A CONTRIBUTION TO THE EMPIRICS OF ENDOGENOUS GROWTH

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INTRODUCTION

Almost a decade of research on the determinants of long-run growth has generated a rich variety of models in which growth depends on resource allocation decisions of rational maximizing agents; it has indicated new channels through which government can influence growth; and it has raised hopes that we are beginning to understand the international growth puzzles that post-war experience has revealed. Above all, it has opened the black box in which neoclassical economics had hidden technological change for over thirty years and, as Romer (1994) has argued, "put us in a position to offer policy-makers something more insightful than the standard neoclassical prescription — more saving and more schooling."

But empirical research on endogenous growth has lagged behind the theoretical advances. Paul Krugman (1990) has noted that many of the new models are notoriously hard to make operational, and that "when we get down to cases we find ourselves using the 35-year-old methods of growth accounting." Econometric research has also remained far removed from the structural models developed during the last decade, often resorting to little more than unit root tests on policy and choice variables. In this paper we attempt to bring theory and empirics closer together. We estimate a modified version of Romer's (1990) well-known model of endogenous growth using international cross-sectional data. The exercise serves two purposes. First, it allows us to test directly the restrictions imposed by a structural model, and to evaluate whether the current state of the art performs adequately. Second, it allows us to test whether endogenous growth is identifiable in cross-sectional data using an estimation strategy that closely parallels Mankiw, Romer and Weil's (1992) estimation of the augmented Solow model.

The next section develops our modifications to the Romer model. Specifically, we remove the scale effects which have attracted critical attention recently, and this allows us to introduce population growth without generating explosive growth equilibria. We also allow human capital to be accumulated over time. The steady-state of the model is characterized by a system of non-linear simultaneous equations in which income per capita depends on the savings rate, the rate of technological change and...
population growth in much the same manner as the Solow model, but in which the rate of technological change is also determined by the endogenous parameters. The final section reports our estimates of this system of equations.

AN IMPLEMENTABLE ROMER MODEL

The Romer model will be familiar to most readers, so we will be brief in describing our modifications. A single homogeneous consumption good is produced under perfect competition. Production of the consumption good requires the input of human capital, labor and a continuum of differentiated intermediate capital goods. Capital goods are produced by a monopolistically competitive industry. Productivity in the final good sector rises each time a new capital good is designed and made available, which in turn requires an initial investment in R&D.

Our main modification is to remove the scale effects implied by the Romer model, an important step since scale effects are inconsistent with observation. Using cross-sectional data, Backus, Kehoe and Kehoe [1992] fail to find any evidence for scale effects at the national level. Theorists have been curiously ambivalent about the role of scale effects in their models. Some writers, notably Grossman and Helpman [1991], have exploited them to predict a link between 'globalization' and growth. Others have tended to downplay their significance. Lucas [1985, 263], for example, has commented that scale effects "carry the unwelcome implication that a country like India should have an enormous growth advantage over a country like Singapore... it is a nuisance implication that we want to dispose of."

Although Lucas decides simply to ignore the scale implications of his model, other theorists have constructed models in which they are absent. For example, Matsuyama [1992] assumes that the number of industries varies directly with the size of an economy, a modification which has the effect of relating growth to the share of the labor force actively engaged in the learning process, as in Lucas' [1985] model of human capital accumulation. More recently, Young [1995] has shown how Matsuyama's assumption can be motivated in a model which combines endogenous vertical and horizontal product differentiation. Our approach to removing scale effects from the Romer model is a little different; we assume designing and launching new products is more difficult in larger markets. Although our microfoundations for this assertion are little more than intuitive, it has the same implication for the steady-state as does Young's formulation.

The state of technology in the capital goods sector is fully captured by a single parameter, \( A(t) \), which is the measure of the number of varieties of capital goods which have been developed by time \( t \). The equation of motion governing the evolution of new capital designs is

\[
d\ln(A(t))/dt = a_h H_e(t)^\alpha h_e(t)^{1-\alpha},
\]

where \( \alpha > 0 \) and \( A(t) \) is the effective human capital devoted to R&D. Effective human capital consists of output produced by two types of inputs: \( H_e(t) \), the number of engineers, and \( h_e(t) \), the effective number of product designers. We assume that the following Cobb-Douglas function relates \( h_e(t) \), \( H_e(t) \), and \( H_r(t) \):

\[
h_e(t) = H_r(t)^{\beta} h_e(t)^{1-\beta}.
\]

The key assumption is that the number of effective designers is related to the number of product designers by

\[
b_e(t) = l H_e(t)/[L(t)]^{\gamma} \Delta
\]

where \( L(t) \) is population, and captures the notion that launching product designs is more difficult in a larger economy. We can write the relationship between the number of engineers, \( H_e(t) \), and the number of designers, \( H_r(t) \), as

\[
H_r(t) = \lambda H_e(t).
\]

The parameter \( \lambda(t) \) depends on a country's education policies as well as on cultural preferences for education. A small value of \( \lambda(t) \) characterizes a country which stresses science and technology in education; a large value implies that artistic and commercial human capital is stressed. Straightforward substitutions of equations (2)-(4) into equation (1) yield an equation of motion for design in terms of actual inputs:

\[
d\ln(A(t))/dt = \gamma(t)H_r(t)/L(t)^{\gamma} \Delta
\]

where \( \gamma(t) = \alpha(l-\beta) \Delta + 1+\lambda(t) \Delta \) and \( H_r = H_e H_r \). An alternative approach that yields the same equation of motion is developed in Dinopoulos and Sturgeon [1996].

This formulation of the innovation technology has some attractive properties. First, it makes a substantive distinction between R&D expenditure and the Ph.D. scientist and engineer count. Second, it stresses that the balance of education between science and commerce is important; \( \gamma \) is maximized when \( \lambda = (1-\beta)/\beta \), and so technological advance can be stifled if either science, or art and commerce, is too heavily stressed. It follows that the observed increases in \( H_r/L \) reported by Jones [1995a] may be consistent with increases, decreases, or no change in the rate of innovation. Third, including the parameter \( \beta \) allows the returns to scale in R&D to be unconstrained. In fact, statistical estimates of \( \beta \) will provide a test of endogenous versus exogenous growth.

We assume that diminishing returns to R&D are external to each individual R&D worker, whose productivity takes the form

\[
dA_0(t)/dt = \psi(t)A_0(t)^{\beta-l}L(t)^{\gamma} \Delta
\]

where \( dA_0(t) \) is the number of designs created by each R&D worker, and \( \chi dA_0(t) \) is a measure of the total designs created. Equation (6) can be obtained by aggregating (6), noting that each R&D worker is endowed with one unit of human capital.

The remaining elements of the model follow Romer [1996] with several minor modifications. The technology for the representative final-good manufacturer is

\[
Y(t) = H_r(t)/L(t)^{\gamma} \Delta
\]

\[
f_a(q) = (1+\gamma)/\gamma \Delta
\]

\[
= [1+\gamma]/\gamma \Delta
\]

\[
= \int f_a(q) \sigma(q) dq \Delta
\]

\[
= \int f_a(q) \sigma(q) dq \Delta
\]
Production requires the use of durable intermediate goods, $x(t)$, unskilled labor, $L_u(t)$, and skilled labor, $H_u(t)$. Note that engineers and designers are assumed to be equally efficient in the manufacturing sector. The economy's capital stock is defined in terms of the intermediate durable goods:

$$K(t) = f_K h(t) x(t) dt.$$ \hfill (8)

The demand for a capital design is given by maximizing profits in the final goods sector:

$$x(t) = \arg\max_{x(t)} f^d(c(t), L_u(t), L_s(t) - x(t)) - p(c(t)) x(t) dt.$$ \hfill (9)

Because of the symmetric treatment of durable goods in the production function, prices and demands are identical for all of them, and argument $t$ can be dropped. This means that the capital stock is $K(t) = A(t) x(t)$, and the aggregate production function can be written as

$$Y(t) = A(t)^{-1}(K(t)^{\alpha} H_u(t)^{1-\alpha})^{-\frac{1}{\alpha}}.$$ \hfill (10)

Intermediate goods producers can create an additional unit of capital by withholding an amount $\delta$ of their good from the market, at a cost of $\delta(t)$. Monopoly profits are consequently given by

$$\pi(t) = \max_{\delta(t)} [p(x(t)) - \delta(t)] x(t).$$ \hfill (11)

Maximizing (11) yields the equilibrium quantity of $x$:

$$Y(t) = [A(t)^{-1}(K(t)^{\alpha} H_u(t)^{1-\alpha})^{-\frac{1}{\alpha}}]^{1-\frac{1}{\alpha}}.$$ \hfill (12)

Finally, profits are given by

$$\pi(t) = \frac{\delta(t)}{\delta(t) + \delta(t)^{-\alpha}}.$$ \hfill (13)

The stock-market valuation of monopoly profits requires that the ratio of return to R&D be equal to the rate of return which could be obtained on a risk-free bond:

$$\pi(t)/P_Y(t) = \delta(t)/P_Y(t) dt = \lambda(t),$$ \hfill (14)

where $P_Y(t)$ is the price of a new design expressed in terms of good $Y$. Free mobility of human capital ensures that the wage of human capital in the manufacturing sector never exceeds the wages earned by engineers and product designers employed in the research sector. We assume that both researchers and designers are employed in the manufacturing sector, in which case equating marginal products of human capital across sectors yields

$$\pi(t) = \delta(t)/\lambda(t) + (1-\alpha).$$ \hfill (15)

where equation (7) has been used.

We proceed by defining an equation of motion for human capital accumulation. To keep matters simple, assume that $x$ measures the fixed proportion of the population being educated. Population grows at a constant rate, $n$, over time. Thus, the full-employment of skilled labor condition is

$$H(t) = H_0(t) + H_1(t),$$ \hfill (16)

where $H(t) = x(t)L(t)$ is the total number of skilled workers and $L(t) = (1-x) L(t)$ is the number of unskilled workers in manufacturing. Both $H(t)$ and $L(t)$ grow at the constant rate of population growth.

Substituting the definition of instantaneous profits from equation (13) into equation (14), and the price of a design from equation (14) into equation (15) yields

$$H_1(t) = \left[\pi(t) - \delta(t) + \delta(t)^{-\alpha}\right] \frac{\lambda(t)}{\delta(t)^{-\alpha}}.$$ \hfill (17)

Because the transitional dynamics in the Romer model are complicated, we will solve for the steady-state equilibrium in which all variables grow at a constant rate, or are constant over time. Along the balanced growth path, the interest rate and the price of an intermediate good $x$ are constant. The endogenous growth rate, $\gamma = \delta(t)/P_Y(t)$, and the raise $H_1(t)/H(t)$ and $H_1(t)/L(t)$ are constant. Consequently, $L$, $H$, $H_1$, $L_0$, $\pi$, and $P_y$ all grow at the common rate, $n$. In the original Romer model, all these variables remain constant along the balanced growth path, because $n=0$ in the absence of population growth.

Substituting $\delta(t)/P_Y(t)$ and equation (16) into equation (15), we can relate the interest rate to the endogenous growth rate, $\gamma$, and the parameters of the model:

$$\pi(t) = \delta(t)/\lambda(t) + (1-\alpha).$$ \hfill (18)

Finally, we need to remove the interest rate from equation (18). A standard approach is to solve for an intertemporal optimization problem for a representative consumer, but it is well known (Deaton, 1992) that these models of saving behavior perform poorly in empirical applications. Instead, we introduce physical capital depreciation into the GDP identity:

$$\pi(t) = \delta(t)/\lambda(t) + (1-\alpha).$$ \hfill (19)

where $O(t)$ is aggregate consumption and $\delta > 0$ is the capital depreciation rate. Dividing both sides of equation (19) by $K(t)$, substituting $\delta K(t) = (1+n)K(t)$, and letting $\delta = (1+n)K(t)$, we obtain the savings rate, we obtain a simple expression for the steady-state capital-output ratio:

$$K(t)/Y(t) = n/(\pi(t) + g + \delta).$$ \hfill (20)
From the monopolist’s first-order condition, \( KV'(T) = a' \eta R(T) \) which, in conjunction with equation (20), yields an expression for the instantaneous interest rate in the steady state:

\[
(21) \quad r = a^2\gamma + g + b(\delta g).
\]

Finally, substituting equation (21) into equation (18) yields an implicit expression for endogenous growth:

\[
(22) \quad s^e = \frac{a'(g\gamma)^{1+1}}{(1-g\gamma)^{1-\beta}} \left[ \left( \frac{a}{\eta} \right)^2 \eta (1-\delta) (1-\alpha) (1-\alpha) \right].
\]

In the absence of diminishing returns, equation (22) can be solved explicitly for the rate of growth. The next task in this section is to derive an expression for steady-state per capita income. We can substitute the steady-state capital-output ratio, (20), the manufacturing human capital-labor ratio, (17), and the human-capital full-employment constraint, (16), into the production function, (10), and take logarithms:

\[
(23) \quad \ln Y(Y)/(L(t)) \approx \alpha (\delta) + (1-\alpha) \ln (1-g\gamma) - \ln (1-\alpha) - \ln (n + g + b) - (1-\alpha) (1-\alpha).
\]

where \( g \) is determined by equation (22).

Equations (22) and (23) constitute an empirically implementable simultaneous equation system. Equation (23) relates steady-state income to the level of capital output, \( \alpha \), the savings rates, and \( s^e \), population growth, \( n \), and the rate of technological progress, \( g \). But before we discuss our estimation strategy, we turn briefly to the long-run implications of the model. First, the model does not exhibit scale effects. The unique steady-state endogenous growth rate is constant and finite despite the presence of positive population growth. The model can admit increases, decreases or no change in the proportion of engineers in R&D, and a constant and endogenous growth rate: deviations of \( \alpha \) from its optimal level can reduce \( g \), but may increase the apparent R&D intensity if the latter is incorrectly measured by \( H(\alpha)/(L(t)) \).

Second, the level effects of the present model are similar to those of the augmented Solow model. However, unlike the neoclassical model, the present model preserves the policy effects on long-run growth that were emphasized in the first-generation endogenous growth models: R&D subsidies are equivalent to a change in the parameter \( \alpha \) and affect long-run growth; educational subsidies that change \( s^e \) or policies that affect the instantaneous interest rate, \( r(T) \), have long-run growth effects.

Third, the convergence properties of the model are more complicated than the ones associated with the neoclassical model, but transitional dynamics arise from the assumption that output can be transformed into capital. While we do not explore the convergence implications of the model in this paper, it is easy to show that growth rates are higher for countries with capital stocks less than their steady-state values.

Finally, the model does not have the undesirable implication that population growth is the only determinant of long-run growth in income per capita. Increases in the rate of population growth rate have an ambiguous effect on long-run growth: if physical capital investment rates are high [low] the impact of increased population growth on the rate of technological advance is positive [negative].

**ESTIMATION**

In this section, we apply Mankiw et al.’s cross-sectional data to the simultaneous equation system derived above. Mankiw et al. provide data on income, saving, education, and population for three samples: (N) a sample of 99 non-oil exporting economies; (I) a sample of 75 intermediate economies, which comprises all countries in sample (N) except those whose data received a grade of 'D' from Summers and Heston [1988]; and (O) the 22 OECD countries with populations in excess of one million. Data on population growth, GDP and investment in physical capital are taken from Summers and Heston [1988]. The rate of investment in human capital is proxied by the percentage of the working-age population in secondary school.

Our estimation of the system of equations (22)-(23) will be carried out in three stages. First, we exploit the expected partial correlations between \( g \) and the exogenous variables to investigate their consistency with the signs of coefficients in a simple linear regression in which growth is the dependent variable. Second, we recover estimates of the parameters by estimating equation (22) alone using the generalized methods of moments (GMM). Finally, we exploit cross-equation parameter restrictions in the system, and estimate the growth and level equations jointly by GMM. Consider first the regression:

\[
(24) \quad \ln Y(t)/(L(t)) = \alpha_2 + \alpha_3 \ln a + \alpha_4 \ln a + \alpha_5 \ln a + \alpha_6 a + \epsilon.
\]

Partial differentiation of equation (22) indicates that \( a_2 \) and \( a_3 \) should be positive, while the coefficient on \( a_5 \) is a priori ambiguous in sign. However, \( a_2 \) will be positive in a cross-section if, on average, \( a_2 > a_5 \), which is likely. These predictions are consistent with the OLS estimates reported in Table 1: for samples (N) and (I) the estimates of \( a_2 \) and \( a_3 \) are positive and significant. The estimates of \( a_6 \) are, however, insignificant, and no significant results are obtained at all from sample (O). Nonetheless, noteworthy in the two larger samples is that the three variables are jointly highly significant, and that as much as 40 percent of the international variation in growth from 1960 to 1985 can be "explained" by the three independent variables. The results for the two capital variables are the same as in Barro [1991, Table IV].

However, we can take the growth regression much further, as the parameters in equations (22) and (23) are identifiable, at least in principle. Because of the implicit nature of equation (22), it is useful to outline our estimation procedure in terms of the GMM estimator. Append an error, \( u \), to the right hand side of equation (22). We assume the errors are country-specific with \( E(u) = 0 \), and we further make the critical assumption that the exogenous variables, \( s^e \), \( g \), and \( n \), are uncorrelated with the disturbances.

\[
(25) \quad E(u \mid a, s^e, g, a, s^e, n, u) = 0,
\]
which yields four orthogonality conditions.

A less restrictive assumption is that a set of instruments exists which are correlated with the exogenous variables, but uncorrelated with \( u \). One would then impose moment restrictions between \( u \) and the instruments. In the absence of useful instruments for our variables, however, we must make the much more restrictive assumptions implied by equation (25). Moreover, equation (25) implies that we will effectively estimate the parameters of the model by non-linear least squares, a special case of GMM. The unknown parameters in equation (22) are \( \gamma, \phi, \beta, \alpha, \delta, \) and \( \gamma \), which is a two more than the number of orthogonality conditions. We therefore need to take outside estimates for two of them: following Mankiw et al., we assume that \( \delta = 0.03 \) for all countries, and we further assume \( \delta = 5,5, \) which allows us to estimate the remaining parameters by finding the values of \( \gamma, \phi, \beta, \) and \( \alpha \) which set the sample analogs of the moment restrictions in equation (25) to zero. \(^{10}\) The endogenous variable is the average annual growth rate from 1960 to 1985; the exogenous variables are as defined in Mankiw et al.

Table 2 reports our estimates of the coefficients in equation (22) for two of the three samples. Attempts to estimate sample (O) failed to achieve convergence which, in view of our failure to obtain a significant linear regression for this sample, is not surprising. The results are mixed. We are, of course, primarily interested in the estimates of the growth parameters, \( \gamma \) and \( \phi \). Recall that a test of \( \phi = 0 \) constitutes a test between neoclassical and endogenous growth. The estimates allow us reject the neoclassical model in favor of our endogenous growth alternative: \( \phi \) is estimated to be about 0.17, with a two-standard error interval of 0.10-0.24 and \( \gamma \) is precisely estimated at about 0.07. Our estimate of \( \phi \) is also consistent with a growing body of evidence in favor of positive, but diminishing, returns to R&D.\(^1\)

The share of physical capital, \( \alpha \), is precisely estimated to be a plausible 0.30-0.34, with standard errors of less than 0.04. However, the estimates of the share of human capital, \( \beta \), are clearly unsatisfactory. The point estimate is 1.05 for sample (N) and 0.80 for sample (O), giving returns to scale of broad capital, \( \alpha + \beta \), of 1.4 for sample (N) and 1.1 for sample (I). Of course, there are considerable problems associated with the measurement of \( \alpha \). The Mankiw et al. schooling data will be positively correlated with \( \beta \), but they are not equivalent. Moreover, inspection of (22) reveals that it would be quite possible to replace the schooling data with some monotonic transformation, and thereby alter our estimate of \( \beta \).\(^1\) We will temporarily resist the temptation to do so. Instead, note that we have still not exploited all the available information in estimating the model. In particular, equations (22) and (23) contain significant cross-equation restrictions which can be exploited by estimating the two equations jointly by GMM.

Table 3 reports our GMM estimates for samples (N) and (I). The results are similar to those we obtained on estimating the growth equation alone. Our estimates of \( \phi \) and \( \gamma \) are about 0.2 and 0.07 respectively, and both are precisely estimated. The share of physical capital is about 0.3, while the share of human capital remains relatively high, at about 0.80; returns to scale of broad capital are about 1.1. Moreover, in exploiting the cross-equation restrictions, we have some degree of freedom with which to test overidentifying restrictions and, as Table 3 shows, \( \chi^2 \) tests cause us to reject them. Clearly, not all is well with the model.

### Table 1: OLS Estimates of Linear Growth Equation

<table>
<thead>
<tr>
<th>Dependent variable: annual per capita GDP growth rate, 1960-1985</th>
<th>Sample (N)</th>
<th>Sample (I)</th>
<th>Sample (O)</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>-0.0076</td>
<td>0.0011</td>
<td>0.0025(a)</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>( e )</td>
<td>0.1264(b)</td>
<td>0.0058</td>
<td>0.0066</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.045)</td>
<td></td>
</tr>
<tr>
<td>( e )</td>
<td>0.0017</td>
<td>0.0065</td>
<td>-0.0055</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.104)</td>
<td></td>
</tr>
<tr>
<td>( n )</td>
<td>1.0895(a)</td>
<td>1.0096(b)</td>
<td>0.0734</td>
</tr>
<tr>
<td>(0.179)</td>
<td>(0.190)</td>
<td>(0.348)</td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.40</td>
<td>0.53</td>
<td>0.20</td>
</tr>
<tr>
<td>F-statistic</td>
<td>20.48(b)</td>
<td>11.89(b)</td>
<td>1.54</td>
</tr>
<tr>
<td>Number of observations</td>
<td>78</td>
<td>22</td>
<td>76</td>
</tr>
</tbody>
</table>

*a. Standard errors in parentheses.  
*b. Significant at the 5 percent level.

### Table 2: GMM Estimates of Growth Equation

<table>
<thead>
<tr>
<th>Dependent variable: annual per capita GDP growth rate, 1960-1985</th>
<th>Sample (N)</th>
<th>Sample (I)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.3432</td>
<td>0.3149</td>
</tr>
<tr>
<td>(0.043)</td>
<td>(0.012)</td>
<td></td>
</tr>
<tr>
<td>( \beta )</td>
<td>1.0547</td>
<td>0.8308</td>
</tr>
<tr>
<td>(0.318)</td>
<td>(0.044)</td>
<td></td>
</tr>
<tr>
<td>( \phi )</td>
<td>0.1077</td>
<td>0.1099</td>
</tr>
<tr>
<td>(0.036)</td>
<td>(0.041)</td>
<td></td>
</tr>
<tr>
<td>( \gamma )</td>
<td>0.0968</td>
<td>0.0699</td>
</tr>
<tr>
<td>(0.005)</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>97(a)</td>
<td>76</td>
</tr>
</tbody>
</table>

*a. Chap was dropped from Mankiw et al. sales data set because of a negative growth rate.  
*a. Standard errors in parentheses. Sample (O) failed to converge.  
*b. Significant at the 5 percent level.
Our estimation procedure has two serious problems. The first, to which we have already alluded, is that our estimates are sensitive to our choice of secondary school enrollment rates as the sole measure of human capital. Table 4 reports estimates of the system when the schooling data are subject to two different positive monotonic transformations. In both cases, the share of human capital falls to plausible levels: a linear transformation of the schooling data reduces beta to 0.33, while a nonlinear transformation reduces it to 0.56. Returns to scale of broad capital in the two cases, at 0.56 and 0.82, are significantly less than one. Of course, other transformations can move beta in the opposite direction, so these estimates should be viewed only as indicators of what can happen with mismeasurement of human capital savings rates.

The second problem concerns estimation of the level equation, (23), in the presence of endogenous growth. Our orthogonality restrictions are equivalent to Mankiw et al.'s assumption that each country's level of technology, A(t), varies from a mean value by a random amount that is independent of savings rates and population growth rates. The assumption is probably questionable even when the growth rate of technology is assumed to be exogenous and common to all countries; but in our model, countries with different savings rates experience different long-run growth rates and their levels of technology cannot be independent of savings rates. In testing the null hypothesis that rho = 0 (i.e., that long-run growth is exogenous), the Mankiw et al. assumption may be reasonable, but once the null is rejected simultaneity problems ensure that we can no longer rely on the parameter estimates. This problem does not arise, of course, when the growth equation is estimated alone, and the fact that we obtained similar results in Tables 2 and 3 indicates that the simultaneity problem may not be empirically important. Nonetheless, the potential for bias that results is an issue we are still attempting to resolve.

NOTES

1. Matsuyama constructs a model in which each firm is headed by an entrepreneur who learns, and in which entrepreneurs are a fixed fraction of the labor force.

2. When a flaw was found in INTLEX's pricing chip, it cost the company over $400 million to replace chips already sold. The cost of such recalls varies directly with the size of the market. The recent launch of Windows 95 was accompanied by an unprecedented media marketing campaign. In the past, such software was typically only advertised in the specialized press but, as market share expanded, consumers became more diverse and must be reached through multiple channels.

3. In (June 1992) intertemporal scale effects are removed by assuming that technological opportunity diminishes over time. An unfortunate implication of his model is that it predicts that long-run growth in GDP per capita is proportional to population growth. Evidence against this proposition is

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**Table 3**

<table>
<thead>
<tr>
<th></th>
<th>Sample (I)</th>
<th>Sample (II)</th>
<th>Sample (III)</th>
<th>Sample (IV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(A)</td>
<td>12.408</td>
<td>12.399</td>
<td>12.399</td>
<td>12.722</td>
</tr>
<tr>
<td></td>
<td>(.384)</td>
<td>(.328)</td>
<td>(.328)</td>
<td>(.328)</td>
</tr>
<tr>
<td>c</td>
<td>.0877</td>
<td>.0877</td>
<td>.0877</td>
<td>.0877</td>
</tr>
<tr>
<td></td>
<td>(.583)</td>
<td>(.563)</td>
<td>(.563)</td>
<td>(.563)</td>
</tr>
<tr>
<td>beta</td>
<td>.0777</td>
<td>.0777</td>
<td>.0777</td>
<td>.0777</td>
</tr>
<tr>
<td></td>
<td>(.773)</td>
<td>(.773)</td>
<td>(.773)</td>
<td>(.773)</td>
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Tests of overidentifying restrictions

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**Table 4**

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Tests of overidentifying restrictions

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a. Chad was excluded from sample (N) because of a negative growth rate.

b. Value for h is a prior restriction.

Standard errors are in parentheses. Instruments used were ln(s), s, ln(gdp). It is assumed to be .03.

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In June 1992, Mankiw's model assumed that the technological opportunity diminishes over time. An unfortunate implication of his model is that it predicts that long-run growth in GDP per capita is proportional to population growth. Evidence against this proposition is...
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easily found. For example, Maddison’s [1991] 16-country long-run data set reveals negative, positive and zero correlations between population growth and GDP growth.

4. Barro [1997] does not include population growth as a regressor. See Levine and Renelt [1992] for a critical review of the so-called “Barro regressions.” They point out that at least fifty variables have been associated with changes in log growth rates, but the measured influences of any one variable is highly sensitive to which others are included as regressors. Barro and Sala-i-Martin [2006] report at least 24 different regressions, highlighting the fragility of their results.

5. With $r = 0.61$, and $s = 0.95$, a value of $s = 5$ implies a steady-state capital-output ratio of about 8.6.

6. The parameters in equation (2) are identified, so that a vector of parameters exists for which the sample data match the orthogonality conditions exactly.

7. For example, Hall, Griliches and Hausman [1988] found that the elasticity of potential with respect to R&D expenditures is between 0.39 and 0.66, depending upon the estimation method chosen. Arroyo, Dinoorgas, and Donald [1990] estimated a structural model of endogeneity growth using aggregate U.S. time-series data and placed the range 0.4-0.5 when the intertemporal elasticity of substitution is in the range 0.5-0.6.

8. Of course, transformations of the schooling data may significantly alter all parameter estimates.

REFERENCES


Krugman, P. Comment on Aten Yama’s “Pull of Two Cities”, NBER Macroeconomic Annual, 1997, 54-6.


MEASURING TECHNOLOGY DIFFUSION AND THE INTERNATIONAL SOURCES OF GROWTH

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Boston University

and

Samuel Kortun
Boston University

Growth accounting based on analysis of time-series data has established that technical change explains much of the increase in worker productivity in this century. Where technical change comes from and how it spreads across countries is less well understood.

Here we review a new methodology to trace the source of technical change to its origins in the inventive activity of different countries. Eaton and Kortun [1996a, 1996b] develop and apply variants of this methodology to infer the sources of growth in the world economy.

The methodology requires the use of indirect evidence since we observe neither the creation nor the diffusion of inventions. Productivity growth serves as a measure of the final benefits of invention, while R&D activity reflects inputs into the inventive process. What we lack is direct evidence of the channels linking increased productivity with the inventive activity that generated it. Our solution is to use patents as an indirect indicator of inventive output and to use information about where patent protection is sought to infer where inventors expect their ideas to be used.

To use these data our model incorporates a decision to patent. The incentive for an inventor from country i to seek patent protection in country j is increasing in the extent to which inventions from country i diffuse to country j. Inferring the pattern of international technology diffusion implied by the pattern of international patenting and other data requires a number of specific modeling assumptions about production technologies, market structure, and inventor behavior, none of which is easy to verify directly. As a consequence, we have employed different sets of assumptions in two distinct implementations of our basic methodology. Reassuringly, the two implementations deliver the same basic message.

Two broad conclusions emerge. (1) The United States, followed by Japan and Germany, are overwhelming the major sources of innovation in the world economy, well over one-half the productivity growth in the countries we consider derives from innovations originating in those three countries. The United States makes the largest contribution to every country’s growth with the exception (in one study) of Germany’s contribution to its own growth. (2) The extent of international technology diffusion among developed countries is substantial, but not complete; an invention is more