indexes.

Country	Productivity Change	EFF - 1 × 100	TECH - 1 × 100	KACC - 1 × 100	HACC - 1 × 100
Argentina	4.6%	-35.3	1.6	59.1	
		-36.1	0.0	26.5	29.4
Australia	42.7	8.8	17.3	11.8	
		3.2	15.8	12.9	5.8
Austria	95.1	-14.6	15.4	98.0	
		-5.9	15.3	58.6	13.4
Belgium	78.4	22.5	15.4	26.3	
		19.5	16.6	20.3	6.5
Bolivia	32.8	-18.5	5.0	55.0	
		-17.1	0.2	45.3	9.8
Canada	54.6	17.9	15.4	13.6	
		-4.6	18.5	15.9	18.0
Chile	16.6	-23.8	1.8	50.2	
		-26.1	0.0	24.2	27.0
Columbia	68.9	7.7	2.4	53.2	
		13.1	1.3	20.6	22.2
Denmark	39.1	-8.1	14.6	32.0	
		-8.2	10.6	25.6	9.0
Dominican Republic	51.8	-29.2	8.6	97.3	
		-33.4	0.4	74.6	30.0
Equador	80.9	-8.9	0.7	97.3	
		-4.8	2.4	33.4	39.0
Finland	96.2	46.0	14.7	17.2	
		0.8	23.2	14.3	38.4
France	78.3	3.8	16.5	47.4	
		2.5	17.9	24.3	18.7

Table 3 (Continued).

Country	Productivity Change	EFF - 1 × 100	TECH - 1 × 100	KACC - 1 × 100	HACC - 1 × 100
Germany, West	70.7	16.3	15.4	27.1	
		7.5	18.6	26.7	5.7
Greece	129.5	4.2	5.7	108.4	
		10.6	6.7	47.8	31.5
Guatemala	28.5	-10.3	9.4	30.9	
		-11.6	0.3	23.9	17.0
Honduras	22.9	-8.5	6.8	25.7	
		-14.3	0.2	9.2	31.0
Hong Kong	251.1	120.2	2.3	55.8	
		116.4	0.0	15.7	40.2
Iceland	66.4	-14.1	4.7	85.0	
		-7.6	4.5	39.7	23.3
India	80.5	12.7	18.2	35.5	
		7.2	1.5	23.8	34.0
Ireland	133.1	12.6	4.2	98.6	
		22.2	3.4	52.2	21.0
Israel	86.1	31.7	5.3	34.2	
		30.3	2.7	14.5	21.6
Italy	117.4	30.3	14.0	46.4	
		31.9	19.1	20.2	15.1
Jamaica	-3.6	-8.1	6.1	-1.1	
		-12.8	0.2	-14.3	28.6
Japan	208.5	3.6	14.9	159.3	
		9.9	15.0	107.6	17.6
Kenya	35.3	14.2	24.2	-4.7	
		19.2	1.7	-12.3	27.1

Table 3 (Continued).

Country	Productivity Change	EFF - 1 × 100	TECH - 1 × 100	KACC - 1 × 100	HACC - 1 × 100
Korea, Republic of	424.5	30.7	7.1	274.6	
		36.7	0.7	143.8	56.2
Malawi	43.9	-8.8	4.7	50.8	
		10.5	0.9	14.1	13.0
Mauritius	57.0	3.6	9.5	38.4	
		-1.1	0.5	21.3	30.3
Mexico	47.5	-13.3	2.0	66.7	
		-17.6	0.0	21.5	47.2
Netherlands	51.5	4.5	13.7	27.4	
		-10.5	14.5	10.9	33.1
New Zealand	7.4	-16.2	14.0	12.5	
		-21.0	9.1	10.5	12.7
Norway	69.7	29.5	31.1	0.0	
		-17.4	40.8	0.0	45.9
Panama	32.9	-27.9	1.2	82.1	
		-27.4	0.0	33.0	37.6
Paraguay	63.2	0.0	12.0	45.8	
		2.3	1.5	19.6	31.5
Peru	-16.1	-32.2	1.5	21.8	
		-38.4	0.0	-0.5	36.9
Philippines	43.8	10.1	7.9	21.0	
		2.7	0.5	3.1	35.2
Portugal	168.8	15.0	5.0	122.6	
		21.9	0.7	67.3	30.9
Sierra Leone	-5.8	-37.5	0.4	50.0	
		-22.3	0.5	8.1	11.6

Table 3 (Continued).

Country	Productivity Change	EFF - 1 × 100	TECH - 1 × 100	KACC - 1 × 100	HACC - 1 × 100
Spain	111.7	-14.9	8.7	128.9	
		-7.3	14.5	56.4	27.6
Sri Lanka	72.1	3.2	3.0	61.8	
		4.7	0.1	37.1	19.9
Sweden	36.0	-4.2	15.1	23.4	
		-14.6	16.6	18.6	15.2
Switzerland	38.7	5.8	27.4	2.9	
		-19.3	35.6	3.8	22.0
Syria	107.9	48.9	2.2	36.4	
		29.3	7.8	0.8	47.9
Taiwan	319.0	10.6	11.6	239.3	
		18.0	9.6	123.1	45.3
Thailand	194.7	28.6	12.4	103.7	
		25.6	1.1	80.6	28.6
Turkey	129.3	10.0	6.6	95.6	
		7.3	0.2	65.2	29.0
United Kingdom	60.7	-9.3	4.4	69.8	
		-1.0	2.8	38.1	14.4
U.S.A.	31.1	0.0	14.5	14.5	
		-9.9	8.6	11.1	20.5
Yugoslavia	88.1	-15.3	6.6	108.4	
		-15.5	0.4	71.9	29.0
Zambia	-33.9	-29.4	16.0	-19.3	
		-31.0	1.0	-30.3	36.2
Zimbabwe	11.4	37.2	2.4	-20.8	
		19.3	0.1	-31.8	36.6
Mean	**78.6**	**3.9**	**9.6**	**58.0**	
		0.7	**7.1**	**29.8**	**26.5**

Table 4: Distribution Hypothesis Tests

Null Hypothesis (H_0)	T-test statistics	Ten-percent significance level (critical value: 1.28)	Five-percent significance level (critical value: 1.64)	One-percent significance level (critical value: 2.33)
1. $f(y_{90}) = g(y_{65})$	4.46	H_0 rejected	H_0 rejected	H_0 rejected
2. $f(y_{90}) = g(y_{65} \times EFF)$	4.58	H_0 rejected	H_0 rejected	H_0 rejected
3. $f(y_{90}) = g(y_{65} \times TECH)$	3.09	H_0 rejected	H_0 rejected	H_0 rejected
4. $f(y_{90}) = g(y_{65} \times KACC)$	1.76	H_0 rejected	H_0 rejected	H_0 not rejected
5. $f(y_{90}) = g(y_{65} \times HACC)$	2.53	H_0 rejected	H_0 rejected	H_0 rejected
6. $f(y_{90}) = g(y_{65} \times EFF \times TECH)$	2.95	H_0 rejected	H_0 rejected	H_0 rejected
7. $f(y_{90}) = g(y_{65} \times EFF \times KACC)$	1.82	H_0 rejected	H_0 rejected	H_0 not rejected
8. $f(y_{90}) = g(y_{65} \times EFF \times HACC)$	2.47	H_0 rejected	H_0 rejected	H_0 rejected
9. $f(y_{90}) = g(y_{65} \times TECH \times KACC)$	0.79	H_0 not rejected	H_0 not rejected	H_0 not rejected
10. $f(y_{90}) = g(y_{65} \times TECH \times HACC)$	1.65	H_0 rejected	H_0 rejected	H_0 not rejected
11. $f(y_{90}) = g(y_{65} \times KACC \times HACC)$	0.45	H_0 not rejected	H_0 not rejected	H_0 not rejected
12. $f(y_{90}) = g(y_{65} \times EFF \times TECH \times KACC)$	0.65	H_0 not rejected	H_0 not rejected	H_0 not rejected
13. $f(y_{90}) = g(y_{65} \times EFF \times TECH \times HACC)$	1.17	H_0 not rejected	H_0 not rejected	H_0 not rejected
14. $f(y_{90}) = g(y_{65} \times EFF \times KACC \times HACC)$	0.71	H_0 not rejected	H_0 not rejected	H_0 not rejected
15. $f(y_{90}) = g(y_{65} \times TECH \times KACC \times HACC)$	0.13	H_0 not rejected	H_0 not rejected	H_0 not rejected