Technological Change, Technological Catch-up, and Capital Deepening: Relative Contributions to Growth and Convergence

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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), and (3) 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 analyze the evolution of the cross-country distribution of labor productivity in terms of the tripartite decomposition, finding that technological change is decidedly nonneutral and that both growth and bipolar international divergence are driven primarily by capital deepening. (*JEL* O30, O47, D24)

Renewed recognition of the enormous potential welfare gains from faster economic growth has led to a resurgence of interest in the theory of the growth process and in the empirical patterns of growth. Unlike the studies of the 1960's, however, the recent empirical literature takes a distinctly international perspective, focusing especially on the question of whether there is a tendency for growth rates—or, more importantly, growth paths—of the world's economies to converge, narrowing the gap between the poor and the rich.

While research over the last 10 to 15 years has considerably improved our understanding of these issues, it has also generated a certain amount of controversy. Exogenous growth theory, building on the pioneering model of Robert W. Solow (1956), points to technological progress as the source of persistent growth, while endogenous growth theory, building on the more recent research of Paul M. Romer (1986) and Robert E. Lucas, Jr. (1988), emphasizes a broad measure of physical and human capital as the principal engine of growth. At the same time, exogenous growth theory focuses on capital accumulation as the source of (conditional) convergence while endogenous growth theory emphasizes differences in technology across countries and over time as the source of the presence or lack of convergence. Beginning with William J. Baumol (1986), these hypotheses have been subjected to extensive empirical testing.

Much of the theoretical and empirical literature is summarized in Robert Barro and Xavier Sala-i-Martin (1995), Jonathan Temple (1999), and the 1996 *Economic Journal* symposium (Andrew B. Bernard and Charles I. Jones, 1996b; Steven N. Durlauf, 1996; Oded Galor, 1996; Danny Quah, 1996b; and Sala-i-Martin, 1996). The concluding paragraph of the cogent summary of these conflicting views by Bernard and Jones (1996b, p. 1043) suggests the direction of future research in this area:

> For the theoretical and empirical reasons outlined here, we think that future work on convergence should focus much more carefully on technology. Why do coun-

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tries have different levels of technology? How do technologies change over time? How do we measure technology—is it sufficient to simply consider a labor-augmenting technology factor or are other differences in the production function important? How much of convergence that we observe is due to convergence in technology versus convergence in capital-labor ratios?

This paper addresses each of these questions (in varying degrees). In particular, we decompose the growth of labor productivity, a crude measure of welfare,[1] into three components: those attributable to (1) technological change, (2) technological catch-up, and (3) capital accumulation. The first component reflects shifts in the world production frontier, determined conceptually by the state-of-the-art, potentially transferable technology; the second reflects movements toward (or away from) the frontier as countries adopt "best practice" technologies and reduce (or exacerbate) technical and allocative inefficiencies; and the third reflects movements along the frontier. The world production frontier at each point in time is constructed using deterministic, nonparametric (mathematical programming) methods (essentially, finding the smallest convex cone enveloping the data) and efficiency is measured as the (output-based) distance from the frontier. These data-driven methods do not require specification of any particular functional form for the technology, nor do they require any assumption about market structure or about the absence of market imperfections; indeed, market imperfections, as well as technical inefficiencies, are possible reasons for countries falling below the worldwide production frontier. We calculate each of the above three components of labor-productivity changes for 57 countries over the 1965–1990 period. These methods serve one important objective of this paper, to develop a link, already established by Rolf Färe et al. (1994), between two voluminous literatures: the macroeconomic convergence literature alluded to above and the (deterministic) frontier production function literature, based on the pioneering work of Michael J. Farrell (1957) and Sydney Afriat (1972) and nicely exposited in Färe et al. (1995).

Very much in the spirit of Quah's (1993, 1996b, 1997) suggested approach (also adopted by Galor [1996] and Jones [1997]), we analyze the evolution of the entire distribution of the three growth factors: technological change, technological catch-up, and capital accumulation. Quah 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 buttressed by the empirical analyses of Quah and others posing a robust stylized fact about the international growth pattern that begs for explanation. A plot of the distribution of output per worker across 57 countries in 1965 and 1990 appears in Figure 1. (The data and the kernel-based method of smoothing the distribution are described below.) Over this 25-year period, the distribution of labor productivity was transformed from a unimodal into a bimodal distribution with a higher mean. This transformation in turn means that, while in 1965 there were many countries in the middle income group, in 1990 the world had become divided, as a stylized fact, into two categories: the rich and the poor. Quah (1996a, b, 1997) refers to this phenomenon as "two-club," or "twin-peak," convergence, a phenomenon that renders suspect analyses based on the first moment (or even higher moments) of this distribution. Our analysis is aimed at explaining this bipolarization of the distribution of output per worker, as well as its growth pattern, in terms of the tripartite decomposition described above. As such, it builds upon Quah's insights about the need to examine the "dynamics of the entire cross-section distribution" (Quah, 1997, p. 29). In addition, we exploit recent developments in nonparametric methods (Yanqin Fan and Aman Ullah, 1999) to test formally for the statistical significance of the relative contributions of the three components of the decomposition of productivity changes to changes in the distribution of labor productivity.

Although the analysis is quite simple, it yields somewhat striking results: (1) While

[1] As pointed out by Jones (1997), labor productivity might well be a better measure of welfare than measured output per capita, especially in countries with substantial nonmarket production activity, since both the numerator and the denominator of labor productivity correspond to the market sector.

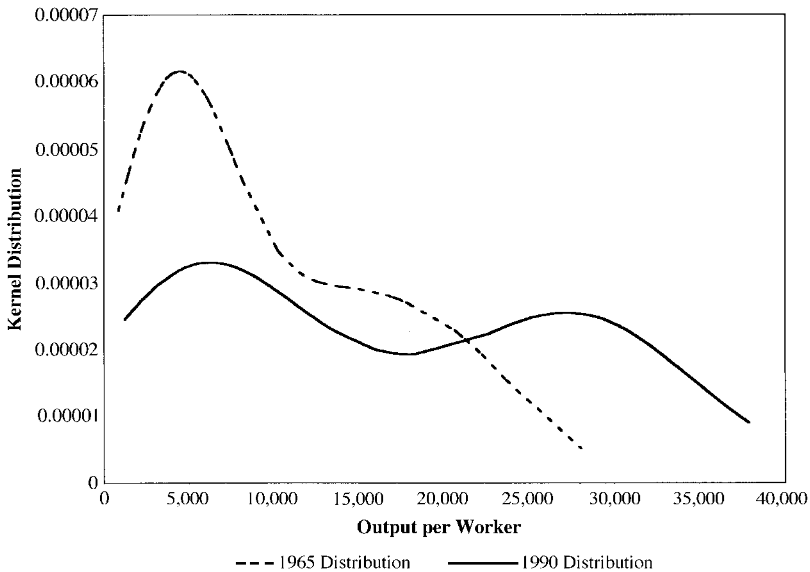

FIGURE 1. DISTRIBUTIONS OF OUTPUT PER WORKER, 1965 AND 1990

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 nonneutral, 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.

We should emphasize at the outset, however, that the analysis, in the tradition of measurement and index number theory, does not purport to provide fundamental reasons for the phenomena that are measured; it is basically a growth-accounting exercise with a new twist. The findings are potentially consistent with different models of economic growth and different fundamental causes of the growth process. Nevertheless, by developing a link between the macroeconomic convergence literature and the (deterministic) frontier production function literature, our approach has certain advantages over the standard (regression-based) growth-accounting literature. It distinguishes between technological catch-up (efficiency improvements) and technological change (shifts in the production frontier), requires no specification of functional form, presumes no particular institutional or market structure, and does not require neutrality of technological change. Our approach also goes beyond the standard growth-accounting literature by attempting to account for the shift over time in the entire ("world-wide") distribution of productivity. Again, it does not purport to provide fundamental reasons for the shifts. Thus, our approach to accounting for the evolution of the distribution of productivity is complementary to and consistent with Quah's (1997) analysis based on the conditioning of the productivity distribution on fundamental factors (specifically, geographical proximity to rich countries and openness to trade).

Section I jointly constructs the world production frontier at the end points of our sample period, 1965 and 1990, and calculates and analyzes efficiency levels—distances from the frontier—of individual economies, using data from the Penn World Tables (Robert Summers and Alan Heston, 1991). Section II constructs and analyzes the tripartite decomposition of changes in labor productivity over the sample period. Section III analyzes the shifts in the overall distribution of productivity in terms of this tripartite decomposition. Section IV concludes.

I. Nonparametric Construction of Technologies and Efficiency Measurement (Technological Catch-up)

A. *Data Envelopment Analysis*

Our approach to constructing the worldwide production frontier and associated efficiency levels of individual economies (distances from the frontier) is nonparametric. 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. This data-driven approach, which is implemented with standard mathematical programming algorithms, requires no specification of functional form, though it does require an assumption about returns to scale of the technology (as well as free input and output disposability).[2] In our simple case, we deal with only three macroeconomic variables: aggregate output and two aggregate inputs: labor and capital. Let $\langle Y_t^j, L_t^j, K_t^j\rangle$, $t = 1, \ldots, T$, $j = 1, \ldots J$, represent T observations on these three variables for each of the J countries. The constant-returns-to-scale reference technology (the "Farrell cone") for the world in period t is defined by

$$(1)\quad \mathcal{T}_t = \left\{ \langle Y, L, K\rangle \in \mathcal{R}_+^3 \;\middle|\; Y \le \sum_j z^j Y_t^j,\ L \ge \sum_j z^j L_t^j,\ K \ge \sum_j z^j K_t^j,\ z^j \ge 0\ \forall\, j \right\}.$$

In this construction, each observation is interpreted as a unit operation of a linear process, z_j represents the level of operation of that process, and every point in the technology set is a linear combination of observed output/input vectors or a point dominated by a linear combination of observed points. The constructed technology is a polyhedral cone, and isoquants are piecewise linear.[3]

Of course, typically some observed input–output combinations will be redundant in constructing the technologies, in that the observed output can be produced by some other process (generated by an alternative observed input–output vector) or by some linear combination of other processes using less of one input and no more of the other. These dominated processes are technologically inefficient. The Farrell (output-based) efficiency index for country j at time t is defined by

$$(2)\quad E(Y_t^j, L_t^j, K_t^j) = \min\{\lambda \,|\, \langle Y_t^j/\lambda, L_t^j, K_t^j\rangle \in \mathcal{T}_t\}.$$

This index is the inverse of the maximal proportional amount that output Y_t^j can be expanded while remaining technologically feasible given the technology $\mathcal{T}_t$ and the input quantities L_t^j and K_t^j; 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, but in multiple-output technologies the index is a radial measure of the (proportional) distance of the actual output vector from the production frontier.

The Farrell efficiency index can be calculated by solving the following linear program for each observation:

[2] As noted in the introduction, a fully general exposition of this approach, based on the early work of Farrell (1957) and Afriat (1972), can be found in Färe et al. (1995). These references are aimed primarily at economists; the management-science approach to essentially the same methods began with the paper by Abraham Charnes et al. (1978), who coined the evocative term "data envelopment analysis" (DEA), and is comprehensively treated in Charnes et al. (1994).

[3] The nonincreasing-returns-to-scale (NIRS) technology is constructed by restricting the process operation levels to satisfy $0 \le z^j \le 1$ for all j, so that observed processes can be radially contracted but not expanded. The variable-returns-to-scale (VRS) technology is constructed by adding the restriction $\sum_j z^j \le 1$, resulting in increasing returns to scale at low levels of inputs. By construction, efficiency indexes calculated under the assumption of constant returns to scale are no higher than those calculated under the assumption of NIRS, which in turn are no greater than those constructed under the assumption of VRS (see Färe et al. [1995] for details).

$$\min_{\lambda, z^1, \ldots, z^J} \lambda \text{ subject to}$$

$$Y^j/\lambda \leq \sum_k z^k Y_t^k$$

$$L^j \geq \sum_k z^k L_t^k$$

$$K^j \geq \sum_k z^k K_t^k$$

$$z^k \geq 0 \ \forall \ k.$$

The solution value of λ in this problem is the value of the efficiency index for country j at time t.

The world production frontier in this construction, and the associated efficiency indexes, should be interpreted quite broadly to encompass institutions and policies as well as purely technological phenomena. Thus, a country can fall short of the frontier because of, for example, inadequate financial institutions or inapposite regulatory intervention. Also, the frontier is defined relative to the "best practice" of those countries in the sample, and of course the "true" frontier could be above the constructed frontier. Nevertheless, in our view, this approach, based on the construction of a global production frontier for the world, has advantages over the standard approach of measuring productivity shortfall and catch-up relative to the U.S. economy, which reduces the best-practice frontier to a point and confounds the consequences of (relative) undercapitalization on the one hand and inefficient utilization of factor supplies on the other hand. Moreover, even studies of technological change based on total factor productivity, while taking account of capital deepening, require Hicks neutrality of technological change in order to represent the state of technology by a scalar, as in the classic study of technological change by Solow (1957).

B. *Data*

We consider a sample of 57 countries over the period 1965–1990, using data from the Penn World Tables (version 5.6).[4] This data set includes developing countries and newly industrialized countries (NICs) as well as the original OECD countries. The included countries are identified in Table 1. Our measure of aggregate output is real gross domestic product (RGDPCH multiplied by POP in the Penn Tables). Our aggregate inputs, capital stock and employment, are retrieved from capital stock per worker and real GDP per worker (KAPW and RGDPW). Real GDP and the capital stock are measured in 1985 international prices.

C. *Technological Catch-up*

Table 1 lists the efficiency levels of each of the 57 countries for the beginning and end years of our sample, 1965 and 1990.[5] Note that not only the United States but also Sierra Leone and Paraguay have efficiency scores of 1.0 in both years, so that all three countries are on the frontier in both years. Also on the frontier in 1965 is Argentina, while Hong Kong and Luxembourg have efficiency scores of 1.0 in 1990.[6]

It might seem peculiar that Paraguay and especially Sierra Leone are on the frontier in both years. The literal interpretation of this finding is that Sierra Leone, one of the poorest countries in our sample, is poor because it is so terribly undercapitalized, not because it makes inefficient use of the meager capital inputs that it has. Another (perhaps more plausible) interpretation is that the DEA method of constructing the best-practice frontier—a lower bound on the frontier under the assumption of constant

[4] These are the countries for which complete data sets are available, though, as is common in the convergence literature, we report our results with two major oil-producing countries, Iran and Venezuela, excluded. Including these two countries has no significant effect on the results, though it is worth noting that when they are included, both are on the production frontier in 1965. All calculations in this paper including these two countries are available (as Appendix B) from the authors upon request.

[5] 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]).

[6] These results contrast with those of Färe et al. (1994), who found that the United States was the only country determining the frontier in each year. The difference is attributable to the fact that they consider only OECD countries.

TABLE 1—EFFICIENCY INDEXES FOR 57 COUNTRIES, 1965 AND 1990

Country	1965	1990
Argentina	1.00	0.65
Australia	0.76	0.82
Austria	0.85	0.73
Belgium	0.70	0.86
Bolivia	0.50	0.41
Canada	0.79	0.93
Chile	0.85	0.65
Colombia	0.41	0.45
Denmark	0.76	0.70
Dominican Republic	0.72	0.51
Ecuador	0.38	0.36
Finland	0.51	0.73
France	0.79	0.83
Germany, West	0.69	0.78
Greece	0.55	0.60
Guatemala	0.81	0.73
Honduras	0.45	0.41
Hong Kong	0.45	1.00
Iceland	0.96	0.87
India	0.37	0.41
Ireland	0.71	0.85
Israel	0.60	0.84
Italy	0.67	0.88
Ivory Coast	0.66	0.47
Jamaica	0.56	0.52
Japan	0.60	0.61
Kenya	0.26	0.29
Korea, South	0.43	0.61
Luxembourg	0.76	1.00
Madagascar	0.37	0.21
Malawi	0.28	0.33
Mauritius	0.94	0.97
Mexico	0.85	0.74
Morocco	0.74	0.86
Netherlands	0.84	0.88
New Zealand	0.84	0.71
Nigeria	0.37	0.40
Norway	0.61	0.78
Panama	0.44	0.33
Paraguay	1.00	1.00
Peru	0.58	0.40
Philippines	0.42	0.47
Portugal	0.67	0.78
Sierra Leone	1.00	1.00
Spain	0.93	0.82
Sri Lanka	0.32	0.33
Sweden	0.81	0.76
Switzerland	0.84	0.86
Syria	0.42	0.65
Taiwan	0.52	0.59
Thailand	0.44	0.56
Turkey	0.50	0.55
United Kingdom	0.99	0.95
United States	1.00	1.00
Yugoslavia	0.69	0.59
Zambia	0.42	0.29
Zimbabwe	0.17	0.23
Mean	**0.642**	**0.658**

returns—fails to identify the "true" but unknown frontier, especially at low capital–labor ratios. We discuss this issue again below, but at this point we note that the DEA method is powerful enough to exclude more than 50 of the 57 countries from the frontier in each of the two years, 1965 and 1990, yet we cannot exclude Sierra Leone from the frontier in either year. Moreover, the levels of operation of more advanced countries cannot be scaled back (radially) to a production point that dominates Sierra Leone by producing its output with less of one input and no more of the other. Finally, other poorly capitalized countries (i.e., other observed points in capital–labor space near Sierra Leone), like Ivory Coast, Madagascar, Malawi, and Sri Lanka, have very low efficiency scores in 1965; they appear to be overwhelmingly dominated, in terms of efficiency, by Sierra Leone.[7]

It has often been argued that nonconvergence or slow convergence in the level of output per worker is primarily caused by slow technological catch-up. For example, Quah (1997) suggests that it is the pattern of technological diffusion that is responsible for the emerging bimodal distribution of productivity, while N. Gregory Mankiw et al. (1992) and Barro and Sali-i-Martin (1995) highlight slow diffusion of technology as the reason for the slow (approximately 2 percent per year) speed of convergence. In the context of our structure, the state of (worldwide) technology is represented by a production surface in output/input space, and technological catch-up is represented by movements toward the frontier, reflected by increases in efficiency. In Figure 2, the dotted line and solid line, respectively, show the distributions of the level of efficiency across countries in 1965 and 1990, obtained under the assumption

[7] Having said this, we should note that these mathematical programming methods take no account of measurement error, sampling error, and other stochastic phenomena. Recent research (Leopold Simar, 1996; Alois Kneip et al., 1998; Irene Gijbels, 1999; Simar and Paul W. Wilson, 2000) has made substantial progress on the use of bootstrapping methods to construct confidence intervals around efficiency indexes. In this paper, we are less concerned about the statistical significance of inefficiency of individual countries than about the statistical significance of changes in the *distributions* of efficiency indexes and the components of the tripartite decomposition of productivity changes. With respect to the latter, we do employ bootstrapping methods to calculate significance levels for distribution shifts in Section III below.

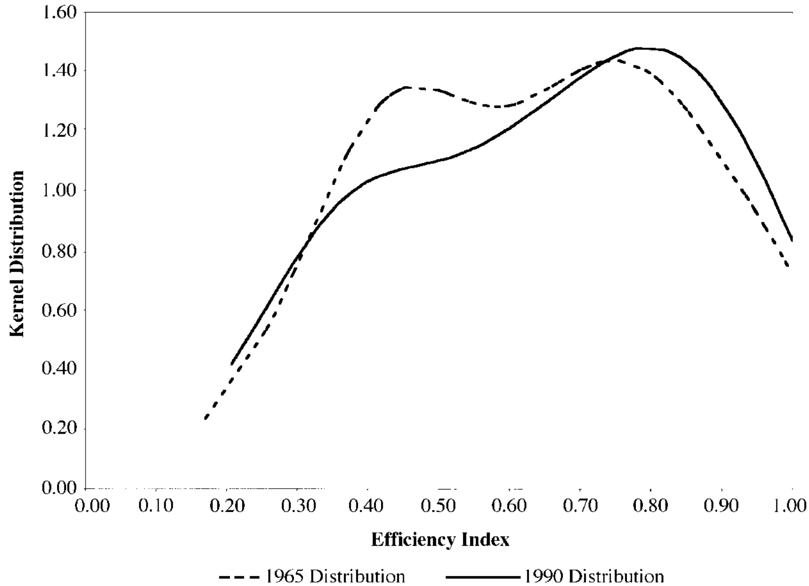

FIGURE 2. DISTRIBUTIONS OF EFFICIENCY INDEX, 1965 AND 1990

of constant returns to scale. The prominent shift in the probability mass towards 1.0 between 1965 and 1990 indicates a predominant move of economies towards the frontier over time.[8] Moreover, a generalized least-squares (GLS) regression of the change in efficiency on the level of efficiency in 1965 has a coefficient of -0.35 with a t-statistic of -2.57, indicating that the less efficient countries in 1965 have, on balance, benefited more from efficiency improvements than have the more efficient countries. These two facts, however, do not necessarily imply that there is a tendency for technology transfer to reduce the gap between the rich and the poor, since it is possible that relatively rich countries, which can also fall short of the frontier, benefit from efficiency improvements as much as or more than poorer countries. We will see in the next section that this appears to be the case.

II. Tripartite Decomposition of the Factors Affecting Labor Productivity

A. *Conceptual Decomposition*

Our decomposition of the factors affecting productivity growth exploits the assumption of constant returns to scale, in which case the benchmark technology sets can be drawn in $\langle k, y\rangle$ space, where $k = K/L$ and $y = Y/L$. Very simple hypothetical (polyhedral) technologies for two periods, say a base period b and a current period c, are drawn in Figure 3. In this simple example, the single kink in each of the polyhedral technologies would indicate that a single economy—the only efficient economy—defines the frontier. The two points, $\langle k_b, y_b\rangle$ and $\langle k_c, y_c\rangle$, represent observed values of the

[8] Additional calculations indicate that this convergence is robust with respect to the assumption about returns to scale. That is, Figure 2 is not perceptibly affected by recalculation of the efficiency indexes under the alternative assumptions of nonincreasing returns to scale or variable returns to scale (defined in footnote 3 above). Of course, a few individual-country efficiency indexes are quite sensitive to the assumption about returns to scale. As would be expected, the significant changes occur at very low levels of productivity. Most notably, under the NIRS assumption, India and Nigeria join Sierra Leone on the low-productivity end of the frontier in both 1965 and 1990, Ivory Coast becomes part of the frontier in 1965, and Morocco and Mexico (both a little higher up the productivity scale) move to the frontier in 1990. Interestingly, relaxation to VRS has no appreciable effect on any index. All of the efficiency indexes calculated under these alternative returns-to-scale assumptions, as well as the associated distributions comparable to Figure 2, are available (as Appendix C) from the authors upon request.

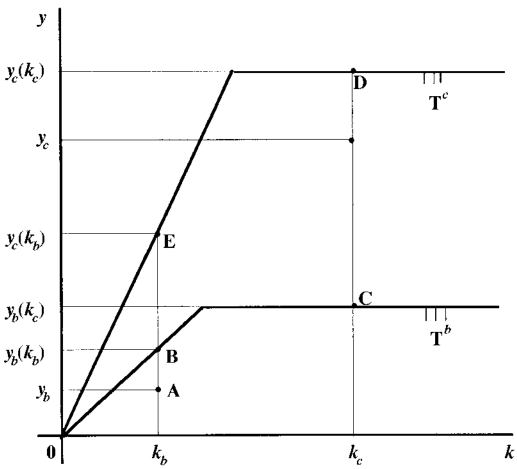

FIGURE 3. ILLUSTRATION OF TRIPARTITE DECOMPOSITION

two ratios in the two periods for some hypothetical economy. By construction, potential outputs for this economy in the two periods are $\bar{y}_b(k_b) = y_b/e_b$ and $\bar{y}_c(k_c) = y_c/e_c$, where e_b and e_c are the values of the efficiency indexes in the two periods, calculated as in (2) above. Therefore,

$$\text{(3)} \qquad \frac{y_c}{y_b} = \frac{e_c \times \bar{y}_c(k_c)}{e_b \times {}_b(k_b)}.$$

Multiplying top and bottom by $\bar{y}_b(k_c)$, the potential output–labor ratio at current-period capital intensity using the base-period technology, we obtain

$$\text{(4)} \qquad \frac{y_c}{y_b} = \frac{e_c}{e_b} \times \frac{\bar{y}_c(k_c)}{\bar{y}_b(k_c)} \times \frac{\bar{y}_b(k_c)}{\bar{y}_b(k_b)}.$$

This identity decomposes the relative change in the output–labor ratio in the two periods into (i) the change in efficiency—i.e., the change in the distance from the frontier (the first term on the right); (ii) the technology change—i.e., the shift in the frontier (the second term); and (iii) the effect of the change in the capital–labor ratio—i.e., movement along the frontier (the third term).

The decomposition in (4) measures technological change by the shift in the frontier in the output direction at the *current*-period capital–labor ratio—from point C to point D in Figure 3—and it measures the effect of capital accumulation along the *base*-period frontier—from point B to point C. We can alternatively measure technological change at the *base*-period capital–labor ratio—from point B to point E in Figure 3—and capital accumulation by movements along the *current*-period frontier—from point E to point D—by multiplying the top and bottom of (3) by the potential output–labor ratio at *base*-period capital intensity using the *current*-period technology, $\bar{y}_c(k_b)$, yielding the decomposition,

$$\text{(5)} \qquad \frac{y_c}{y_b} = \frac{e_c}{e_b} \times \frac{\bar{y}_c(k_b)}{\bar{y}_b(k_b)} \times \frac{\bar{y}_c(k_c)}{\bar{y}_c(k_b)}.$$

Thus, the decomposition of (discrete) productivity changes (not attributable to efficiency changes) into the technological-change and capital-deepening components is path dependent, and the choice between (4) and (5) is arbitrary. There is no avoiding this arbitrariness, unless technological change is Hicks neutral, in which case the proportional vertical shift in the frontier is independent of the value of the capital–labor ratio. It is this assumption (along with constant returns to scale) that enabled Solow (1957), and the legions of growth accountants who have followed his lead, to unambiguously decompose productivity growth into components attributable to technological change and capital deepening. But without constraining technological change to be Hicks neutral, the proportional (vertical) shift in the frontier varies in unspecified ways. In fact, this arbitrariness is not, per se, attributable to the decomposition itself. It is endemic to the basic task of measuring technological change, as is evident in the necessity of normalizing on one of two technologies in the (Malmquist) productivity index proposed in the pioneering paper of Douglas W. Caves et al. (1982a).[9]

[9] In fact, it is a geometric average of two indexes of technological change, normalized on different technologies, that is "exact" for a translog production technology (with certain intertemporal restrictions on the translog second-order coefficients). For subsequent "ideal"

We have carried out the subsequent analysis following both paths, and while the results differ significantly for many countries, the overall distribution of changes, and hence our basic results, are not sensitive to the path chosen.[10] For the purpose of reporting our results, we follow the approach of Caves et al. (1982a) and Färe et al. (1994b) 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) by $(\bar{y}_b(k_c)\bar{y}_c(k_b))^{1/2}$:

$$(6)\quad \frac{y_c}{y_b} = \frac{e_c}{e_b}\left(\frac{\bar{y}_c(k_c)}{\bar{y}_b(k_c)} \times \frac{\bar{y}_c(k_b)}{\bar{y}_b(k_b)}\right)^{1/2} \times \left(\frac{\bar{y}_b(k_c)}{\bar{y}_b(k_b)} \times \frac{\bar{y}_c(k_c)}{\bar{y}_c(k_b)}\right)^{1/2}$$

$$=: EFF \times TECH \times KACCUM.$$

B. *Empirical Results*

We have carried out the above calculations for each five-year interval in our sample, but concentrate here on an analysis of the change from the beginning to the end of our sample period, 1965–1990.[11] Table 2 lists the percentage changes from 1965 to 1990 in labor productivity and each of the three components: (i) change in efficiency, (ii) technological change, and (iii) capital deepening, for all 57 countries, along with the sample mean percentage changes. The overall averages provide striking evidence that most of the worldwide productivity improvement over this period was attributable to capital accumulation, with technological progress and efficiency changes (technological catch-up) accounting for less than 15 percent and 10 percent, respectively, of the growth.[12]

A few observations about individual economies are worth making. Note first that our calculations suggest that 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), have substantially different explanations in terms of our tripartite decomposition: the Japan, South Korea, and Taiwan growth spurts were driven primarily by capital accumulation, whereas that of Hong Kong resulted primarily from efficiency improvements, although capital accumulation was important as well.[13] On the other side of the ledger, the Argentina stagnation (with a mere 5-percent increase in productivity over this period) is primarily attributable—perhaps surprisingly—to a collapse in efficiency, with a relatively slow rate of technological change also a factor, whereas growth attributable to capital accumulation in Argentina was above average. Finally,

productivity index number developments based on Caves et al. (1982a), see Caves et al. (1982b), W. E. Diewert (1992), Färe et al. (1994), and Bert M. Balk (1998).

[10] Calculations carried out for each of these alternative paths are available (as Appendix D) from the authors upon request.

[11] All calculations for the five-year intervals are available as Appendix E from the authors.

[12] The finding that capital deepening has been a major contributor to growth, while consistent with some of the standard, regression-based, growth-accounting studies [see, e.g., Temple (1998) for citations], is at odds with others. Most notably, Robert E. Hall and Jones (1999), using very different growth-accounting methods, find that physical capital, along with human capital (educational attainment), do not account for a large proportion of the difference in productivity across countries. Their (model-based) method differs not only from ours but also from standard regression-based, growth-accounting methods in that they decompose differences in output per worker into that attributable to differences in the capital–output ratio, educational attainment, and differences in (Hicks-neutral) technology. The motivation for attributing to capital only the productivity change generated by changes in the capital–output ratio rather than by changes in the capital–labor ratio is that, along a neoclassical, steady-state growth path driven entirely by technological progress, the capital–output ratio would be constant while the capital–labor ratio would rise, so that standard growth-accounting methods would (erroneously) attribute much of the growth of labor productivity to capital deepening. It would seem that a similar type of decomposition could be carried out using the nonparametric methods of this paper. Such a study would probably attribute less of the productivity change to capital and more to technological change than does our approach. But the results would be model dependent.

[13] These results appear to be roughly consistent with the conclusions of the thorough analysis of these growth phenomena by Alwyn Young (1995).

TABLE 2—PERCENTAGE CHANGE OF TRIPARTITE DECOMPOSITION INDEXES, 1965–1990

Country	Output per worker, 1965	Output per worker, 1990	Percentage change in output per worker	Contribution to percentage change in output per worker of: Change in efficiency	Change in technology	Capital deepening
Argentina	12,818	13,406	4.6	−35.48	1.79	59.26
Australia	21,246	30,312	42.7	8.20	13.87	15.80
Austria	13,682	26,700	95.1	−14.60	15.42	97.98
Belgium	17,790	31,730	78.4	22.41	12.68	29.31
Bolivia	4,005	5,315	32.7	−18.70	5.15	55.24
Canada	22,245	34,380	54.6	16.67	11.72	18.58
Chile	10,169	11,854	16.6	−23.87	1.92	50.24
Colombia	5,989	10,108	68.8	7.59	2.41	53.17
Denmark	17,955	24,971	39.1	−7.69	12.84	33.52
Dominican Republic	4,544	6,898	51.8	−29.23	8.64	97.44
Ecuador	4,993	9,032	80.9	−3.62	−2.11	91.73
Finland	13,938	27,350	96.2	43.07	11.65	22.85
France	17,027	30,357	78.3	4.13	16.33	47.18
Germany, West	17,282	29,509	70.7	13.28	14.38	31.78
Greece	7,721	17,717	129.5	9.58	3.08	103.14
Guatemala	5,784	7,435	28.5	−10.22	9.42	30.85
Honduras	3,633	4,464	22.9	−8.64	6.88	25.84
Hong Kong	6,502	22,827	251.1	120.00	2.39	55.85
Iceland	15,010	24,978	66.4	−9.57	2.08	80.26
India	1,792	3,235	80.5	12.40	15.65	38.88
Ireland	10,322	24,058	133.1	19.49	1.20	92.75
Israel	12,776	23,780	86.1	39.50	2.34	30.38
Italy	14,163	30,797	117.4	31.86	13.32	45.52
Ivory Coast	2,674	3,075	15.0	−29.11	−7.03	74.49
Jamaica	5,336	5,146	−3.6	−8.29	6.22	−1.00
Japan	7,333	22,624	208.5	3.07	15.19	159.87
Kenya	1,377	1,863	35.3	14.37	24.16	−4.72
Korea, Republic of	3,055	16,022	424.5	41.72	2.87	259.73
Luxembourg	21,238	37,903	78.5	32.00	24.40	8.68
Madagascar	2,220	1,561	−29.7	−44.19	17.86	6.90
Malawi	846	1,217	43.9	17.33	−42.66	113.80
Mauritius	6,496	10,198	57.0	2.91	9.88	38.83
Mexico	11,536	17,012	47.5	−13.33	2.07	66.71
Morocco	4,428	6,770	52.9	17.24	16.57	11.87
Netherlands	20,628	31,242	51.5	5.31	11.16	29.38
New Zealand	23,658	25,413	7.4	−15.60	9.27	16.48
Nigeria	1,481	2,082	40.6	8.00	−13.85	51.10
Norway	17,233	29,248	69.7	26.36	33.04	0.96
Panama	6,020	7,999	32.9	−24.83	−0.86	78.32
Paraguay	3,910	6,383	63.2	0.00	−14.57	91.08
Peru	8,162	6,847	−16.1	−32.02	1.41	21.68
Philippines	3,326	4,784	43.8	10.28	7.88	20.90
Portugal	6,189	16,637	168.8	15.50	4.80	122.06
Sierra Leone	2,640	2,487	−5.8	0.00	−57.74	122.92
Spain	12,451	26,364	111.7	−12.30	7.08	125.47
Sri Lanka	3,337	5,742	72.1	3.28	2.98	61.78
Sweden	20,870	28,389	36.0	−5.34	12.63	27.59
Switzerland	23,660	32,812	38.7	2.59	28.44	5.25
Syria	7,634	15,871	107.9	54.90	0.19	33.96
Taiwan	4,394	18,409	319.0	14.79	9.60	233.01
Thailand	2,292	6,754	194.7	28.25	12.61	104.05
Turkey	3,765	8,632	129.3	9.94	6.61	95.60
United Kingdom	16,645	26,755	60.7	−3.81	1.37	64.85
United States	28,051	36,771	31.1	0.00	9.89	19.29
Yugoslavia	5,320	10,007	88.1	−15.29	6.60	108.32
Zambia	3,116	2,061	−33.9	−29.50	16.13	−19.21
Zimbabwe	2,188	2,437	11.4	37.15	2.50	−20.77
Mean			**75.06**	**5.23**	**6.14**	**58.54**

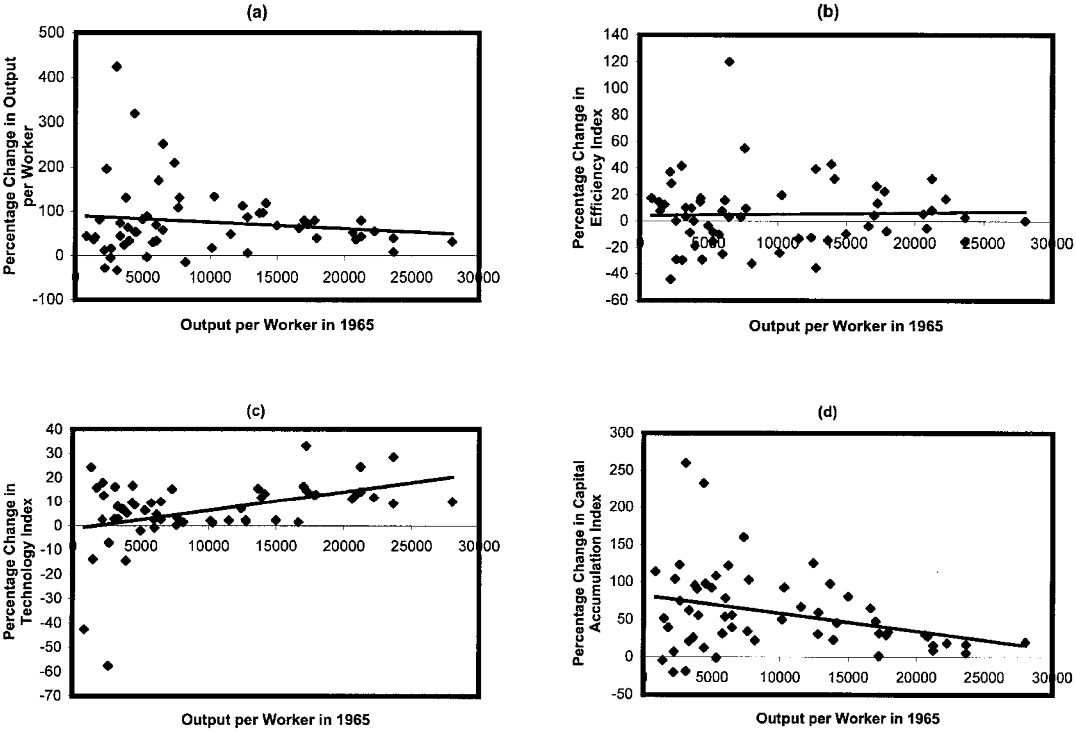

FIGURE 4. PERCENTAGE CHANGES BETWEEN 1965 AND 1990 IN OUTPUT PER WORKER AND THREE DECOMPOSITION INDEXES, PLOTTED AGAINST 1965 OUTPUT PER WORKER

Note: Each panel contains a GLS regression line.

the disastrous 30-percent collapses of productivity in two African countries—Madagascar and Zambia—were generated primarily by the deterioration in efficiency, with slow or negative capital accumulation also a factor.

Figure 4 summarizes these calculations by plotting the four growth rates (labor productivity and its three components) against output per worker in 1965. GLS regression lines are also plotted. Figure 4(a) indicates that the increase in average productivity reflects positive growth over this period for almost all countries. The prominent spikes at the lower incomes reflect the economic emergence of the Asian "miracle" countries and is consistent with our earlier observation about the movement of probability mass from the lower-middle-income group to the higher-income group in the cross-country income distribution. The negative slope coefficient of the regression line, while not statistically significant without inclusion of critical conditioning variables, is essentially the empirical result that has led many to argue that worldwide productivity growth patterns support convergence, an argument that has met with cogent criticism from Quah (1993, 1996a, b, 1997) and his suggestion that we need to study the entire distribution of growth patterns to understand these complex issues.

Figure 4(b), 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, illustrated by the substantial movement of probability mass toward full efficiency in Figure 2, has done little, if anything, to lower income inequality across countries. Apparently, technology

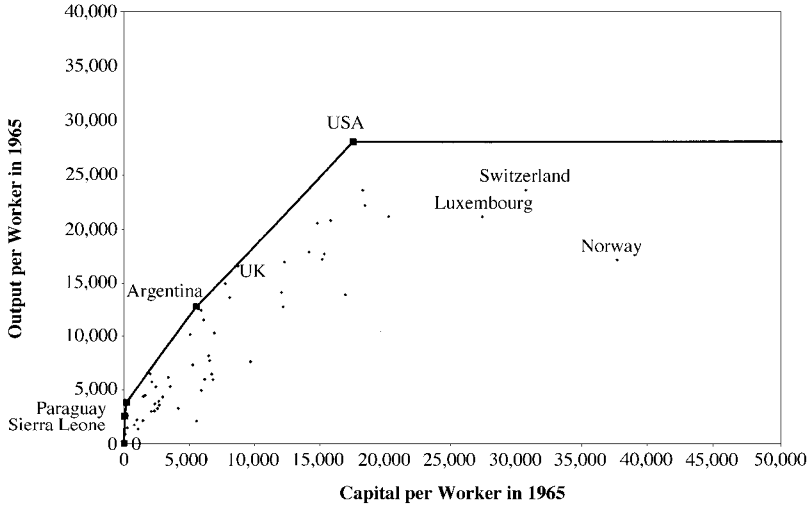

FIGURE 5. 1965 WORLD PRODUCTION FRONTIER

transfer has benefited relatively rich countries as much as relatively poor countries.

Figure 4(c) indicates that, while technological change has contributed positively to growth for most countries, the pattern is very dissimilar to that of overall productivity growth, with some striking examples of technological regress for low-income countries and larger-than-average contributions to growth for most high-income countries. The positive regression slope coefficient is statistically significant, suggesting that relatively wealthy countries have benefited more from technological progress than have less developed countries.

Figure 4(d), on the other hand, suggests that the pattern of productivity growth attributable to capital accumulation is remarkably similar to the overall pattern of changes in labor productivity. Indeed, the regression slope coefficients are almost identical in panels (a) and (d). Thus, it appears that the growth pattern may have been driven primarily by the pattern of capital accumulation.

Figures 5 and 6 contain the empirically constructed production frontiers in 1965 and 1990, along with scatterplots of labor productivity and the capital–labor ratio. Each kink is an actual observation on these ratios for an (indicated) economy with a 1.0-efficiency index for that year. Figure 7, which superimposes these two production frontiers, provides strong evidence that technological change over this period has been decidedly nonneutral. In particular, Hicks-neutral technological change would shift the frontier in k-y space vertically by the same proportional amount at all capital–labor ratios, a shift that is inconsistent with the results in Figure 7.[14] Although, owing to the scale, there is not much visual resolution in this figure at very low capital–labor ratios, it is nevertheless evident that there appears to be some substantial implosion of the frontier at the very lowest capital–labor ratios (note the large negative technological-change indexes in Table 2 for very poor—and very poorly capitalized—countries like Malawi, Nigeria, and Sierra Leone), an outward shift of about 20 percent in the frontier for higher but still quite low capital–labor ratios, very little change in the frontier for the middle of the distribution of capital–labor ratios, and a sizable 30-percent expansion of potential output at very high capital–labor ratios (note the large technological-change indexes for Norway and Switzerland in Table 2).

[14] The shift in the technologies is also inconsistent with Harrod-neutral (labor-augmenting) technological change, which would shift the frontier radially (i.e., by equal proportional factors along rays from the origin).

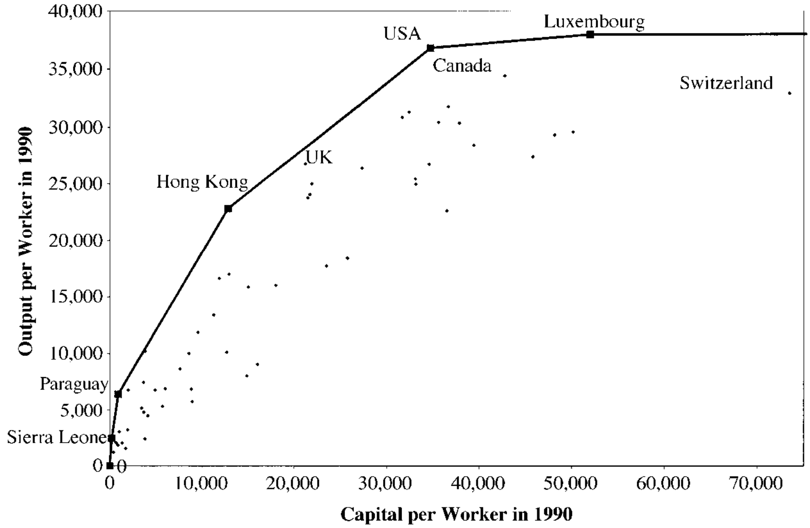

FIGURE 6. 1990 WORLD PRODUCTION FRONTIER

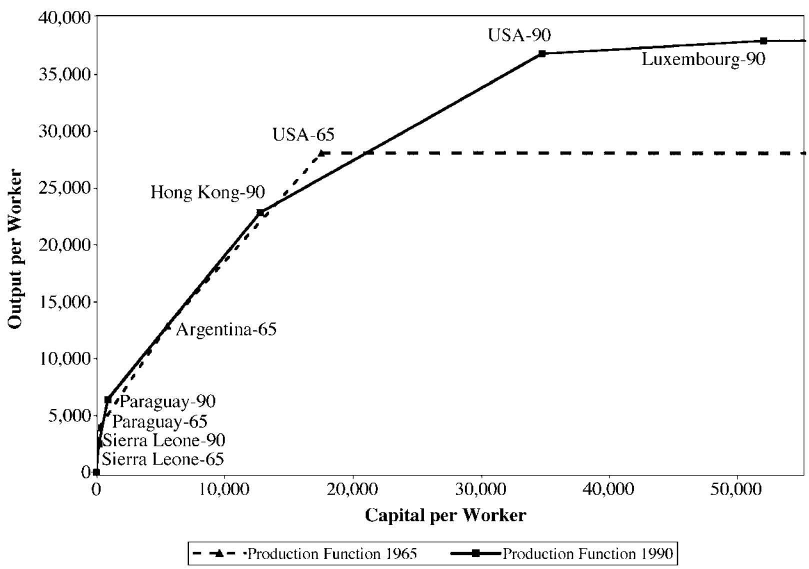

FIGURE 7. 1965 AND 1990 WORLD PRODUCTION FRONTIERS

As highly capitalized countries also tend to be countries with high per capita incomes, the substantial outward shift in the frontier at high capital–labor ratios in Figure 7 means that technological change has primarily benefited high-income countries, an observation that is consistent with Figure 4(c) above. Perhaps this is not surprising, assuming that technological change takes place primarily in highly capitalized economies.

The technological degradation apparent at very low capital–labor ratios should be taken

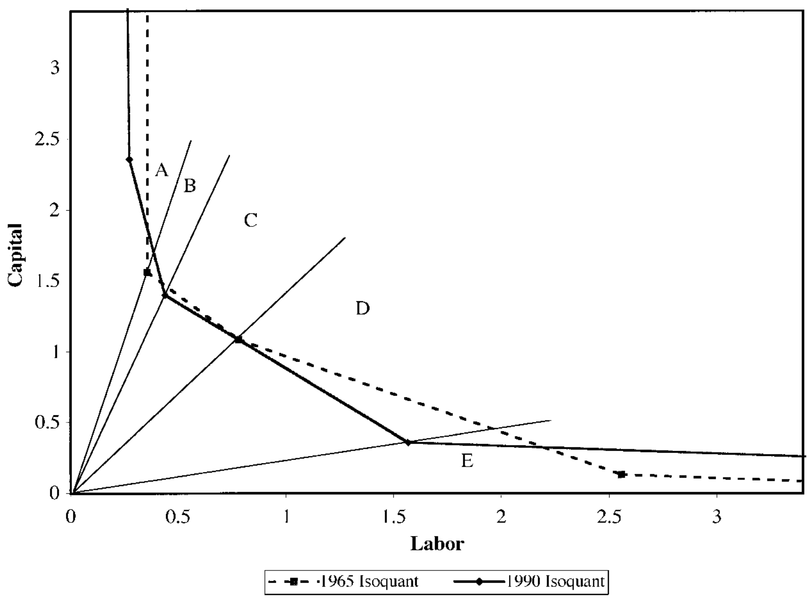

FIGURE 8. 1965 AND 1990 ISOQUANTS

with a grain of salt. For one thing, it is not clear how the world frontier *could* implode at some capital–labor ratios. Does knowledge decay? Were "blueprints" lost? It is perhaps more likely that the "best-practice" frontier constructed by the DEA technique is well below the "true" but unobservable frontier at very low capital–labor ratios and therefore that the apparent technological degradation at these low levels of capitalization are in fact efficiency declines.

The nature of technological change between 1965 and 1990 can be further explicated by referring to "unit isoquants" for the two years, drawn in Figure 8. (Under the maintained assumption of constant returns, isoquants in each year are simply radial expansions or contractions of these "unit" isoquants.) The shift in the unit isoquant reflects technological progress in those regions of capital–labor space where the unit isoquant has shifted inward and technological regress in those regions where the unit isoquant has shifted outward. Again, the largest salutary shifts in the unit isoquant occur at very high capital–labor ratios, where the radial contraction is on the order of 25 percent, indicating that the 1990 technology could produce a given output with about 25 percent less capital and labor than could the 1965 technology.[15] The implosion of the frontier at very low capital–labor ratios is reflected by the outward movement of the unit isoquant near the labor axis, indicating that producing the same output in 1990 as in 1965 at these low levels of capitalization require very large proportional increases in the two factors of production (on the order of 30 percent).

Technological change is labor saving (capital using) when the slope of the isoquant becomes less steep and capital saving (labor using) when it becomes steeper. Because of homogeneity of the technology, these shifts are constant along rays; hence, the regions of labor-saving and capital-saving technological change are cones. The isoquant map in Figure 8 is partitioned into five cones; technological change is labor saving in the cones labeled A, C, and E, and capital saving in those labeled B and D.[16]

[15] This construction is an informal rendition of the *input-based* measure of technology change; see Färe et al. (1995) for details.

[16] Formally, the "slope" at cusps of the polyhedral technology must be defined in terms of subdifferentials; in any event, in regions of labor-saving technological change the capital–labor ratio would be either unchanged or increased

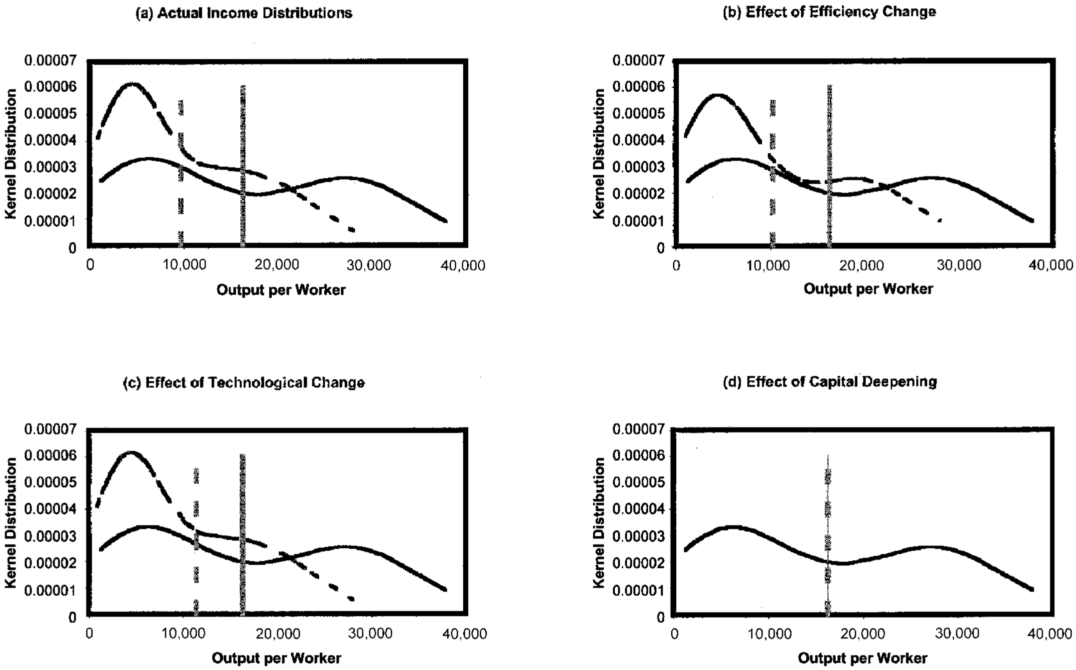

FIGURE 9. COUNTERFACTUAL DISTRIBUTIONS OF OUTPUT PER WORKER

Notes: In each panel, the solid curve is the actual 1990 distribution and the solid vertical line represents the 1990 mean value. The dotted curve in panel (a) is the actual 1965 distribution and the dotted vertical line represents the 1965 mean value. The dotted curves in panels (b) and (c) are counterfactual distributions isolating, sequentially, the effects of efficiency change and technological change on the 1965 distribution, and the dotted vertical lines represent the respective counterfactual means.

III. Analysis of Productivity Distributions

We now turn to an analysis of the distribution dynamics of labor productivity. As emphasized by Quah (1996a, b, 1997), this approach is likely to be more informative than summary measures like the conditional mean or variance, as is implicit in regression analysis. First and second moments of a distribution are, of course, especially uninformative in the case of bimodal distributions like that in Figure 1. In particular, our objective is to assess the degree to which each of the three components of productivity change account for the deformation of the distribution of labor productivity from a unimodal to a bimodal distribution with a higher mean between 1965 and 1990, illustrated in Figure 1 and repeated here in Figure 9(a). The distributions we employ are nonparametric kernel-based density estimates, essentially "smoothed" histograms of productivity levels.[17]

Rewrite the tripartite decomposition of labor-productivity changes in equation (6) as follows:

$$(7) \quad y_c = (EFF \times TECH \times KACCUM)y_b.$$

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

at given factor prices under the assumption of output-constrained cost minimization.

[17] See the Appendix for the particulars.

The counterfactual 1990 labor-productivity distribution of the variable

$$y^E = EFF \times y_b \tag{8}$$

isolates the effect on the distribution of changes in efficiency only, assuming a stationary world production frontier and no capital deepening; this distribution is illustrated in Figure 9(b), along with the (actual) 1990 distribution. To facilitate interpretation of this counterfactual distribution, note that if efficiency did not change for any country, the "counterfactual" distribution in Figure 9(b) would be identical to the actual 1965 distribution in Figure 9(a). The mean of the counterfactual distribution of y^E is indicated, along with the actual 1965 and 1990 means, by a vertical line. The small shift in mean labor productivity from 1965 reflects the contribution of the gain in efficiency to the world average output per worker. The gain in probability mass at the upper-middle-income level and a loss at the lower-middle-income zone is consistent with conventional wisdom, confirmed in Figure 1, that many newly developed countries have moved their economies significantly towards the production frontier. Nevertheless, the single-peaked character of the distribution of per capita income is more or less maintained.

The counterfactual distribution of the variable

$$y^{ET} = (EFF \times TECH)y_b = TECH \times y^E \tag{9}$$

drawn in Figure 9(c), then isolates the effect of technological change, as compared to the distribution in Figure 9(b), and the joint effect of efficiency change and technological change, as compared to the distribution in Figure 9(a). The small change in average output per worker from that in Figure 9(b) reflects the fact that technological change has not contributed much to the increase in worldwide per capita income. The shift of probability mass toward both tails of the distribution indicates that technological change has contributed to the welfare of relatively rich countries more than to that of poorer countries. This result is, of course, consistent with the shift in the production frontier during this period. The world distribution of income per worker remains unimodal after adjusting for efficiency changes and technological progress (or regress).

For completeness, the distribution in Figure 9(d) reflects all three adjustments of the labor-productivity distribution and therefore is coincident with the actual distribution in 1990. As compared to Figure 9(c), this distribution isolates the effect of capital accumulation. Comparison of these two distributions, including their means, provides strong evidence that capital accumulation is the primary driving force in increasing labor productivity, and differences across countries in capital-accumulation histories are primarily responsible for the emergence of the bimodal structure of the distribution of labor productivity.

Of course, the order in which the three adjustments of labor productivity are introduced is arbitrary. Nevertheless, essentially the same story emerges in every case. In Figure 10, for example, we first introduce the effects of technological change, then efficiency change, and finally capital accumulation; again, the bimodal distribution emerges only at the last stage.

Figure 11, which first introduces the effect of capital accumulation provides perhaps the most dramatic evidence that it is this factor that primarily accounts for bipolarization, since the bimodal distribution emerges immediately in Figure 11(b) and persists with the other adjustments, first for technological change and then for efficiency change.

Figure 12, however, provides some evidence that efficiency changes have also contributed to the bipolarization of productivities. The introduction of the effect of efficiency changes in panel (c) accentuates the bipolarization generated by capital accumulation in panel (b), as mass is shifted from the middle of the distribution to the upper end. Technological change then ameliorates this effect somewhat in panel (d).

We can exploit recent developments in nonparametric methods to test formally for the statistical significance of differences between distributions in Figures 9–12—to test indirectly, that is, for the statistical significance of the relative contributions of the three components of the decomposition of productivity changes to changes in the distribution of labor productivity. In particular, Fan and Ullah

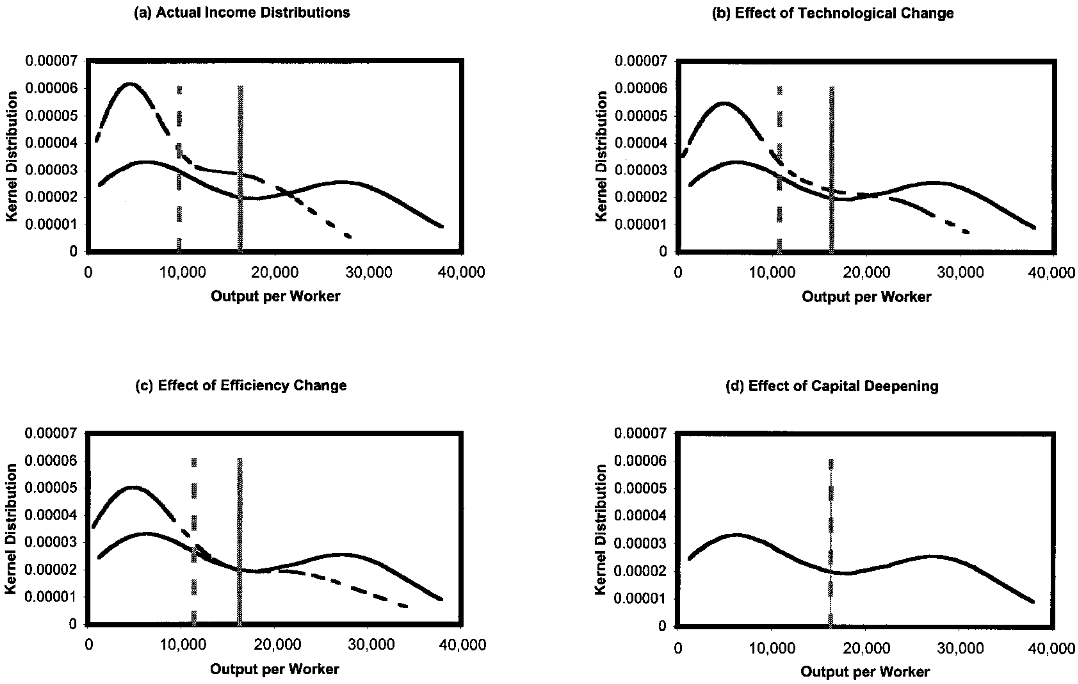

FIGURE 10. COUNTERFACTUAL DISTRIBUTIONS OF OUTPUT PER WORKER

Notes: In each panel, the solid curve is the actual 1990 distribution and the solid vertical line represents the 1990 mean value. The dotted curve in panel (a) is the actual 1965 distribution and the dotted vertical line represents the 1965 mean value. The dotted curves in panels (b) and (c) are counterfactual distributions isolating, sequentially, the effects of technological change and efficiency change on the 1965 distribution, and the dotted vertical lines represent the respective counterfactual means.

(1999) have proposed a nonparametric 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.[18]

Some test statistics, along with critical values for various significance levels, are shown in Table 3. The first row indicates that the baseline distributions in panel (a) of each of the diagrams—the actual 1965 and 1990 distributions—are significantly different, even at the 1-percent significance level. The null hypothesis of no difference between the actual 1990 distribution and the counterfactual 1990 distribution assuming changes in efficiency only (with no technological change and no capital deepening) is similarly rejected at the 1-percent level (row 2). At the 1-percent level, it is not possible to reject the equivalence of the 1990 distribution and the counterfactual distribution assuming only technological change, but this hypothesis is rejected at the 5-percent level. Because of the small size of our sample, the T-test is likely to have very low power; hence, a 1-percent significance level is likely to be far too stringent. In row 4, we are unable to reject the hypothesis that the 1990 distribution and the counterfactual distribution incorporating only capital deepening are the same, even at the 10-percent level. Finally, in the last two rows of Table 3, we test for differences between the 1990 distribution and the counterfactual distributions incorporating the effects of efficiency changes *and* capital accumulation (row 5) and of technological change *and* capital accumulation (row 6); it is not possible to reject the

[18] See the Appendix for an exact description of the test statistic.

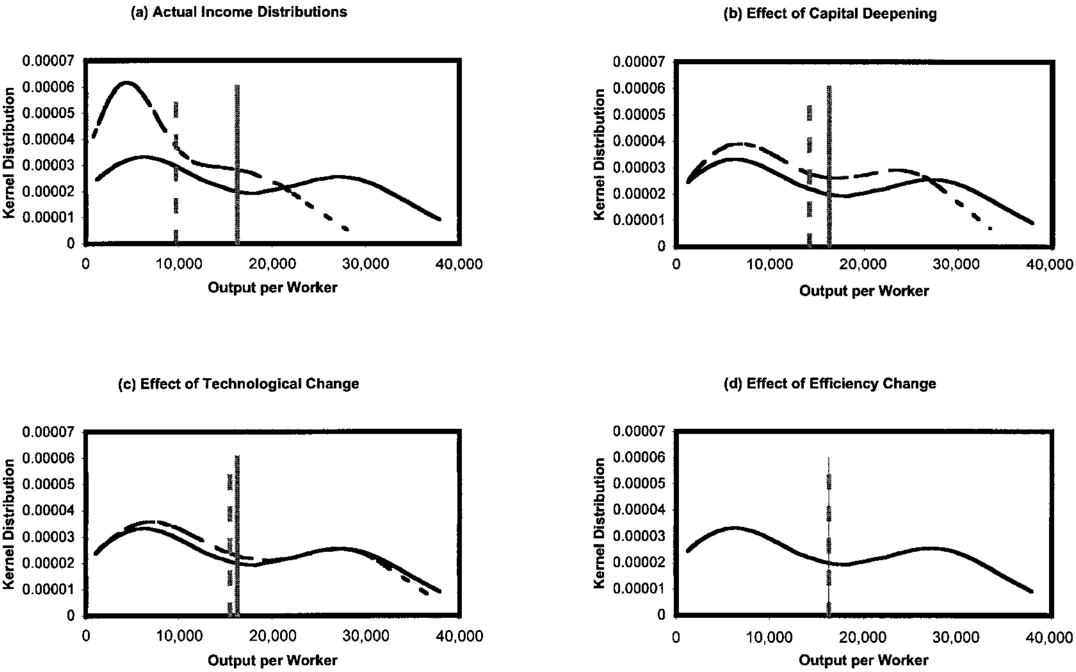

FIGURE 11. COUNTERFACTUAL DISTRIBUTIONS OF OUTPUT PER WORKER

Notes: In each panel, the solid curve is the actual 1990 distribution and the solid vertical line represents the 1990 mean value. The dotted curve in panel (a) is the actual 1965 distribution and the dotted vertical line represents the 1965 mean value. The dotted curves in panels (b) and (c) are counterfactual distributions isolating, sequentially, the effects of capital deepening and efficiency change on the 1965 distribution, and the dotted vertical lines represent the respective counterfactual means.

hypothesis of identical distributions in either case at the 10-percent level.

Thus, at both the 5-percent and the 10-percent significance levels, the gestalt conclusions drawn from examination of Figures 9–12—namely, that capital deepening is the driving force behind the bipolar divergence of the productivity distribution over our sample period—are (robustly) confirmed by these statistical tests.

IV. Concluding Remarks

Several caveats need to be emphasized. First, as noted at the outset, the analysis, in the tradition of measurement and index number theory, does not purport to provide reasons for the phenomena that are measured; it is basically a growth-accounting exercise with a new twist. As in the original growth-accounting paper by Solow (1957), we provide only proximate—as opposed to fundamental—contributions of the three identified factors to growth and convergence; the resultant allocations to the three factors could be consistent with more than one model of economic growth. On the other hand, our approach, unlike standard growth-accounting exercises, does not require neutrality of technological change or specification of a functional form for the technology.

Second, we have focused in this paper on the three macroeconomic variables commonly used in empirical studies of convergence; potentially important variables (e.g., human capital and natural resources) are omitted. Third, as is well known, the capital stock data in the Penn World Table are measured with considerable error, and this should be taken into account in assessing our results. Fourth, the level of aggregation is highly macroeconomic, and some recent convergence papers (see, e.g., Bernard and Jones, 1996a) have suggested that industry-specific analyses might be more appropriate for the study of convergence, especially that attribut-

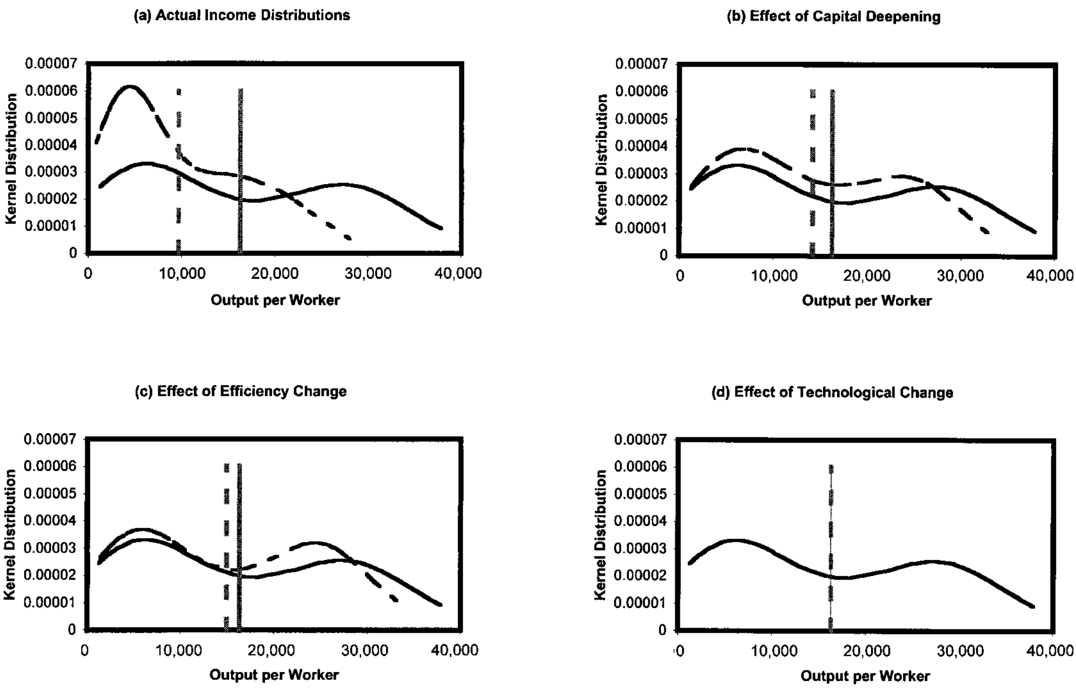

FIGURE 12. COUNTERFACTUAL DISTRIBUTIONS OF OUTPUT PER WORKER

Notes: In each panel, the solid curve is the actual 1990 distribution and the solid vertical line represents the 1990 mean value. The dotted curve in panel (a) is the actual 1965 distribution and the dotted vertical line represents the 1965 mean value. The dotted curves in panels (b) and (c) are counterfactual distributions isolating, sequentially, the effects of capital deepening and technological change on the 1965 distribution, and the dotted vertical lines represent the respective counterfactual means.

TABLE 3—DISTRIBUTION HYPOTHESIS TESTS

Null hypothesis (H_0)	T-test statistics	10-Percent significance level (critical value: 1.28)	5-Percent significance level (critical value: 1.64)	1-Percent significance level (critical value: 2.33)
$f(y_{90}) = g(y_{65})$	3.54	H_0 rejected	H_0 rejected	H_0 rejected
$f(y_{90}) = g^E(y_{65} \times EFF)$	2.80	H_0 rejected	H_0 rejected	H_0 rejected
$f(y_{90}) = g^T(y_{65} \times TECH)$	2.06	H_0 rejected	H_0 rejected	H_0 not rejected
$f(y_{90}) = g^K(y_{65} \times KACCUM)$	0.77	H_0 not rejected	H_0 not rejected	H_0 not rejected
$f(y_{90}) = g^{EK}(y_{65} \times EFF \times KACCUM)$	0.68	H_0 not rejected	H_0 not rejected	H_0 not rejected
$f(y_{90}) = g^{EK}(y_{65} \times TECH \times KACCUM)$	−0.08	H_0 not rejected	H_0 not rejected	H_0 not rejected

Notes: The functions $f(\cdot)$ and $g(\cdot)$ are (kernel) distribution functions for the actual data in 1990 and 1965, respectively; $g^E(\cdot)$, $g^T(\cdot)$, $g^K(\cdot)$, $g^{EK}(\cdot)$, and $g^{TK}(\cdot)$ are counterfactual distributions obtained by adjusting the 1965 data for the effects of, respectively, efficiency changes, technological change, capital deepening, both efficiency changes and capital deepening, and both technological change and capital deepening.

able to technology transfer. Fifth, our long-run analysis has not taken short-run economic fluctuations into account. Finally, our sample of 57 countries is arbitrary, determined by the criterion that consistent data were available for all of them and not for others in the Penn World Tables. Each of these caveats suggests topics for additional research.

Nevertheless, we believe that our simple approach to decomposing labor productivity shifts into three factors and analyzing the shift in the distribution of productivity as well as the shift in the production frontier and distances of economies from the frontier is quite responsive to the questions posed by Bernard and Jones (1996b) and quoted in our introductory remarks. It provides a method of measuring separately the effects of technological catch-up, technical change, and capital accumulation on labor productivity without imposing any assumption about the functional form of the production function or about allocative or technical efficiency, as required by estimation methods using standard econometric techniques. This method suggests the following answers to the Bernard/Jones questions:

(1) There is substantial evidence of technological catch-up, as countries have, on average, moved toward the worldwide production frontier, even as the frontier itself has moved outward at most capital–labor ratios, but this catch-up does not seem to have been a force for convergence as relatively rich as well as relatively poor countries have benefited from catch-up.
(2) Technological change has been decidedly nonneutral, apparently benefiting rich countries more than the poor.
(3) It is primarily capital deepening, as opposed to technological change or technological catch-up, that has contributed the most to both growth and bipolar international divergence of economies.

Appendix

Each distribution in the paper is a kernel-based estimate of a density function, $f(x)$, 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 $n \uparrow \infty$. We assume that k is a symmetric standard normal density function, with nonnegative images. See Adrian 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, $I(f, g) = \int_x (f(x) - g(x))^2 dx$, is

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

where

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

and

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

Qi Li (1996) has established that this test statistic is valid for dependent as well as independent variables. As shown by Fan and Ullah (1999), the test statistic asymptotically goes to the standard normal, but the sample in our study contains only 51 observations. Thus, we do a bootstrap approximation with 500 replications to find the critical values for the statistic at the 5-percent and 1-percent levels of significance.

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