Total Factor Productivity and the Convergence Hypothesis

Stephen M. Miller*

and

Mukti P. Upadhyay

February 2000

Abstract

We study the convergence, or lack thereof, of total factor productivity and real GDP per worker for a pooled (cross-section, time-series) sample of developed and developing countries, adding breadth and depth to the convergence debate. We first estimate total factor productivity from a parsimonious specification of the aggregate production function involving output per worker, capital per worker, and the labor force, both with and without the stock of human capital. Then we test for absolute and conditional convergence of total factor productivity and real GDP per worker, using cross-section and cross-section, time-series data. Fixed-effect estimates across countries converts the cross-section test of absolute convergence into a pooled test of conditional convergence, since it controls for country-specific effects. Our tests consider both β- and σ-convergence. Our findings strongly support both absolute and conditional β-convergence of total factor productivity, but only conditional convergence of real GDP per worker. Further, σ-convergence tests must by definition measure absolute convergence, since conditional convergence assumes that an equilibrium dispersion of total factor productivity or real GDP per worker exists. We find mixed evidence for absolute σ-convergence.

Correspondence:

Stephen M. Miller
Department of Economics
University of Connecticut
Storrs, CT 06269-1063
USA
(860) 486-3853 (voice)
(860) 486-4463 (fax)
SMILLER@UCONNVM.UCONN.EDU (e-mail)

* Professor and Head of Economics, University of Connecticut, Storrs, CT and Assistant Professor of Economics, Eastern Illinois University, Charleston, IL.

1. Introduction

Growth theory has reemerged as an important topic of investigation and has consequently refocused much of the debate toward how public policy can affect economic growth. The standard neo-classical growth models [i.e., the descriptive growth model of Solow (1956), the optimal growth model of Ramsey (1928), or the overlapping generations model of Samuelson (1958), as well as their descendants] have been challenged by the literature on endogenous growth (e.g., Romer 1986 and Lucas 1988). The neo-classical paradigm considers technological change as an exogenous process whereas the endogenous growth literature makes this process endogenous, looking for possible driving forces. Mankiw (1995) provides a recent, clearly articulated defense of the neoclassical model. After noting three practical empirical problems associated with the neo-classical approach, he proposes a solution. To wit, he modifies one parameter, the returns to capital, by defining capital to include both physical and human capital, and argues that this one change goes a long way toward rescuing the neo-classical model.[1,2]

The neo-classical models imply convergence in real income per capita. Absolute convergence tests whether real income per capita converges to a steady-state value, irrespective of other conditions within a given country. Conditional convergence, on the other hand, allows each country to have a different level of real income per capita toward which it is converging. Differences in steady-state values of real per capita

---

[1] Romer (1995), a leading proponent of endogenous growth theory, disagrees strongly with Mankiw's conclusion that changing the capital share rescues the neo-classical model.

[2] An alternative view of the production process argues that physical capital contains mixes of different vintages and that human capital contains mixes of different skills. Measures of human capital attempt to reflect the skill mix within a country, recognizing that such measures are typically crude indices of the average level of education or training. To our knowledge, no comparable measure of the technology base that reflects the mix of capital vintages exists. Moreover, we can argue that the vintage mix of capital and the skill mix of labor reflect the existing stock of technological advantage extant within a given country's economy. As such, we should logically look for the effect of human capital on total factor productivity growth rather than include it directly into the production function. An agnostic approach, which we adopt, examines both possibilities for the effect of human capital on the growth process.

income across countries reflect differences in such factors as the steady-state saving rate, population growth rate, and so on.

Empirical tests of the convergence hypothesis (e.g., Baumol 1986, Barro 1991, Barro and Sala-i-Martin 1995, De Long 1988, Islam 1995, and Mankiw, Romer, and Weil 1992) generally conclude that evidence exists of absolute convergence only for developed (e.g., OECD) countries. Samples that include both developed and developing countries usually do not find evidence of absolute convergence. Nonetheless, evidence of conditional convergence generally emerges, even for samples that include developed and developing countries. Tests for conditional convergence include variables (e.g., population growth, investment to GDP, and so on) that capture country-specific effects. We employ a pooled cross-section, time-series data set of developed and developing countries. The fixed-effect technique, which we adopt, adjusts the estimates for those steady-state differences across countries.

Economists, at least since the time of Solow (1957), explain output growth in terms of the accumulation of factor inputs and of the growth of total factor productivity. The explosion of growth accounting regressions in the last decade or so has commonly searched for additional determinants of growth beyond the basic factors of production. In effect, these studies treat all possible determinants of output growth as inputs. Such an approach may be conceptually inaccurate, since many of the included determinants may have only indirect effects on output. Rather, these determinants affect the efficiency of the real inputs, physical capital, labor, and possibly human capital. Consequently, these additional determinants of output growth directly affect total factor productivity.

Our analysis evolves in two steps. First, we calculate two measures of total factor productivity derived from production function specifications that exclude and include human capital as an input. Second, we test for convergence both in real gross domestic product (GDP) per worker and in total factor productivity in our full sample and in sub-samples of low-, medium-, and high-income countries. Both steps employ the pooled cross-section, time-series data set, which provides new depth to the convergence tests for real GDP per worker. Moreover, the convergence tests for total factor productivity add new breadth to the convergence literature.[3]

We can state our basic findings simply. First, human capital has a significant effect on output when it is included as a factor of production. The incorporation of human capital in the production function lowers the elasticity of output with respect to labor when compared to the production function without human capital as an input. The elasticity of output with respect to physical capital remains essentially unaltered by the introduction of human capital as an input.

Second, we find evidence of absolute convergence in real GDP per worker only for the OECD countries in our sample, a finding consistent with the existing literature. But we also uncover evidence of absolute convergence of total factor productivity for the whole sample of developed and developing countries.[4] That is, the convergence of total factor productivity does not hinge on the relative position of a given country, as is the case for real GDP per worker (i.e., conditional convergence).

Our paper progresses as follows. In the next section, we estimate parsimonious production functions and determine the levels of total factor productivity under two specifications -- one with and one without the stock of human capital as an input. In section 3, we report the results of tests for convergence of real GDP per worker and of total factor productivity. Finally, we conclude in section 4.

2. Estimates of the Production Function and Total Factor Productivity

The measurement of total factor productivity requires the estimation of a production function from which we derive the total factor productivity measure. To keep

---

[3] Fewer studies test for the convergence of total factor productivity (e.g., Bernard and Jones 1996b).

[4] Despite evidence of absolute convergence, we do not detect much support for a narrowing of the spread of income distribution over time, except for the sub-sample of high-income countries.

the analysis simple, we adopt, as a first approximation, the Cobb-Douglas production function. Thus, our two production functions, one excluding and one including the stock of human capital, are expressed as follows:

(1) $$Y = A\, K^{\alpha} L^{\beta}, \qquad 0 < \alpha < 1 \text{ and } 0 < \beta < 1, \text{ and}$$

(2) $$Y = A\, K^{\alpha} H^{\gamma} L^{\beta}, \qquad 0 < \alpha < 1,\ 0 < \gamma < 1, \text{ and } 0 < \beta < 1,$$

where Y equals real GDP, K equals the total physical capital stock, L equals the number of workers (labor force), H equals our measure of human capital, and A equals an index of total factor productivity. We allow for the possibility of non-constant returns to scale by not restricting $(\alpha + \beta)$ or $(\alpha + \beta + \gamma)$ to equal one.

Dividing equations (1) and (2) by the labor force (L) expresses output, the physical capital stock, and the human capital stock on a per worker basis. That is,

(3) $$y = A\, k^{\alpha} L^{\alpha+\beta-1}, \text{ and}$$

(4) $$y = A\, k^{\alpha} h^{\gamma} L^{\alpha+\beta+\gamma-1},$$

where y equals real GDP per worker, k equals the stock of physical capital per worker, and h equals the stock of human capital per worker. These production functions display increasing, constant, or decreasing returns to scale as $(\alpha + \beta)$ or $(\alpha + \beta + \gamma)$ are greater than, equal to, or less than one, respectively.

Rewriting equations (3) and (4) in natural logarithms yields the following:

(5) $$\ln y = \ln A + \alpha \ln k + (\alpha + \beta - 1) \ln L, \text{ and}$$

(6) $$\ln y = \ln A + \alpha \ln k + \gamma \ln h + (\alpha + \beta + \gamma - 1) \ln L.$$

Thus, the tests for constant returns to scale involve whether the coefficient of $\ln L$ equals zero.

The inclusion of human capital as an input in the production function is controversial. Mankiw, Romer, and Weil (1992) advocate such an approach on both theoretical and empirical grounds, and obtain a better fit after including human capital in their cross-section regressions. Islam (1995), using panel regressions, finds that human capital does not contribute significantly to explaining output in the Mankiw-Romer-Weil specification. He does suggest that human capital significantly affects total factor productivity, but leaves a more definitive statement for future research.

Benhabib and Spiegel (1994) also incorporate human capital into a logarithmic-differenced (i.e., growth-rate) estimation of the production function. They discover insignificant or negative coefficients for the human capital variable (i.e., the growth rate of human capital). This finding leads them to consider more complex paths (i.e., through interaction terms) whereby human capital affects growth. They conclude that human capital does not enter the production function as an input, but rather influences growth through its effect on total factor productivity.

We use, as does Islam (1995), panel data to estimate the production function. Our data cover the 1960 to 1989 time period (1959 to 1989 for any growth rate) for a sample of 83 countries. The following regions are represented in our data set : Africa (19 countries), Caribbean, Central America, and North America (13), South America (11), Asia (16), Europe (20), and Oceania (4). The Data Appendix, Table A, lists the countries included in our sample. Data availability limited the country sample. Our panel combines data in five-year blocks as follows: 1960-64, 1965-69, 1970-74, 1975-79, 1980-84, and 1985-89. Usually, the data are averages of the five years in each block.

The data for estimating the production function come largely from the Summers and Heston (1991) Penn World Table 5.6 (PWT5.6). The output measure is real GDP per worker (1985 international prices) averaged over five-year blocks. The labor force is derived from the reported data on real GDP per capita, real GDP per worker, and population. The labor force is also averaged over five-year blocks. The physical capital stock per worker was not available for all years in all countries. Thus, to keep sufficient numbers of countries in the panel, we estimated the capital stock from investment flow data and some benchmark stocks of physical capital. (See the Data Appendix for details.) Finally, the average years of schooling per adult reported by NBER/Barro and Lee (1994) define the stock of human capital. (See the Appendix for details.) Due to data availability, we measure the stock of human capital at the beginning of each five-year period rather than an average over the period (i.e., 1960 for the 1960-64 time period).

Our data encompasses 498 observations (83 countries and 6 time blocks). Our estimating equations emerge by adding random errors to equations (5) and (6). Those error terms incorporate the effects of omitted variables. Classical regression analysis assumes that the omitted variables are independent of the included right-hand-side variables and are independently, identically distributed. When using panel data, however, we can further classify the omitted variables into three groups -- country-varying time-invariant, time-varying country-invariant, and country- and time-varying variables.[5]

The estimation of equations (5) and (6) without consideration of possible country-specific or time-specific effects can generate misleading results for ordinary-least-squares regressions. Two alternative, but related, procedures exist for addressing these problems -- fixed- and random-effect models. We restrict our attention to fixed-effect estimation since the random-effects estimation requires that the omitted variables are uncorrelated with the included right-hand-side variables -- an unrealistic assumption in the context of our model.

Our problem, however, has few elements in the time dimension. Thus, rather than adjusting the data as deviations from the mean across countries, we include time-specific dummy variables (i.e., six dummy variables for the six time periods). We still adjust the data as deviations from the means over time within each country rather than include country-specific dummy variables, which would necessitate 83 additional variables.

---

[5] For more detailed discussion of panel estimation, consult Hsiao (1986) and Greene (1990).

The estimated equations are as follows:[6]

(7) $$lny = lnA + \alpha\, lnk + (\alpha + \beta - 1)\, lnL, + \sum_{i=1}^{6} \theta_i\, time_i + \varepsilon_t \quad \text{and}$$

(8) $$lny = lnA + \alpha\, lnk + \gamma\, lnh + (\alpha + \beta + \gamma - 1)\, lnL\ , + \sum_{i=1}^{6} \theta_i\, time_i + \varepsilon_t,$$

where $time_i$ (i = 1, ..., 6) represent the time dummy variables and the variables for each country measure deviations from their country means over time. We then calculate the country-specific fixed effects of intercepts ($cint_j$) as follows:

(9) $$cint_j = \overline{\ln y}_j - \hat{\alpha}\, \overline{\ln k}_j - \hat{\delta}_1\, \overline{\ln L}_j \quad \text{and}$$

(10) $$cint_j = \overline{\ln y}_j - \hat{\alpha}\, \overline{\ln k}_j - \hat{\gamma}\, \overline{\ln h}_j - \hat{\delta}_2\, \overline{\ln L}_j\ ,$$

where a bar over a variable indicates the mean of that variable, a caret over a parameter indicates the estimate of that parameter, $\delta_1 = (\alpha + \beta - 1)$, $\delta_2 = (\alpha + \beta + \gamma - 1)$, and j = {1,2,3,...,83} is the index across countries. Note that the time-specific fixed effects appear directly as the respective coefficients of the time dummy variables.

Table 1 reports the estimates of equations (7) and (8) as well as two modifications of equation (7). Column one gives the estimate of equation (7). The coefficient of *ln L* (i.e., -0.0988), although only significant at the 20-percent level, indicates that the production function exhibits slightly decreasing returns to scale. The coefficient of *ln k* assigns a value of 0.4756 to the elasticity of output with respect to the physical capital stock. These two coefficients combine to generate the implied elasticity of output with respect to the labor force of 0.4256. Thus, after accounting for country- and time-specific effects, the output elasticities with respect to labor and physical capital sum to a value of 0.9012.

Column two in Table 1 reports the estimates of equation (8), where the stock of human capital per worker in logarithmic form enters the production function.[7] Now, the

---

[6] The estimation of an aggregate production function confronts the researcher with numerous problems. One major concern is the possible endogeneity of physical and human capital, since these factors are accumulated over time. Benhabib and Spiegel (1994) examine this issue and conclude that the coefficients of physical and human capital probably over-estimate their effects while the coefficient of labor probably under-estimates its effect. The reader needs to keep these potential biases in mind when interpreting our findings.

output elasticity with respect to human capital equals 0.1136, which is significantly different from zero at the 10-percent level. The output elasticity with respect to physical capital remains essentially unchanged from the specification without human capital at 0.4712. The combined elasticity of output with respect to physical and human capital totals 0.5848, a result not too far from the findings of Mankiw, Romer, and Weil (1992). The implied elasticity of output with respect to the labor force falls to 0.2769, suggesting that the coefficient of labor in the specification without human capital captures much of the influence of human capital. In sum, our results on the effect of human capital in the production function support the findings of Mankiw, Romer, and Weil (1992) and differ from those of Islam (1995) and Benhabib and Spiegel (1994).

An alternative method of incorporating human capital into estimates of the production function allows for the interaction of human capital with either physical capital or the labor force.[8] That is, changes in human capital affect either the elasticity of output with respect to physical capital or the labor force. Column three of Table 1 reports the results of interacting the stock of human capital with the stock of physical capital per worker while column four, human capital and the labor force. The elasticity of output with respect to physical capital is significantly affected by the stock of human capital; the elasticity of output with respect to labor is not. So, once again, we find evidence suggesting a link between human and physical capital rather than human capital and the labor force.

The time-specific dummy variables tell a consistent story. That is, total factor productivity increases over each five-year time span, beginning in 1960-64 and ending

---

[7]In fact, we measure the stock of human capital as the average years of schooling per adult. We assume that the variable provides a good proxy for the average years of schooling per worker.

[8] To calculate the total stock of human capital, we multiply our measure of human capital (i.e., average years of schooling per worker) times the number of workers to get the average years of schooling in the labor force.

in 1975-79. The last two time spans -- 1980-84 and 1985-89 -- suggest a stagnation in total factor productivity growth.

We employ the estimates of equations (7) and (8) (i.e., columns one and two in Table 1) to produce total factor productivity estimates for each country across the six time blocks. Table A in the Appendix reports the ranking of the 83 countries for our two different estimates of total factor productivity averaged across the six time blocks. These two sets of rankings possess a rank correlation of 0.9761, indicating a consistent pattern of country rankings across the two different estimates of total factor productivity. Moreover, the correlation between our two measures of total factor productivity and real GDP per worker equals 0.68 and 0.60 for the measures that exclude and include human capital in the production function, respectively.

3. Convergence Tests

A large literature tests for the convergence of real income per capita, beginning with Baumol (1986) and extending through Barro (1991), Mankiw, Romer, and Weil (1992), and Barro and Sala-i-Martin (1995). The *Economic Journal* (1996) published a symposium discussing the "Controversy on the Convergence and Divergence of Growth Rates." In this symposium, Sala-i-Martin (1996) defends the traditional cross-section regression method of investigating convergence. Quah (1996) presents a strong critique of this traditional approach, arguing in favor of examining the distribution of real income per capita over time. In another critique, Bernard and Jones (1996a) argue that the traditional approach over-stresses the role of capital accumulation and ignores or under-emphasizes the importance of technological diffusion in understanding convergence or divergence issues.

We test for the convergence of real GDP per worker as well as for the convergence of total factor productivity. The tests for convergence of total factor productivity provide some new insight as to the spread, adoption, and convergence of technological advances. As such, our tests offer some insight into the questions raised by Bernard and Jones (1996a). Finally, our tests also may shed some light on the argument about whether technology is a public or a private good. That is, if technology is a public good that can speedily transit international boundaries, then we should find convergence of total factor productivity.

The neo-classical growth models each imply convergence of real income per worker. The various empirical tests for convergence fall under two categories -- tests of unconditional (absolute) or conditional convergence. Absolute convergence means that each country moves toward the same steady-state real GDP per worker. Conditional convergence suggests that each country possesses its own steady-state real GDP per worker to which it is converging. The steady state in each country is conditioned on the state of its economy. For example, the Solow (1956) growth model implies that the steady-state real GDP per worker across countries depends on the steady-state saving and population growth rates in each country.

Two types of convergence exist in the literature -- β-convergence and σ-convergence. Convergence of the β-type considers whether the growth rates of countries exhibit a negative correlation with the level of real GDP per worker. That is, β-convergence implies that countries with low real GDP per worker possess faster growth rates than countries with high real GDP per worker. Convergence of the σ-type considers whether the dispersion of real GDP per worker diminishes over time. That is, σ-convergence implies that the distribution of real GDP per worker across countries gets tighter over time, thus reducing some measure of dispersion.

Tests for β-convergence regress the growth rate of real GDP per worker onto the initial value of real GDP per worker to test for absolute convergence and onto the initial value of real GDP per worker and other control variables (e.g., investment to GDP) to test for conditional convergence. Tests for σ-convergence consider the movement of a measure of dispersion of real GDP per worker over time. As such, σ-convergence must of necessity measures absolute convergence. For example, if all countries have the identical level of steady-state real GDP per worker, then σ-convergence implies that the measure of dispersion approaches zero over time. On the other hand, if all countries have different levels of steady-state real GDP per worker, then the dispersion of steady-state real GDP per worker must represent the steady-state level of dispersion to which real GDP per worker is converging. That is, σ-convergence in this case implies that the measure of dispersion approaches the steady-state dispersion of real GDP per worker. As a result, if the measure of dispersion is below its steady-state level, then convergence implies a rising, not falling, measure of dispersion.

Empirical studies of β-convergence typically find evidence of absolute convergence only for samples of developed (OECD) countries. Samples that include both developing and developed countries or samples that include only developing countries typically do not exhibit evidence of absolute convergence. Evidence of conditional convergence, however, does frequently emerge in samples that include both developing and developed countries. Empirical tests of σ-convergence are much fewer (e.g., Friedman 1992, Sala-i-Martin 1996, and Bernard and Jones 1996b). Nonetheless, they tell a similar story as that associated with absolute convergence, which we might expect.[9]

We first test for absolute β-convergence in two ways -- a cross-section test and a pooled cross-section, time-series test. All regressions of absolute convergence have the following form:

$$g_{yt} = \ln y_t - \ln y_{t-1} = \alpha + \beta_y \ln y_{t-1} + \varepsilon_{yt}, \qquad (11)$$

where g_{yt} is the growth rate of real GDP per worker from $(t-1)$ to t (approximated by the logarithmic difference), y_{t-1} is the level of real GDP per worker in $(t-1)$, and ε_{yt} is the random error. We calculate the growth rates and levels of real GDP per worker using

[9] Quah (1996) argues that this increased emphasis on σ-convergence still misses the point of whether "... poor countries are catching up with rich countries" (p. 1053). Quah (1996) also provides a discussion of his alternative views on economic growth and convergence.

the average levels of real GDP per worker in each time block of five years. That is, we have average levels of real GDP per worker in 1960-64, 1965-69, ... , and 1985-89 for each country. The growth rate for the cross-section test calculates g_{yt} as the logarithmic difference between real GDP per worker in 1985-89 and 1960-64 divided by 25 and the lagged logarithm of real GDP per worker is for 1960-64 (i.e., the initial time period in the cross-section test).[10] The growth rates for the pooled cross-section, time-series tests calculate g_{yt} as the logarithmic difference of real GDP per worker between 1965-69 and 1960-64, between 1970-74 and 1965-69, ... , and between 1985-89 and 1980-84, each divided by 5; and the corresponding lagged logarithms of real GDP per worker are for 1960-64, 1965-69, ... , and 1980-84.[11]

Similar regressions are performed where total factor productivity replaces real GDP per worker. That is, the regressions for β-convergence of total factor productivity have the following form:

(12) $$g_{tfpt} = \ln tfp_t - \ln tfp_{t-1} = \alpha + \beta_{tfp} \ln tfp_{t-1} + \varepsilon_{tfpt},$$

where *tfp* equals total factor productivity. The same construction of variables for the growth rates and lagged logarithms hold as described for real GDP per worker in the prior paragraph.[12]

Finally, the pooled cross-section, time-series regressions were implemented using the fixed-effect technique that we applied to the estimation of the production functions in the previous section. All variables in each country were constructed as deviations from the means over time. And we included time dummy variables to capture the time fixed effects in our pooled cross-section, time-series regressions. Since the

---

[10] We divide the logarithmic difference between real GDP per worker in 1985-89 and 1960-64 by 25 to approximate the annual growth rate between 1962 and 1987, the two midpoints of the 1960-64 and 1985-89 periods, respectively.

[11] Now, the logarithmic difference between real GDP per worker in 1965-69 and 1960-64 implies a five-year difference between the midpoints of the two five-year time blocks (i.e., 1962 and 1967, respectively).

[12] We conduct tests of equation (12) for our two measures of total factor productivity -- measures that exclude and include the stock of human capital in the first-stage production function estimation.

regressions involve growth rates, we lose 83 observations (one for each country) in our pooled cross-section, time-series regressions.

The results of our β-convergence tests appear in the top part of Table 2. Several items deserve mention. The pure cross-section test for β-convergence of real GDP per worker (row 1 in Table 2) tells a story consistent with the existing literature. That is, no evidence exists of β-convergence for the whole sample of 83 countries or for the two sub-samples of the 22 low-income countries or the 38 middle-income countries.[13] Evidence exists of β-convergence at the 10-percent level for the high-income countries only.

A much different story emerges for the cross-section β-convergence tests for total factor productivity (row 2 in Table 2).[14] Here, evidence of β-convergence of total factor productivity exists for the full sample of countries as well as for each sub-sample of low-, middle-, and high-income countries. The evidence for β-convergence strengthens as the focus moves from low-income countries (significant at the 20-percent level) to middle-income countries (significant at the 10-percent level) to high-income countries (significant at the 1-percent level). In addition, the β coefficient is negative and significant at the 1-percent level for the full sample.

What do these results tell us? To the extent that total factor productivity captures the technological character of the production process, these convergence findings suggest more evidence of convergence of technology than real GDP per worker. Of course, as noted above, the neoclassical growth models do not imply absolute

[13] We divided our sample into low-, middle-, and high-income countries based on real GDP per worker in the 1960-64 period. The World Bank divides countries into low-, middle-, and high-income countries based on real GDP per capita. Using a number in the range of 2 to 2.5 to measure the ratio of population to the number of workers, we convert these ranges into ranges based on real GDP per worker. Low-income countries had an average income for 1960-64 below $3,000 per worker; middle-income countries, between $3,000 and $10,000 per worker; and high-income countries, above $10,000 per worker.

[14] We report only the results for the total factor productivity measure that excludes the stock of human capital in the first-stage production function estimation. The results for our second measure of total factor productivity mirrors closely the reported results. These additional results are available on request.

convergence of real GDP per worker, since differences in economic conditions (e.g., steady-state savings rates and population growth rates) lead to different steady states. No similar argument, to our knowledge, applies to the convergence of technology. Rather convergence in total factor productivity associates with the view that technology is a public good while non-convergence associates with technology as a private good.[15] As a result, the stronger findings for the convergence of technology may indicate that the public-good nature of technology dominates any private-good dimension.

We also test for β-convergence using our pooled cross-section, time-series data set.[16] In general, the findings of β-convergence are strengthened when compared to the single cross-section results reported in the previous paragraphs. The panel tests for β-convergence of real GDP per worker (row 3 in Table 2) indicate significant evidence of convergence for the full sample at the 1-percent level unlike the insignificant findings for the single cross-section. Similarly, we now uncover evidence of β-convergence of real GDP per worker for the low-, middle-, and high-income groups at the 20-, 10-, and 1-percent levels, respectively.

How might such differences in findings emerge? First, the panel data tests allow for each country's growth rate to respond to changes in its level of real GDP per worker accomplished over prior five-year periods. For example, a country with low income may experience rapid growth in accordance with the convergence hypothesis. To the extent that this country closes the gap on high-income countries, then the convergence hypothesis suggests that its growth rate should slow. The panel data estimates facilitate such scenarios whereas the single cross-section regression rules them out. That is, in

---

[15] In fact, non-convergence can associate with technology that is a public good, if the high-income innovative countries discover new technology at a rate faster than the diffusion and adoption of old technology by the poorer countries.

[16] Islam (1995) provides similar tests for β-convergence using panel data constructed with time periods of five-year duration. Miller (1996) and Miller and Russek (1997b) test for β-convergence using panel data where each year is a separate entry in the panel. Miller and Russek (1997a) test for β-convergence across the states in the United States using panel data also where each year is a separate entry in the panel.

single cross-section regression, a country's growth rate averaged over the entire period is linked to its initial real GDP per worker.

Second, the panel data approach controls for country and time fixed effects. To the extent that this method accommodates differences across countries and allows different steady states for each country, the test actually transforms into a test of conditional convergence, conditional on those fixed effects across countries. As such, finding more evidence of convergence in the panel estimation appears reasonable.

Similar results emerge for the β-convergence tests for total factor productivity (row 4 of Table 2). The panel results indicate more support for convergence than found in the single cross-section results with one exception. Now, the panel results suggest weaker evidence of convergence in total factor productivity for the high-income countries. That is, all results are significant at the 1-percent level except for the high-income countries where the significance level is 20-percent. Moreover, the β-convergence test is not significant for the high-income countries when we use the other measure of total factor productivity (not reported).[17]

The weak or no finding for convergence of total factor productivity for the panel data regressions in the high-income countries may reflect to some extent the arguments of Bernard and Jones (1996a). That is, if, in fact, technological advance occurs in the high-income countries as a rule and technology flows from the technological innovators to the other countries, then we may expect convergence in total factor productivity among those countries who are adopting existing technology, but no convergence among the innovators. Our findings are consistent with this story.

Our results for σ-convergence appear in the bottom part of Table 2. We measure σ-convergence by the standard deviation of real GDP per worker or total factor productivity over the five-year sub-periods. Once again, several observations deserve

[17] Not only does this finding differ with our cross-section results, it differs from that of Bernard and Jones (1996b), where productivity convergence remains strong, albeit driven largely by services.

mention. The σ-convergence of real GDP per worker provides little evidence of convergence. The standard deviation tends to increase over the six five-year sub-periods for the full sample of countries as well as for the low-income and middle-income samples. We do observe a declining standard deviation for the high-income country sample. But even here, the standard deviation increases in the 1980s. In addition, the upward movement in the standard deviation of real GDP per worker for the whole sample and for the samples of low-income and middle-income countries also rises more dramatically during the 1980s.

The σ-convergence of total factor productivity deviates somewhat from the findings for real GDP per worker.[18] Now, the standard deviation of total factor productivity declines gradually for the full sample to 1980-84 before rising in 1985-89. Also, the decline in this standard deviation is monotonic for the high-income countries. Low-income countries saw the standard deviation of total factor productivity falling through 1975-79 and increasing thereafter while the standard deviation for the middle-income countries was fairly stable until increasing in the 1980s.

Quah (1996) argues strenuously that the convergence debate misses the point -- that is, the churning of the income distribution among countries over time. He suggests that evidence exists of convergence toward twin peaks or of convergence clubs. To examine this issue, we arrange countries by income into 8 groups and plot the number of countries in each group versus income in each time period.[19] This provides a rough-and-ready method of looking for twin peaks or convergence clubs. We observe a single-peaked distribution in 1960-64 that becomes triple-peaked in 1965-69 at low-, middle-, and high-income levels. The picture reverts to a single peak in 1970-74, 1975-79, and

---

[18] Although unreported, similar findings emerge for our other measure of total factor productivity that includes the stock of human capital in the first-stage production function estimation. These results are available on request.

[19] The income ranges expressed in the logarithm of real GDP per worker extend from 6.5 to 10.5 in increments of 0.5.

1980-84 before shifting to twin peaks at reasonably high-income levels in 1985-89. Thus, multiple clustering of countries at different parts of the income scale occurs on some occasions, but the clustering is by no means systematic.[20]

In sum, our analysis of convergence uncovers several new observations. We find stronger evidence of convergence of total factor productivity than of real GDP per worker. In addition, we discover for our pooled tests strong evidence of convergence of total factor productivity for low- and middle-income countries, but somewhat weaker evidence for high-income countries.

4. Conclusion

We study the convergence hypothesis for both real GDP per worker and total factor productivity for a pooled cross-section, time-series sample of developed and developing countries. We first estimate total factor productivity from a parsimonious specification of the aggregate production function involving output per worker, capital per worker, and the labor force, both with and without the stock of human capital. We next consider the convergence hypothesis for real GDP per worker and for total factor productivity.

Our convergence results generally conform to the results in the existing literature. Some new results do emerge regarding our tests for convergence of total factor productivity. First, we discover stronger evidence of convergence for total factor productivity than for real GDP per worker, suggesting that technological convergence is an important phenomenon. Second, we find for our pooled tests strong evidence of convergence of total factor productivity for low- and middle-income countries, and somewhat weaker evidence of convergence for high-income countries. These findings support the view that technological change is more a public than a private good. New

[20] Quah (1996) provides a thorough discussion of the twin peaks or convergence clubs ideas. Charts of the distribution of countries by income are available to interested readers on request.

technological innovations cross country borders, facilitating the convergence of total factor productivity.

References:

Barro, Robert J. “Economic Growth in a Cross Section of Countries.” *Quarterly Journal of Economics* 106 (May 1991), 407-43.

Barro, Robert J., and Jong-Wha Lee. "Data Set for a Panel of 138 Countries," Internet site, nber.harvard.edu/pub/barro.lee, (Revised January, 1996)

Barro, Robert J., and Xavier X. Sala-i-Martin. *Economic Growth*. New York: McGraw Hill, 1995.

Baumol, William J. “Productivity Growth, Convergence, and Welfare: What the Long-Run Data Show.” *American Economic Review* 76 (December 1986), 1072-85.

Benhabib, Jess, and Mark M. Spiegel. “The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-Country Data.” *Journal of Monetary Economics* 34 (October 1994), 143-73.

Bernard, Andrew B., and Charles I. Jones. “Technology and Convergence.” *Economic Journal* 106 (July 1996a), 1037-44.

Bernard, Andrew B., and Charles I. Jones. “Comparing Apples and Oranges: Productivity Convergence and Measurement Across Industries and Countries.” *American Economic Review* 86 (December 1996b), 1216-38.

De Long, J. Bradford. “Productivity Growth, Convergence, and Welfare: Comment.” *American Economic Review* 78 (December 1988), 1138-54.

Easterly, William, Michael Kremer, Lant Pritchett, and Lawrence H. Summers. "Good Policy or Good Luck? Country Growth Performance and Temporary Shocks.” *Journal of Monetary Economics* 32 (December 1993), 459-83.

Economic Journal. “Controversy on the Convergence and Divergence of Growth Rates.” 106 (July 1996), 1016-69.

Friedman, Milton. “Do Old Fallacies Ever Die?“ *Journal of Economic Literature* 30 (December 1992), 2129-32.

Greene, William H. *Econometric Analysis.* New York: MacMillan, 1990.

Hsiao, Cheng. *Analysis of Panel Data.* Cambridge, UK: Cambridge University Press, 1986.

Islam, Nazrul. “Growth Empirics: A Panel Data Approach.” *Quarterly Journal of Economics* 110 (November 1995), 1127-70.

King, Robert, and Ross Levine, "Capital Fundamentalism, Economic Development and Economic Growth," *Carnegie-Rochester Conference Series on Public Policy*, 40 (June 1994), 259-92.

Lucas, Robert E. ""On the Mechanics of Economic Development." *Journal of Monetary Economics* 22 (July 1988), 3-42.

Mankiw, N. Gregory. “The Growth of Nations.” *Brookings Papers on Economic Activity.* Washington, DC: Brookings Institution. (1) 1995, 275-310.

Mankiw, N. Gregory, David Romer, and David N. Weil. “A Contribution to the Empirics of Economic Growth.” *Quarterly Journal of Economic* 107 (May 1992), 407-37.

Miller, Stephen M. “A Note on Cross-Country Growth Regressions.” *Applied Economics* 28 (August 1996), 1019-26.

Miller, Stephen M., and Frank S. Russek. “Fiscal Structures and Economic Growth at the State and Local Level.” *Public Finance Review* 25 (March 1997a), 213-37.

Miller, Stephen M., and Frank S. Russek. “Fiscal Structures and Economic Growth: International Evidence.” *Economic Inquiry* 35 (July 1997b), 603-13.

Quah, Danny. “Twin Peaks: Growth and Convergence in Models of Distribution Dynamics.” *Economic Journal* 106 (July 1996), 1045-55.

Ramsey, Frank P. “A Mathematical Theory of Saving.” *Economic Journal* 38 (December 1928), 543-59.

Romer, Paul. "Increasing Returns and Long Run Growth." *Journal of Political Economy* 94 (October 1986), 1002-37.

Romer, Paul. “Comments and Discussion” *Brookings Papers on Economic Activity*. Washington, DC: Brookings Institution, (1 1995), 313-20.

Sala-i-Martin, Xavier X. “The Classical Approach to Convergence Analysis.” *Economic Journal* 106 (July 1996), 1019-36.

Samuelson, Paul A. “An Exact Consumption-Loan Model of Interest With or Without the Social Contrivance of Money.” *Journal of Political Economy* 66 (December 1958), 467-82.

Solow, Robert. “A Contribution to the Theory of Economic Growth.” *Quarterly Journal of Economics* 70 (February 1956), 65-94.

Solow, Robert. “Technical Change and the Aggregate Production Function.” *Review of Economics and Statistics* 39 (August 1957), 312-20.

Summers, Robert, and Alan Heston. “The Penn World Tables (Mark 5): An Expanded Set of International Comparisons, 1950-1988.” *Quarterly Journal of Economics* 106 (May 1991), 327-68.

Table 1: Production Function Estimates

	ln y	*ln y*	*ln y*	*ln y*
ln k	0.4756*	0.4712*	0.3951*	0.4751*
	(18.86)	(18.64)	(9.38)	(18.81)
ln L	-0.0988‡‡	-0.1383‡	-0.1988**	-0.1510‡‡
	(-1.32)	(-1.78)	(-2.39)	(-1.40)
ln h		0.1136‡		
		(1.81)		
ln H ln k			0.0091**	
			(2.38)	
ln H ln L				0.0025
				(0.67)
$time_1$	-0.1097*	-0.1005*	-0.0936*	-0.1071*
	(-3.99)	(-3.55)	(-3.25)	(-3.80)
$time_2$	-0.0339‡	-0.0268‡‡	-0.0224	-0.321‡‡
	(-1.66)	(-1.30)	(-1.08)	(-1.56)
$time_3$	0.0316**	0.0360**	0.0379**	0.0326**
	(2.13)	(2.40)	(2.53)	(2.19)
$time_4$	0.0426*	0.0456*	0.0441*	0.0460*
	(3.04)	(3.01)	(2.91)	(3.03)
$time_5$	0.0330‡‡	0.0263	0.0215	0.0312‡‡
	(1.60)	(1.26)	(1.02)	(1.50)
$time_6$	0.0328	0.0195	0.0125	0.0293
	(1.23)	(0.71)	(0.45)	(1.08)
$\bar{R}^2$	0.7860	0.7872	0.7885	0.7857
SEE	0.1269	0.1266	0.1262	0.1270

Note: All regressions employ the fixed-effect technique. Each variable is measured as a deviation from its mean over time, except the 6 time dummy variables (i.e., $time_i$, i = 1, 2, ..., 6) that capture the fixed effects over time. The variables are defined as follows: *y* equals real GDP per worker; *k* equals the capital stock per worker; *L* equals the stock of workers; *H* equals the stock of human capital; and *h* equals the stock of human capital per worker. See the Data Appendix for more details about the definitions and sources of data. $\bar{R}^2$ is the adjusted coefficient of determination and *SEE* is the standard error of estimation.

* means significant at the 1-percent level.
** means significant at the 5-percent level.
‡ means significant at the 10-percent level.
‡‡ means significant at the 20-percent level.

Table 2: Real Per worker GDP and Total Factor Productivity Convergence

		All Countries (83)	Low-Income (22)	Middle-Income (38)	High-Income (23)
β-Convergence: Single Cross-Section:					
β_y		-0.0005	-0.0045	-0.0056	-0.0184**
		(-0.26)	(-0.43)	(-0.61)	(-2.74)
		[81]	[20]	[36]	[21]
β_{tfp}		-0.0084*	-0.0087‡‡	-0.0114‡	-0.0212*
		(-3.29)	(-1.68)	(-1.96)	(-4.40)
		[81]	[20]	[36]	[21]
β-Convergence: Panel Data:					
β_y		-0.0349*	-0.0220‡‡	-0.0375*	-0.0517*
		(-4.55)	(-1.49)	(-3.24)	(-3.03)
		[326]	[82]	[146]	[86]
β_{tfp}		-0.0573*	-0.0615*	-0.0572*	-0.0296‡‡
		(-6.47)	(-3.39)	(-4.36)	(-1.65)
		[326]	[82]	[146]	[86]
σ-Convergence:					
σ_y					
	(1960-64)	0.8969	0.4455	0.2934	0.2737
	(1965-69)	0.9005	0.4326	0.3038	0.2369
	(1970-74)	0.9128	0.4400	0.3414	0.1844
	(1975-79)	0.9253	0.4879	0.3446	0.1702
	(1980-84)	0.9289	0.5415	0.4073	0.2055
	(1985-89)	0.9724	0.6476	0.4752	0.2567
	(1960-89)	0.9386	0.5217	0.4267	0.2793
σ_{tfp}					
	(1960-64)	0.4446	0.4968	0.3009	0.2957
	(1965-69)	0.4342	0.4689	0.2997	0.2866
	(1970-74)	0.4281	0.4359	0.3063	0.2580
	(1975-79)	0.4291	0.4396	0.3115	0.2446
	(1980-84)	0.4251	0.4769	0.3175	0.2174
	(1985-89)	0.4342	0.4834	0.3394	0.2124
	(1960-89)	0.4340	0.4597	0.3198	0.2532

Table 2: (continued)

Note: See Table 1. The βs come from estimating equation (12) and the σs are the standard deviation of real GDP per worker (*y*) and total factor productivity (*tfp*) as measured by the production function that excludes our measure of human capital.

*	means significant at the 1-percent level.
**	means significant at the 5-percent level.
‡	means significant at the 10-percent level.
‡‡	means significant at the 20-percent level.

Data Appendix:

As noted in the text, the panel data set includes information from 83 countries over the 1960 to 1989 period. Observations are generally averaged over five year sub-periods -- 1960-64, 1965-69, 1970-74, 1975-79, 1980-84, and 1985-89. Thus, the panel includes 498 observations (83 countries and 6 time periods). Table A lists the countries ranked by their total factor productivity calculated from the production function that excludes human capital. The Table also lists the ranking of the countries based on the total factor productivity estimated when human capital was included in the production function. The rest of this Data Appendix provides more information about the sources and in some cases estimation of the data.

Physical Capital

Most data on the physical capital stock comes from the Penn World Table 5.6 (PWT5.6). Data for some countries in some years were missing from this table. To maintain a reasonably large sample, we estimate the capital stock series for some countries, where either the data on important components of the capital stock are available, or where data on the total capital stock are available for some years. We considered the following procedures in estimating the capital stock series.

1. For those countries that do not have capital stock data available for the beginning of the sample, we choose the steady-state method to estimate missing values. At the steady state, the capital-output ratio (K/Y) is constant. This implies that the rates of change in capital and output are equal. Furthermore,

$$dK_t = I_t - \delta K_t \ , \Rightarrow (dK_t/K_t)\ (K_t/Y_t) = (I_t/Y_t) - (\delta K_t/Y_t).$$

Since the steady-state levels of output and capital grow at the same rate, we have the following:

$$(dY_t/Y_t)\ (K_t/Y_t) = (I_t/Y_t) - (\delta K_t/Y_t) \Rightarrow (g_t + \delta)\ (K_t/Y_t) = (I_t/Y_t).$$

Thus, solving for the steady-state capital-output ratio gives the following:

$$(K_t/Y_t)^* = (I_t/Y_t)^*/(g^*_t + \delta),$$

where "*" refers to steady-state values and δ equals 7 percent.

The steady-state growth rate of output (g^*) does not equal the actual growth rate for any country. Rather, as assumed by King and Levine (1994), we use the following relationship:

$$g^* = \lambda g + (1 - \lambda) g_W,$$

where g is the period-average actual growth rate for the country in question, g_W is the actual world growth rate estimated at 4 percent per year, and λ = 0.25, a measure of mean reversion in the growth rates, following Easterly et al. (1993). This, then produces the steady-state capital-output ratio [$(K_t/Y_t)^*$].

Finally, multiplying the steady-state capital-output ratio by the average output for the five-year period yields the average capital stock for the period, and dividing by the average number of workers for the same period produces the per worker capital stock.

2. When the capital stock in the initial years is available, we follow the perpetual inventory method to calculate the capital stock as follows:

$$K_t = I_t + (1 - \delta) K_{t-1}.$$

Finally, the estimated numbers are adjusted based on any discrepancy, in the first year the actual numbers are again available, between the estimated and actual numbers.

Human Capital

We employ the average educational attainment (years of schooling) for the adult population, available from the NBER/Barro-Lee (1994) data set.

Table A

Country	Rank *tfp*	Rank *tfph*	Country	Rank *tfp*	Rank *tfph*
United States	1	1	Hong Kong	43	45
Trinidad-Tobago	2	7	Mauritius	44	49
United Kingdom	3	3	Fiji	45	57
France	4	4	Israel	46	55
Bangladesh	5	2	Uganda	47	39
Jordan	6	12	Greece	48	51
Venezuela	7	9	Haiti	49	42
Netherlands	8	13	Turkey	50	41
Argentina	9	11	Syria	51	50
Canada	10	14	Portugal	52	46
Algeria	11	8	South Korea	53	53
Brazil	12	5	Malta	54	63
Iran	13	6	Senegal	55	52
Australia	14	18	Paraguay	56	61
Mexico	15	10	India	57	38
West Germany	16	16	Iceland	58	64
Italy	17	15	Dominican Republic	59	59
New Zealand	18	28	Thailand	60	54
Belgium	19	24	Ghana	61	56
Japan	20	17	Colombia	62	58
Austria	21	22	Philippines	63	60
Sweden	22	27	Peru	64	62
South Africa	23	20	Cyprus	65	66
Uruguay	24	30	Ecuador	66	65
Yugoslavia	25	26	Swaziland	67	69
Spain	26	23	Bolivia	68	67
El Salvador	27	29	Jamaica	69	70
Mozambique	28	19	Panama	70	72
Tunisia	29	25	Botswana	71	71
Denmark	30	36	Papua New Guinea	72	68
Pakistan	31	21	Honduras	73	73
Nicaragua	32	33	Guyana	74	77
Guatemala	33	32	Zambia	75	74
Barbados	34	48	Lesotho	76	78
Chile	35	37	Sri Lanka	77	76
Malaysia	36	34	Malawi	78	75
Singapore	37	40	Kenya	79	79
Ireland	38	43	Niger	80	80
Indonesia	39	31	Togo	81	81
Norway	40	44	Zimbabwe	82	82
Finland	41	47	Guinea-Bissau	83	83
Zaire	42	35			

Table A: (continued)

Note: The countries are ranked based on the logarithm of total factor productivity calculated from the production function specifications that exclude (*tfp*)and include (*tfph*) our measure of human capital. The actual values of the logarithm of total factor productivity are available on request.