MODELING THE EFFECTS OF HEALTH ON ECONOMIC GROWTH[1]

Alok Bhargava

Dean T. Jamison

Lawrence Lau

Christopher JL Murray

GPE Discussion Paper Series: No. 33

Evidence and Information for Policy

World Health Organization

[1] This study was supported by the Global Programme on Evidence for Health Policy (through a Global Health Leadership fellowship awarded to the first author) and by the Economics Advisory Service of the World Health Organization, Geneva, Switzerland. The authors are indebted to D. Evans for useful suggestions, and to A. Tandon and J. Wang for their valuable help. The views contained in the paper are exclusively those of the authors.

Table of Contents

Executive Summary

This paper investigated the effects of health indicators such as adult survival rates (ASR) on economic growth rates at 5-year intervals in the period 1965-90 in developed and developing countries. This is an important topic because economic performance of developing countries could conceivably be enhanced by improving health of the citizens. Because of the previous findings regarding the life expectancy-income relationship by Preston (1976), the extent to which additional resources should be invested in health is likely to depend on the Gross Domestic Product (GDP) of the country. While health can be defined more broadly to include indicators of physical and mental health of the population especially by age cohorts, data on health indicators at the national level typically comprise of variables such as life expectancy, child mortality, adult survival rates, etc.

Panel data were analyzed in this paper on Gross Domestic Product (GDP) series based on purchasing power adjustments (Penn World Table; PWT) and a GDP series based on official exchange rates (World Development Indicators; WDI) using several econometric methodologies. It was important to use two alternative GDP series because purchasing power comparisons in the PWT invoke several assumptions about prices of goods in countries where the data were unavailable and used certain smoothing procedures. The analysis of growth rates would be more reliable if the use of two GDP series led to similar results. First, we developed a framework for modeling the inter-relationships between GDP growth rates and explanatory variables by re-examining the life expectancy-income relationship. It is argued that, while the effects of ASR are likely to taper off at relatively low GDP levels, a broader view of health entails focusing on human development, including the formation of human capital. Nutrition and learning are essential components of human development.

Second, the stochastic properties of the GDP series were analyzed by applying classical tests for unit roots in a fixed effects framework; a dynamic random effects framework was subsequently used for specification testing. The GDP series showed persistence and heteroscedasticity over time; growth rates seemed amenable to econometric modeling. The analysis provided important insights for using the appropriate models for growth rates. Third, models for growth rates were estimated using panel data, taking into account the interaction between ASR and lagged GDP level that is essential for understanding the associations between economic growth and measures of health. The problems of simultaneity of explanatory variables, namely, lagged investment/GDP ratio, ASR, GDP, and interaction between these variables was addressed in a static random effects framework. Fourth, we computed the confidence intervals for the net effect of ASR and on GDP growth rates. This enabled a systematic treatment of the GDP levels beyond which the effects of ASR on growth rates were not statistically significant. We also developed and applied a test for parameter stability to GDP growth rates outside the sample period (in 1995) using the GDP data from the WDI. The results indicated that our model for growth rate performed better outside the sample period when the simultaneity of some of the explanatory variables was taken into account.

Overall, the results showed the importance of ASR on growth rates for poor countries; the GDP levels beyond which ASR had a zero impact on growth rates using data from PWT and WDI were, respectively, 3554 international dollars and 690 dollars in 1987 prices. While these figures indicate that benefits of health apply primarily to poor countries, it is argued in the paper that other measures

of health such as disease prevalence rates and cognitive functioning are important for maintaining a steady supply of skilled labour; skilled labour is an important ingredient in economic production. The collection of more comprehensive data on the prevalence of various diseases by age cohorts in future work is likely to afford sharper insights into the effects of health on the economic growth, even for countries in the middle and high income groups.

1. Introduction

The twentieth century has seen remarkable gains in health. Average life expectancy in developing countries was only 40 years in 1950 but had increased to 63 years by 1990 (World Bank, 1993). Factors such as improved nutrition, better sanitation, innovations in medical technologies, and public health infrastructure have gradually increased the human life span. The relative contribution of these factors depends on the level of economic development; there are synergisms between the underlying factors operating in complex ways. Thus, for example, while recognizing various determinants of life expectancy, Preston (1976) emphasized economic development as the most important factor. However, since life expectancy is strongly influenced by child mortality, low-cost interventions such as the provision of ante natal care and vaccination programs in poor countries can be effective instruments for raising life expectancy. More generally, economic development depends on the level of skills acquired by the population and on capital formation. The former is influenced by child nutrition, educational infrastructure, and households' resources, including parents' physical health and cognitive attainment (e.g. Fogel, 1994, Scrimshaw, 1996, Bhargava, 1998a, 1999a). Capital accumulation depends on the savings rate that is also influenced by adult health.

Analyses of the inter-relationships between health and economic productivity can be conducted at the individual level, at regional levels within a country, and for aggregate data on countries. In developing countries, there are numerous micro studies in biological and social sciences showing benefits of better health on productivity (e.g. Basta et al., 1979, Spurr, 1983, Bhargava, 1997, Strauss and Thomas, 1998). Quantifying the relationship between health indicators and economic productivity is more subtle in developed countries. For example, the effects of disability on employment status have been investigated in the Netherlands (Stronks et al., 1997); the relationship was stronger in physically demanding occupations where earnings are typically low. The earnings of a large proportion of the population, however, depend on their general health and well-being, including mental health. While psychologists have investigated the decline with age in components of cognitive abilities (Horn and Hofer, 1992), the effects on such factors on individuals' productivity remain largely unknown.

Recently, aggregate data at the country level for the post war period have become accessible (Summers and Heston, 1991 (PWT); World Development Indicators (WDI), 1998). Panel data on countries have been extensively used to elucidate economic relationships (e.g. Barro and Sala-i-Martin, 1995, Barro, 1997). Because many countries have experienced demographic and health transition in this period, studies can yield insights into the sources of economic growth. The quality of the data, however, can be poor especially in less developed countries where many of the variables are “projections” from statistical models. For example, the purchasing power parity indices commonly used for constructing the real Gross Domestic Product (GDP) series in the PWT are based on information on a subset of countries. Further, most countries face different socioeconomic and infrastructural constraints that are difficult to approximate in the analyses. Pooling data across countries can lead to spurious results, especially if the investigators fail to address stochastic properties of the dependent variable in econometric modeling (Sargan, 1964). Such problems are exacerbated in models explaining aggregate variables such as the GDP. Moreover, growth rates averaged over long time periods (e.g. 25 years) tend to describe economic activity in a way that is similar to the GDP. By contrast, the 5-year average growth rates analyzed in this paper show considerable variation but are less noisy than the annual growth rates.

The purpose of this paper is to model the proximate determinants of economic growth with emphasis on variables that approximate health of the population. In so doing, we develop an analytical framework within which issues of demographic transition, human development, and capital formation can be discussed. In addition, the models incorporate the stochastic properties of the GDP series and take into account the data limitations. Section 2 describes the data used in the analysis. The analytical framework for modeling the effects of health on economic growth is developed in Section 3.1; the econometric framework is outlined in the Appendix. Stochastic properties of the GDP series from the PWT and WDI were investigated in a fixed effects framework and also using dynamic random effects models in Section 4 (Bhargava et al., 1982, Bhargava and Sargan, 1983, Bhargava, 1987). In Section 5.1, average growth rates at 5 year intervals are modeled using a model similar to Barro (1997) but allowing for simultaneity and interactions between some regressors. Instrumental variables estimation methods were used and certain maintained hypotheses were tested (Bhargava, 1991). In Section 5.2, we elaborate on the role of the interaction between lagged adult survival rate and GDP from a policy standpoint. Stability of the estimated parameters is tested by a Wald test using out-of-sample observations for 1995 on GDP from the WDI in Section 5.3. Finally, the conclusions are summarized in Section 6.

2. The Data

The data used in the analysis were primarily from the Penn World Table (PWT; Summers and Heston, 1991) and the World Development Indicators (WDI; World Bank, 1998). The GDP series in the PWT are in “international 1985 dollars” that were based on purchasing power comparisons for a subset of countries; GDP series from the WDI based on the official exchange rates was in 1987 constant dollars. The WDI GDP series was likely to show greater variability because exchange rate fluctuations can induce distortions especially for small countries. However, the PWT GDP series involves estimation of the purchasing power parity indices for countries where the data were not available (Summers and Heston, 1991, Ahmad, 1992). The statistical models used to estimate relative prices utilized certain explanatory variables that may also be important for explaining growth rates. Conclusion from our analysis will be strengthened if GDP series based on purchasing power comparisons and exchange rates yield similar results.

The total fertility rate, life expectancy, and population variables were available in the PWT and WDI data sets. In addition to life expectancy, we used the adult survival rate (ASR; probability of surviving the 60th birthday after reaching the age 15 years; mean=0.702, standard deviation=0.14) from Bos et al. (1998). The ASR is less sensitive to child mortality rates and was constructed from World Bank demographic files containing mortality data on many countries; figures for some countries were projections from demographic models. Typically, data on life expectancy, total fertility rate and adult survival rates were compiled in PWT and WDI at irregular intervals. To reduce the effects of projections on the empirical results, we analyzed panel data that were separated by 5 year intervals i.e. 6 time observations on the countries (in 1965, 1970, 1975, 1980, 1985, 1990) were used (first observation in WDI series was for 1966).

The education series (average years of education for population aged 15-60) for the 6 time periods were from Barro and Lee (1996). Data on geographical variables such as the area in the tropics, if the country is “land-locked”, different indicators for the prevalence of malaria, and an index of openness to trade were taken from Gallup and Sachs (1998); alternative measures were utilized for variables such as openness from the PWT. Overall, the GDP data covered 125 countries in the PWT and 107 countries in the WDI. However, because of missing observations on explanatory variables, the sample sizes used in the estimation were lower for the models for growth rates.

It is also feasible to estimate aggregate production functions for the countries; some preliminary results were presented in Jamison et al. (1998). However, data on physical capital stock were available for only 58 countries in the PWT. Collins and Bosworth (1996) and Nehru and Dhareshwar (1993) have imputed the data on physical capital for a larger number of countries under certain assumptions on depreciation rates. Because these assumptions are not standard and because the focus of our analysis was on the relationship between health indicators and economic growth, we do not report the results for aggregate production functions in this paper.

3. A framework for modeling the effects of health on economic output

3.1 The conceptual framework

Preston (1976) analyzed cross-country data on life expectancy and national incomes for the approximate periods 1900, 1930 and 1960 and observed that the curves showed an upward shift over time; for a given income level, life expectancy was highest in 1960's. Moreover, percapita GDP above $600 (in 1963 prices) had little impact in raising the highest life expectancy (approximately 73 years) in the 1960's. While recognizing that shifts in the curves had multiple causes, Preston attributed approximately 15% of the gains in life expectancy to income growth but was less optimistic about the role played by nutrition and literacy. However, recent analyses of historical data suggest larger benefits from improved nutrition (Flood et al., 1991, Fogel, 1994). Furthermore, public health programs reducing sicknesses have beneficial effects on health by preventing the loss of vital nutrients due to infection (Scrimshaw et al., 1959).

Life expectancy (or the adult survival rate) in a country is a broad measure of population health, though it need not accurately reflect the productivity of the labor force. For example, suppose that due to poor childhood nutrition, ability of individuals to perform productive tasks diminishes at an early age but, because of easy access to medical care, life expectancy is high (the Indian state of Kerala can be described by these attributes; IIPS, 1995). Then productivity loss will be under-estimated if life expectancy was used as the sole indicator of health. Indices measuring disabilities of the working population in various occupations would be insightful for assessing productivity loss (e.g. Murray and Lopez, 1996).

At a general level, capital formation requires that a high proportion of the skilled labor force remains active for a number of years; experience is important for technical innovations that take years of investments in research and development. Because detailed information on such variables cannot be utilized in national comparisons, a broader view of health is helpful for interpreting the results. In particular, investments in education and training critically depend on survival probabilities; expenditure on children's education is influenced by parents' subjective probabilities of child survival. All these factors are potentially important for explaining economic growth.

Panel data on developing and developed countries provide an opportunity to disentangle some of the effects of demographic, health, and economic variables on growth because the countries are at different stages of economic and social development. In certain developing countries, for example, high fertility rates hamper investments in child health and education. Poor child health is likely to lead to reduced physical work capacity when the children turn into adults (Spurr, 1983). Thus, in the absence of natural resources, countries may not be able to escape from the poverty trap. Because many developing countries have prospered during the sample period (1965-90) while others have not, a model for the proximate determinants of economic growth can shed some light on these issues.

The dependence of life expectancy on incomes up until a certain threshold suggests that it would be useful to model the GDP or growth rates using a flexible production function such as the trans-logarithmic function (Christensen et al. 1973, Sargan, 1971). Boskin and Lau (1992) estimated aggregated production functions for 5 highly developed (G-5) countries using annual observations in the postwar period. Kim and Lau (1994) extended the analysis to cover 4 countries in the Pacific basin where good data on the physical capital stock were available. From the standpoint of modeling the effects of health on growth rates, the flexible functional form approach underscores the possible interaction between explanatory variables and the importance of squared terms in the model. While precise estimation of coefficients of high order terms would require large sample sizes, the work by Preston (1976) demonstrated certain asymmetries in the life expectancy-incomes relationship. It is therefore likely that the impact of health indicators such as the adult survival rate (ASR) on growth rates would depend on the level of GDP. For example, ASR should be important for explaining economic growth at low levels of GDP. In more affluent settings, investments in education and training and other measures of health such as the decline in cognitive abilities with age, and age-specific disease prevalence rates, may be of greater importance. The methodological framework used in the paper is described in detail in the Appendix.

4. Empirical Results for the Penn World Table and World Development Indicators GDP series

4.1 Stochastic properties of the GDP series in a fixed effects framework

The GDP data from the PWT were based on purchasing power comparison and covered 125 countries at 5-yearly intervals in 6 time periods (1965-90); GDP series from the WDI covered 107 countries and were in constant 1987 dollars, converted using the official exchange rates. The generalized Durbin-Watson ratio (A.3) for natural logarithm of the PWT and WDI series were, respectively, 0.4277 and 0.4585. The five percent significance limit for testing the unit root null hypothesis was interpolated to be 0.94 from Table V in Bhargava et al. (1982). Thus, the unit root null hypothesis cannot be rejected for both the GDP series. By contrast, the Durbin-Watson ratio for the corresponding GDP growth rates were 1.511 and 1.925, respectively. The unit root null hypothesis was firmly rejected for growth rates. Moreover, the significance limit at 5% for testing for *serial independence* (i.e. a=0) was 1.87 from Table I in Bhargava et al. (1982). Thus, one would accept the null hypothesis that the GDP growth rates in the WDI were serially independent; there was slight positive serial correlation in growth rates based on the PWT GDP data.

The above results indicated a high degree of persistence in the GDP series from the PWT and WDI. One would expect persistence to be higher in the former series because of the methods used to smooth the data and also because movements in exchange rates were likely to induce noise in the WDI GDP series. Note that the Durbin-Watson statistic did not control for macro trends underlying the GDP series i.e. means in different time periods were assumed to be the same. Including the time dummies in the model, the sample criteria for the Durbin-Watson statistics for the two GDP series increased to 0.456 and 0.488, respectively. This slight increase did not alter the conclusions in any significant way. It therefore seemed likely that trends affecting aggregate GDP series were of a more complex nature.

Next, we postulated the presence of country specific trends as in (A.5) and tested the unit root null hypothesis using the ratio (A.6). The sample criteria of R_{2P} for the PWT and WDI GDP series were 1.366 and 1.527, respectively. The exact significance limit of R_{2P} for PWT where N=125 (T=6) was calculated to be 1.62794; the limit when N=107 (WDI) was 1.62120. The unit root null hypothesis was accepted in both cases though the sample criteria for R_{2P} were substantially higher than in the situation where the simple Durbin-Watson ratio (A.3) was used to test for a unit root. The F statistics (A.7) for testing that the N coefficients of the drift terms were zero were 4.791 and 4.450, respectively, for the PWT and WDI GDP series. Thus, the null hypotheses of zero drifts were rejected; the data appeared to contain a fair amount of heterogeneity. This, however, should not be interpreted as implying that we have arrived at a reasonable specification for the GDP series. For, the model fitted N country specific dummy variables and another N drifts parameters to the data (there were 250 and 214 parameters estimated, respectively, for the PWT and the WDI data sets). Moreover, insofar as T was fixed, further analysis of stochastic properties of the error terms such as changes in variances over time was infeasible in the fixed effects framework due to the incidental parameters.

From an econometric modeling standpoint, the estimated coefficients of country specific time trends reflect the time path of economic and demographic variables affecting GDP. An econometric model should be able to capture these trends in a parsimonious way. Because the properties of parameter estimates in the fixed effects model are adversely affected by incidental parameters, it was useful to investigate stochastic properties of the GDP series in a random effects framework. In the next section, we used dynamic random effects models to estimate the parameters and test alternative specifications for the errors. Subsequently, in Section 5, econometric models for growth rates were estimated taking into account the conceptual and methodological issues discussed above.

4.2 Stochastic properties of the GDP series in a dynamic random effects framework

Table 1 presents the maximum likelihood estimates of the first order non-stationary autoregression for natural logarithm of percapita GDP series and for growth rates from the PWT and WDI. The models for GDP included four dummy variables for time periods; for growth rates, at most three such variables can be included. There are several noteworthy features of the results. First, coefficients of the lagged dependent variables for logarithm of the GDP exceeded unity for both the PWT and WDI data series. The ratio of between to within variance [i.e. $var(d_i)/var(w_{it})$ in (A.10)] were not significantly different from zero which could be due to the modest number of countries in the data set (Fisher, 1973). Second, the likelihood ratio statistics rejected the constraints implied by the non-stationary first order autoregression against the alternative that the variance covariance matrix of the errors (v's) was of a more general type for both the series. However, as noted in the Appendix, parameters of the dynamic model with unrestricted variance covariance matrix may not be identified.

Third, for growth rates, coefficient of the lagged dependent variable for PWT data was small but significantly different from zero; the coefficient using WDI series was insignificant at the 5 percent level. By contrast, between to within variance ratio was not statistically significant for the PWT data but was significant for the WDI. Because of the modest number of countries in the sample, statistical errors in estimating parameters such as the between/within variance ratio were likely to be large. Fourth, both the PWT and WDI growth rate series accepted the constraints implied by the non-stationary random effects model; growth rate series appeared to have attractive stochastic properties. The results broadly supported the conclusions reached in Section 4.1, where the Durbin-Watson statistic was applied to the fixed effects model. In particular, the growth rates exhibited slight persistence over time and mild heterogeneity across countries.

The empirical results for the first order stationary model are presented in Table 2; coefficient of the lagged dependent variable was constrained to be smaller than unity in this formulation. However, the estimated coefficients for the logarithm of the GDP were very close to unity; the estimated between/within variance ratio was very close to zero indicating a boundary solution. Taken together, the results suggested that the stationary model is too restrictive a formulation for GDP series. By contrast, parameter estimates from the model for growth rates were similar in Tables 1 and 2. For growth rates, the main difference between the estimates was that the PWT data accepted the constraints implied by the stationary model whereas the WDI data rejected these constraints. In view of the different procedures used to create the GDP series, one would expect some dissimilarities between the empirical results. This issue will again be addressed below.

Table 3 presents the results for testing various stochastic specifications on an unconstrained estimate of the variance covariance matrix of the errors w's in (A.11) using a sequence of Wald statistics. The statistics were computed under the assumption that the true distribution function of the errors may be non-normal. The Wald statistics are presented for the PWT and WDI GDP series. The results for growth rates were suppressed; as seen in Tables 1 and 2, growth rates possessed rather simple stochastic properties. Note that with T=6, the w's in equation (A.11) can be assumed to follow at most a third order moving average (MA(3)) process. Moreover, Wald tests were sequential in the sense that we would not test the null hypothesis that the errors follow a second order moving average (MA(2)) if we had previously rejected the MA(3) process. It is desirable to test the sequential hypotheses at an overall significance level that is higher than the conventional level 5% (e.g. 10%; see Anderson, 1971).

First considering the results for the PWT data, Wald statistics firmly rejected the random effects models with MA(3) errors where the errors on (A.11) were assumed to have constant variance over time. Thus, it was necessary to work with a more general formulation allowing the variances of the w's to change over time. The next set of results in Table 3 assumed that the variances changed linearly over time. The Wald test accepted the null hypothesis that the errors followed a MA(3) process. Further, the null hypothesis that errors were generated by an MA(2) process was also accepted. However, the data firmly rejected the MA(1) model. The diagonal elements of the variance covariance matrix accepted the linear and exponential formulations for variances of w's over time.

The results for GDP data from WDI in Table 3 supported the conclusions from the PWT data. Again, Wald statistics rejected specifications assuming homoscedastic variances of the w's. In the heteroscedastic case, the MA(2) process was accepted by the WDI data. The Wald statistics were also applied to the model where GDP was regressed on the population variable. The conclusions were broadly similar indicating that the structure of the unconstrained variance covariance matrix of the errors was not critically affected by identification problems discussed in Section 3.2.

In summary, aggregate GDP series appeared to possess complex stochastic properties; growth rates can be modeled using parsimonious formulations. In both cases, however, it is appealing to invoke weak assumptions on the error structures affecting the models. In Section 5.1, we estimate growth models of the type suggested by Barro (1997) while addressing endogeneity issues; variance covariance matrix of the errors will be assumed to be unconstrained in the estimation.

4.3 Empirical results for models for growth rates

Table 4 presents the empirical results for average growth rates for 92 countries at 5 year intervals using the PWT GDP series; results using differenced logarithms of GDP were very similar. The model is similar in spirit to Barro (1997) but, as will be apparent from the discussion, it differs in a number of important respects. Specification 1 treated the explanatory variables as exogenous; lagged values of investment/GDP ratio, adult survival rate (ASR), GDP, and interaction between ASR and GDP were treated as endogenous variables in Specification 2. The estimation method for Specification 2 assumed a random effects type decomposition (A.13) for correlation between endogenous variables and the errors; variance covariance matrix of the errors was unrestricted. The models were also estimated assuming a general correlation pattern between explanatory variables and the errors. However, for reasons outlined in Section 3.2 such as the data on explanatory variables at various points in time were projections, identification conditions in the general case appeared to have been violated. In the discussion, we therefore focus on the correlation structure (A.13).

The main results can be summarized as follows. First, the coefficient of the percentage of area of the country in the tropics was estimated with a negative sign that was statistically significant. However, coefficients of various indices for prevalence of malaria were all insignificant (cf. Gallup and Sachs, 1998). Because many determinants of economic growth are crudely approximated by national averages, cross-country regressions often attribute the influence of such factors to variables that are correlated with them. Such problems are exacerbated in modeling aggregate variables such as the GDP that is affected by the interaction between a large number of socioeconomic and demographic factors. Moreover, growth rates averaged over long time periods tend to describe economic activity in a way that is similar to the movements in the GDP levels. By contrast, 5-yearly average growth rates retain some properties of variability inherent in economic growth but are less noisy than annual figures. It is evident that some of the associations found using long-term average growth rates will not be substantiated by our approach.

Second, openness of the economy was positively associated with growth rates; magnitude of the coefficient was robust to the use of alternative definition from the PWT. The log of total fertility rate (TFR) was negatively associated with growth rates and was statistically significant. High fertility rates are common in many developing countries and increase the demand on resources for health care and education; the work force does not increase equiproportionately with the population. Also, high fertility rates in developing countries often reflect unwanted fertility that adversely affects households' resource allocation decisions (Bhargava, 1998b). For example, the ratio of skilled to unskilled labor is likely to be negatively associated with TFR due to diminished resources available for education; these factors suggest that TFR is likely to be negatively associated with economic growth.

Third, the lagged investment/GDP ratio had a positive coefficient that was statistically significant. Economic growth was affected by decisions to invest in physical capital and in skilled labor that are essential for innovations, management, health care, etc. The fact that the coefficient of the investment/GDP ratio was small suggests that one should not dismiss proximate determinants of growth because of their small magnitudes. Of course, coefficients should be statistically significant and robust to changes in model specification. However, the extent to which one can investigate adequacy of models for growth rates is limited by difficulties such as the large variation in growth rates, modest number of countries in the sample, measurement errors in the explanatory variables, etc. For example, one might have expected a variable such as the average years of education for the population aged 15-60 (Barro and Lee, 1996) to be positively associated with economic growth. This was not the case in the present models in part because variation in this variable was relatively small for a number of developing countries.

Fourth, the lagged adult survival rate (ASR) and interaction between ASR and GDP were highly significant predictors of economic growth. The impact of ASR was positive at low levels of GDP and, for example, approached zero in Specification 1 when the GDP was 2,474 international dollars. We discuss this issue in greater detail in Section 5.2. The empirical results were similar when ASR was replaced by life expectancy though the model where ASR was included provided a better fit. This was perhaps not surprising since life expectancy is strongly influenced by child mortality. Because child mortality is itself affected by unwanted fertility in developing countries, TFR and ASR are reasonably good indicators of the health infrastructure.

Fifth, the estimated coefficient of lagged GDP was negative showing a tendency of regression towards the mean. Chi-square test indicated that the estimates from Specification 2 where the lagged investment/GDP ratio, ASR, GDP, and interaction between ASR and GDP were treated as endogenous variables was preferable. While the results in Specifications 1 and 2 were close, the impact of ASR and interaction between ASR and GDP were both larger in magnitude in Specification 2. This increased the level of GDP at which the effect of ASR on growth rate was zero to 3,554 international dollars. It is possible to compute the confidence intervals for the net effect of ASR on growth rates. Because the treatment of endogeneity led to different results using the WDI GDP series, we postpone this discussion until Section 5.2.

The empirical results for growth rates based on official exchange rates from the WDI are in Table 5. The results in Tables 4 and 5 were similar for most explanatory variables indicating that data smoothing procedures in the PWT appear to have had a small impact on the estimates. However, the level of GDP at which the impact of ASR on growth rate was zero in Specifications 1 and 2 were, respectively, 938 and 690 constant 1987. These estimates were lower than the corresponding figures for the PWT data when converted from international dollars to 1987 dollars. Overall, because the WDI data were not interpolated for most countries, there was a greater variation in the GDP series. The effects of smoothing procedures will be evident in the next section where we investigated the dependence of the net impact of ASR on the GDP level.

4.4 The net impact of adult survival rates of GDP growth rates

The adult survival rate (ASR) for a country is likely to be influenced by economic development, access to and quality of medical care, and the public health infrastructure. However, beyond a certain threshold, increases in ASR are difficult to achieve and may contribute disproportionately to older age groups. By contrast, for countries at low levels of GDP, one would expect significant effects of ASR on economic growth due to the contribution of labor in prime years. Thus, models for growth rates should allow some forms of non-linearities. Because of the modest number of countries in the data set and because the average life expectancy in the sample was around 60 years, only the interaction between lagged ASR and GDP was found to be statistically significant. For illustrative purposes, we re-write the net effect of a change in ASR on growth rate as

$$b_1 = b_2 + b_3 \text{ (GDP)} \qquad (1)$$

where b_2 and b_3 are, respectively, the (partial) coefficients of the logarithm of ASR and interaction between logarithms of ASR and GDP in the model (A.12). The coefficient b_1 can be computed at different levels of GDP and a confidence interval can be calculated from noting that

$$\text{var}(b_1) = \text{var}(b_2) + \text{var}(b_3).(\text{GDP})^2 + 2 \text{ cov}(b_2,b_3).(\text{GDP}) \qquad (2)$$

Thus, we can tabulate the effects of a unit change in ASR on growth rates and the corresponding confidence intervals for countries in the sample at mean GDP levels. The results for the PWT data are presented in Figures 1 and 2, where Figure 2 plots the results for the case where the explanatory variables lagged investment/GDP ratio, ASR, GDP, and interaction between ASR and GDP were treated as endogenous. The impact was plotted against mean of the natural logarithm of GDP during the sample period. Corresponding results for the WDI data are in Figures 3 and 4.

The results from PWT in Figure 1 showed significant positive effects of ASR on growth rates until the logarithm of the GDP was approximately 6.86 (953 international dollars); the corresponding result where some of the explanatory variable were endogenous was 7.5 (1,380 international dollars). Once these points are crossed, the net effect approached zero and subsequently assumed negative values. Note, however, that the negative impacts of ASR on growth rates were not statistically different from zero. This was true in both Figures 1 and 2.

The results using WDI GDP series were similar for low income countries except for the fact that the threshold where the impact of ASR was zero was reached earlier in these data. The standard errors of the effects were typically larger because the WDI GDP series exhibited greater noise. The main difference between the results for PWT and WDI GDP series was that once the coefficients of the ASR became negative, they were statistically significant for certain countries at the high end of the income distribution in the WDI exchange rate based GDP series. However, as noted in the Appendix, this should not be narrowly construed as implying harmful effects of ASR on growth rates. Rather, some of the affluent countries especially in Europe had achieved high ASR while experiencing slower growth rates in the sample period, presumably due to historical and institutional reasons. Fluctuations in exchange rates following the oil crisis may have also contributed to the distortions.

4.5 A Wald test for parameter stability outside the sample period and its application to the WDI series

A Wald type statistic can be developed within the random effects framework to test if the parameters remain constant outside the sample period; assuming that the number of countries (N) is large, this statistic would be asymptotically equivalent to the appropriate likelihood ratio test. The Wald statistic can be computed by estimating the model for the N out-of-sample observations in time period (T+1); coefficients estimated from the model (A.12) for the observations in the first T periods are then substituted as parameter values under the null hypothesis. Formally, apart from the intercept term, let b be the (kx1) vector of efficient estimates of the unknown coefficients in (A.12) and let b^* be the corresponding estimates from the cross section regression for time period (T+1). Then, defining the variance covariance matrix of b^* by $V(b^*,b^*)$, the Wald statistic for parameter stability is given by

$$W = (b^*-b)' \, [V(b^*,b^*)]^{-1} \, (b^*-b) \qquad (3).$$

Under the null hypothesis of parameter stability, for large N, W is distributed as a Chi-square variable with k degrees of freedom.
Because GDP data were available in the WDI for 1995 (the data for 1995 are not as yet available in the PWT), we applied the statistic W to test the constancy of coefficients of the variables tropics, openness, and lagged total fertility rate, investment/GDP ratio, ASR, interaction between ASR and GDP, and GDP in two situations. First, lagged investment/GDP ratio, ASR, GDP, and interaction between ASR and GDP were assumed to be exogenous. In the second case, these variables were treated as endogenous. The sample criteria for the W statistics in the two cases were 19.09 and 15.23, respectively. For a Chi-square variable with 7 degrees of freedom, the critical values at 5% and 2.5% are 14.1 and 16.0, respectively. Thus, the test accepted the null hypothesis of parameter constancy at approximately 3.5% significance level in the situation where the four explanatory variables were treated as endogenous.

In the present application, there is additional uncertainty in applying Wald statistics because the model in time period (T+1) was estimated using least squares. It is possible to extend the Wald test to situations where the model is estimated for the out-of-sample period treating the four explanatory variables are endogenous. This would entail using at least two observations per country for the out-of-sample period. However, given only 5 time observations on growth rates and the fact that the sample criterion for the Wald statistic was close to its critical level in the endogenous explanatory variables case, it seemed reasonable to accept the parameter stability null hypothesis using the WDI GDP data.

5. Conclusion

This paper modeled the proximate determinants of economic growth at 5 yearly intervals using panel data on GDP series based on purchasing power comparisons in the Penn World Table, and on exchange rate conversions from the World Development Indicators. In the conceptual framework of the analysis, the demographic literature relating life expectancy to income (Preston, 1976) was integrated with models commonly specified for economic growth (Barro and Sala-i-Martin, 1995). Appropriate econometric estimators and test procedures were used in the analysis to draw inferences. While the stochastic properties of the two GDP series were complex, the empirical results from estimating growth models and from specification tests for model adequacy were quite similar.

Although the health of individuals in a country can only be roughly approximated in national averages, the models showed significant effects of adult survival rate (ASR) on economic growth for low income countries. Thus, for example, for the poorest countries, a 1% change in ASR was associated with an approximate 0.05% increase in growth rate. While the magnitude of this coefficient was small, a similar increase of 1% in investment/GDP ratio was associated with a 0.014% increase in growth rate. A novel aspect of the analysis was that we were able to estimate the threshold point beyond which ASR had a negligible effect on growth rates; confidence intervals for the net impact of ASR on economic growth highlighted the asymmetries for poor and rich countries (Figures 1-4).

The specification tests based on instrumental variables estimates showed that the explanatory variables lagged ASR, investment/GDP ratio, GDP, and the interaction between ASR and GDP, should be treated as simultaneously determined with growth rates. This was due to the likely correlation between the unobserved country specific random effects and the explanatory variables. Moreover, the test developed in the paper for testing constancy of the model parameters outside the sample period rejected the null hypothesis when the four explanatory variables were assumed to be exogenous; the statistic was closer to the 5% significance limit when these explanatory variables were treated as endogenous.

From the viewpoint of the conceptual issues addressed in the paper, it is important that future research compile more elaborate data on health indicators. Thus, for example, ASR in poor countries reflects the levels of nutrition, smoking prevalence rates, infectious diseases, health infrastructure, and factors such as accidents leading to premature deaths. By contrast, differences in ASR in middle and high income countries may be strongly influenced by genetic factors and by the timeliness and costs of preventive health care. Because investments in skill acquisition in poor countries depend on the ASR, the years for which skilled labor remains productive is likely to be important for explaining economic productivity. It would be useful to augment statistics such as percentages of skilled and unskilled labor in countries by measures of physical and mental health. For example, work days lost due to ill health can be estimated from household surveys or using other methodologies (e.g. Murray and Lopez, 1996). Measures of cognitive function in different age cohorts may also be useful for explaining economic performance of countries. Analyses based on elaborate data sets would afford sharper insights into the likely impact of health on economic growth.

APPENDIX

a) The econometric framework

The GDP series on countries are aggregated data that are likely to exhibit a high degree of persistence. We begin by investigating the stochastic properties of the GDP series by testing for alternative forms of non-stationarity. The models fitted to the GDP series will also be estimated for growth rates. A comparison of the properties of the GDP series and growth rates will facilitate selection of the appropriate modeling approach (e.g. Easterly et al., 1993). The econometric analysis in this paper used four sets of methodologies that we now outline.

b) Non-stationarity in the fixed effects framework

The classical von Neumann ratio (1941) or the Durbin-Watson (1950) statistic can be used to test for a unit root against stationary alternatives within a fixed effects framework (Bhargava et al., 1982). The main advantage in using this test is that it is a uniformly most powerful test against the stationary first order autogression in small samples. Moreover, the model includes country specific fixed effects (dummy variables) that capture differences in the mean levels of GDP. Let y_{it} be the natural logarithm of the real percapita GDP (i=1,...,N; t=1,...,T). Then we can write the first order autoregression as:

$$y_{it} = f_i + u_{it} \qquad (A.1)$$

with

$$u_{it} = a\, u_{it-1} + e_{it} \qquad (A.2)$$

where f_i are country specific dummy variables and e's are independently distributed normal random variables. The Durbin-Watson statistic for panel data is defined as:

$$d_P = \frac{\sum_{i=1}^{N} \sum_{t=2}^{T} (y_{it} - y_{it-1})^2}{\sum_{i=1}^{N} \sum_{t=1}^{T} (y_{it} - \bar{y}_i)^2} \qquad (A.3)$$

where $\bar{y}_i = \sum_{t=1}^{T} y_{it} / T$ (i=1,...,N).

Note that dummy variables for (T-1) time periods can be included in equation (A.1) to partially control for trends affecting the series in the sample period. The unit root null hypothesis a=1 can be tested by comparing the sample criterion (A.3) with the bounds tabulated by Bhargava et al. (1982). At the given significance level, the null hypothesis is rejected in favor of the stationary alternative ($0 < a < 1$), if d_P is greater than the tabulated limit.

In addition to the differences in GDP levels across countries, it is plausible that growth rates exhibit some form of heterogeneity across countries. A possible mechanism is the presence of country-specific time trends in the means and variances of the GDP series (Lee et al., 1997). For example, equation (A.1) may be replaced by

$$y_{it} = \phi_i + \beta_i t \quad + \qquad + u_{it} \tag{A.4}$$

where the u's are given by (A.2). Then, under the null hypothesis $\alpha=1$, equation (4) implies

$$\Delta y_{it} = \beta_i \qquad + v_{it} \tag{A.5}$$

whereas, under the alternative, the means of the y's depend on country specific time trends. The finite sample framework is well-suited to testing the unit root null hypothesis because a large number (2N) of "incidental" parameters (coefficients of fixed effects and country specific trends) need be estimated. Increase in the number of parameters with the sample size (N) vitiates some of the desirable properties of asymptotic procedures when T is fixed (Neyman and Scott, 1948). By contrast, we can define a test for the null hypothesis $\alpha=1$ that is invariant with respect to the values of the incidental parameters and is valid for fixed values of N and T. The test is based on the ratio (Bhargava, 1999b):

$$R_{2P} = \frac{\sum_{i=1}^{N} \left\{ \sum_{t=2}^{T} (y_{it} - y_{it-1})^2 - \frac{1}{(T-1)} (y_{iT} - y_{i1})^2 \right\}}{\sum_{i=1}^{N} \left\{ \frac{1}{(T-1)^2} \sum_{t=1}^{T} [(T-1)y_{it} - (t-1)y_{iT} - (T-t)y_{i1} - (T-1)\{\bar{y}_i - 0.5(y_{i1}+y_{iT})\}]^2 \right\}} \tag{A.6}$$

The exact distribution of R_{2P} is a weighted average of independently distributed Chi-square variables and can be calculated using the Imhof algorithm (Koerts and Abrahamse, 1969). The test would reject the unit root null hypothesis for "large" values of R_{2P}. Further, if the unit root null hypothesis cannot be rejected, then the F statistic for testing the null hypothesis that coefficients (β_i) of the heterogeneous trends in equation (A.4) are zero is given by:

$$F(N,NT-2N) = (T-2) \left\{ \frac{\sum_{i=1}^{N} \sum_{t=2}^{T} (y_{it} - y_{it-1})^2}{\sum_{i=1}^{N} \sum_{t=2}^{T} (y_{it} - y_{it-1})^2 - \frac{1}{(T-1)} (y_{iT} - y_{i1})^2} - 1 \right\} \tag{A.7}$$

c) Non-stationarity in a random effects framework

In equations (A.1) and (A.2), the variance covariance matrix of the errors (u_{it}) cannot be consistently for large N and fixed T because the number of parameters estimated increase with the sample size N. It is therefore useful to treat the country specific effects as randomly distributed variables and estimate the parameters of a dynamic model for GDP (Bhargava and Sargan, 1983). Equations (A.1) and (A.2) can be re-formulated as:

$$y_{i1} = g_1 + \qquad v_{i1} \quad i=1,...,N \tag{A.8}$$

$$y_{it} = g_t + a\, y_{it-1} + v_{it} \quad t=2,...,T;\ i=1,...,N \tag{A.9}$$

where

$$v_{it} = d_i + w_{it} \tag{10}.$$

Here, d_i are country specific random effects and w_{it} are independently distributed random variables. Note, however, that for fixed T, initial observations (y_{i1}) must be treated as endogenous variables in maximum likelihood estimation (Anderson and Hsiao, 1981, Bhargava and Sargan, 1983). Further, alternative assumptions on y_{i1} lead to different estimators. We consider two alternative assumptions: y_{i1} are drawings from a normal distribution such that the process (y_{i1}, y_{i2},...,y_{iT}) is stationary. In this formulation, it is necessary to assume that $-1 < a < 1$. The alternative assumption is that y_{i1} are drawing from a normal distribution with an arbitrary variance but the covariance between y_{i1} and the remaining (y_{i2},...,y_{iT}) is the same. This non-stationary formulation has the advantage that a can exceed unity which is useful in the present application analyzing aggregate data.

The model given by equations (A.8)-(A.10) has certain implications for "convergence" in per capita GDP hypothesis; previous researchers have noted that high values of a imply slower convergence (e.g. Barro and Sala-i-Martin, 1995, Islam, 1995, Nerlove, 2000). However, the discussion has ignored the role of country specific random effects (d_i) in determining the equilibrium GDP level. Consider the dynamic random effects model (A.8)-(A.10) where y_{i1} are drawings from a stationary normal distribution. Then, apart from an overall mean (and time dummies), equilibrium level of GDP of a country is given by $[d_i/(1-a)]$. A country can start at some GDP level but will converge in the long run to this equilibrium level. This is not the case under the second assumption where y_{i1} have arbitrary variance and when $a>1$. Because of the unobserved country specific component of the error term in (A.10), dynamic random effects models allow long-term differences in equilibrium levels of GDP. It is more complex to define convergence in growth models containing explanatory variables.

d) Wald tests on the variance-covariance matrix of the errors in the random effects framework

The stochastic properties of the v_{it} affecting equations (A.8) and (A.9) can be further investigated using a sequence of Wald tests (Bhargava, 1987). This is important in the growth context because variances of the transitory components (w_{it}) of the v_{it} need not be constant over time (Sala-i-Martin, 1996). Typically, "shocks" to the economic system are likely to cause heteroscedasticity over time in the errors. Moreover, inasmuch as the coefficient of d_i in (A.10) depends on time, models for growth rates will be affected by the country specific random effects. This is a much more parsimonious formulation than assuming the existence of heterogeneous trends as in equation (A.4) involving a large number of parameters. We postulated that the w_{it} follow a q-th order moving average process:

$$w_{it} = \sum_{j=0}^{q} ?_j \, e_{i(t-j)} , \quad ?_0 = 1 \quad i=1,...,N; \; t=1,...,T \qquad \text{(A.11).}$$

It was further assumed that the variance of the e’s depend on time in a linear or in an exponential fashion (Bhargava, 1987). Wald statistics, that are robust to the mis-specification of the distribution function of the v’s, will be used in the analysis. The robustness property is useful because researchers have reported bimodal distributions for GDP series (e.g. Quah, 1996). In such circumstances, the fourth order moments of the GDP series are likely to be less than the appropriate value 3 for the normal distribution, thereby leading to more frequent rejection of the null hypothesis.

The constrains implied by (A.11) and by heteroscedasticity in the e’s can be tested using maximum likelihood estimate of the unrestricted variance covariance matrix of the v’s. In contrast with the regression model (Bhargava and Sargan, 1983), however, some of the parameters of the model may not be identified because there are no exogenous variables in the model. This can lead to a failure of the rank condition. Because the model is non-linear in parameters, the rank condition is sufficient for identification but is not necessary (Sargan, 1983). In such circumstances, identification can be achieved by regressing the GDP on population that is commonly assumed to be an exogenous variable in growth models (Solow, 1958). This formulation would afford an identified model where Wald statistics can be applied to an unconstrained estimate of the variance covariance matrix of the errors. To ensure reliable inferences, we will compare the results from using Wald statistics in the model for real percapita GDP with those where real GDP is regressed on logarithm of the population.

e) Estimation of static models with endogenous regressors in a random effects framework

The final methodology used in the analysis is for estimation of static models for growth rates (or GDP level) in a random effects framework in situations where some of the explanatory variables may be endogenously determined (Bhargava, 1991). Let the model is given by

$$y_{it} = \sum_{j=1}^{m} z_{ij} \, ?_j + \sum_{j=1}^{n_1} x_{1ijt} \, ?_j + \sum_{j=n_1+1}^{n} x_{2ijt} \, ?_j + u_{it} \qquad \text{(A.12)}$$

where the z’s are time invariant variables, x_1 and x_2 are, respectively, exogenous and endogenous time varying variables; coefficients of the variables are denoted by Greek letters. Two alternative assumptions are possible for the endogeneity of x_2. First, x_2 may be correlated with the errors u_{it} in a general way; x_{2jt} would therefore be treated as different endogenous variables in each time period. This assumption may be reasonable in longitudinal studies compiling information at the firm or the individual level. However, for national averages, observations on important variables such as Adult Survival Rates (ASR) are compiled only at certain points in time; remaining observations are projections. Extrapolation of data is therefore likely to violate the rank condition for identification of the parameters under the general correlation pattern.

The second assumption on the endogeneity pattern is to assume that only the country-specific random effects d_i are correlated with x_{2ijt} :

$$x_{2ijt} = ?_t\, d_i + x^{*}_{2ijt} \qquad (A.13)$$

where x^{*}_{2ijt} are uncorrelated with the d_i. While this may seem a restrictive formulation, it allows countries to possess unobserved "permanent" characteristics that in turn can influence the levels of explanatory variables. For example, countries with high saving rates may invest greater resources in health and education sectors. This will cause the errors affecting the equation for growth rates to be correlated with variables such as the ASR because of the presence of d_i in the model. Moreover, in the type of models estimated by Barro and Sala-i-Martin (1985), lagged GDP is used for explaining growth rates; lagged GDP is likely to be influenced by country specific random effects. The advantage in using the correlation pattern (A.13) is that deviations of the x_{2ijt} from their time means:

$$x^{+}_{2ijt} = x_{2ijt} - \bar{x}_{2ij} \quad t=2,...,T;\ j=1,...,k;\ i=1,...,N \qquad (A.14),$$

where

$$\bar{x}_{2ij} = \sum_{t=1}^{T} x_{2ijt}/T \quad j=1,...k;\ i=1,...,N$$

can be used as [(T-1)k] additional instrumental variables to facilitate model identification (Bhargava and Sargan, 1983). An efficient Three Stage Least Squares type instrumental variables estimator will be used to estimate equation (A.12), assuming the two types of correlation patterns for x_{2jt} and u_{it}. The variance covariance matrix of u_{it} is assumed to be unconstrained; this formulation contains the random effects specification (A.10) as a special case. It is possible to test the exogeneity of the explanatory variables using Chi-square statistics; the tests are valid for large N and fixed T (Bhargava, 1991).

References

1. **Ahmad S** (1992). Regression estimates of per capita GDP based on purchasing power parities. Working Paper #WPS 956, International Economics Department, The World Bank.

2. **Anderson TW** (1971). Statistical analysis of time series. (New York: John Wiley)

3. **Anderson TW, Hsiao C** (1981). Estimation of dynamic models with error components. *Journal of American Statistical Association*, 76, 598-606.

4. **Barro RJ** (1997). Determinants of economic growth. (Cambridge, MA: MIT Press).

5. **Barro RJ, Lee JW** (1996). International measures of school years and schooling quality. *American Economic Review, Papers and Proceedings,* 86, 218-223.

6. **Barro RJ, Sala-i-Martin X** (1995). Economic growth. (New York: MCGraw Hill)

7. **Basta SS, Soekirman MS, Karyadi D, Scrimshaw NS** (1979). Iron deficiency anemia and the productivity of adult males in Indonesia. *American Journal of Clinical Nutrition*, 32, 916-925.

8. **Bhargava A** (1986). On the theory of testing for unit roots in observed time series. *Review of Economic Studies* 53, 369-384.

9. **Bhargava A** (1987). Wald tests and systems of stochastic equations. *International Economic Review*, 28, 789-808.

10. **Bhargava A** (1991). Identification and panel data models with endogenous regressors. *Review of Economic Studies*, 58, 129-140.

11. **Bhargava A** (1997). Nutritional status and the allocation of time in Rwandese households. *Journal of Econometrics*, 77, 277-295.

12. **Bhargava A** (1998a). A dynamic model for the cognitive development of Kenyan schoolchildren. *Journal of Educational Psychology* 90, 162-166.

13. **Bhargava A** (1998b). Family planning, gender differences and infant mortality: Evidence from Uttar Pradesh, India, Discussion Paper, University of Houston.

14. **Bhargava A** (1999a). Modeling the effects of nutritional and socioeconomic factors on the growth and morbidity of Kenyan school children. *American Journal of Human Biology* 11, 317-326.
15. **Bhargava A** (1999b). Inference for unit roots in dynamic panels where the time dimension is

fixed: A comment. Discussion Paper, University of Houston.

16. **Bhargava A, Franzini L, Narendranathan W** (1982). Serial correlation and the fixed effects model. *Review of Economic Studies* 49, 533-549.

17. **Bhargava A, Sargan JD** (1983). Estimating dynamic random effects models from panel data covering short time periods. *Econometrica* 51, 1635-1660.

18. **Bloom D, Canning D** (2000). Health and wealth of nations. Science (in press).

19. **Bos E** (1998). Basic demographic, health and health systems data. Technical Report # , Washington: The World Bank.

20. **Boskin M, Lau LJ** (1992). Post-war economic growth in the group-of-five countries: A new analysis. Discussion Paper, Stanford University.

21. **Christensen LR, Jorgenson DW, Lau LJ** (1973). Transcendental logarithmic production frontiers. *Review of Economics and Statistics*, 55, 28-45.

22. **Collins SM, Bosworth BP** (1996). Economic growth in East Africa: Accumulation versus assimilation. Brookings Papers on Economic Activity, 2, 135-203.

23. **Durbin J, Watson GS** (1950). Testing for serial correlation in least squares regression I. *Biometrika* 37, 409-28.

24. **Easterly W, Kramer M, Pritchett L, Summers L** (1993). Good policy or good luck? Country growth performance and temporary shocks. *Journal of Monetary Economics,* 32, 1-25.

25. **Fisher R A** (1973). Statistical methods for research workers. 14th edition. New York: Hafner Publishing Company.

26. **Floud R, Wachter K, Gregory A** (1991). Height, health and history. Cambridge: Cambridge University Press.

27. **Fogel RW (**1994). Economic growth, population health and physiology: The bearing of long-term processes on the making of economic policy. *American Economic Review*, 84, 369-395.

28. **Gallup JL, Sachs JD** (1998). Geography and economic development. Discussion Paper, Harvard Institute for International Development.

29. **Horn J, Hofer SM** (1992). Major ability and development in the adult period. In Intellectual Development, edited by Sternberg, R.J. and Berg, C.A. Cambridge: Cambridge University Press.

30. **International Institute of Population Sciences** (1995). The national family health survey. Mumbai (India).

31. **Islam N.** (1995). Growth empirics: A panel data approach. *Quarterly Journal of Economics*, 110, 1127-1170.

32. **Jamison DT, Lau LJ, Wang J.** (1998). Health's contribution to economic growth. Discussion Paper, University of California, Los Angeles.

33. **Kim JI, Lau LJ** (1994). The sources of economic growth in the East Asian Newly Industrialized Countries. *Journal of Japanese and International Economies*, 8, 235-271.

34. **Koerts J, Abrahamse APJ** (1969). On the theory and application of the general linear model. Rotterdam: Rotterdam University Press.

35. **Lee K, Pesaran MH, Smith R** (1997). Growth and convergence in a multi-country empirical stochastic Solow model. *Journal of Applied Econometrics*, 12, 357-392.

36. **Murray CJL, Lopez A** (1996). The global burden of disease. Cambridge: Harvard University Press.

37. **Nehru V, Dhareshwar A** (1993). A new database on physical capital stock: Sources, methodology and results. *Revista de Aanalisis Economico*, 8, 37-59.

38. **Nerlove M** (2000). Growth rate convergence, fact or artifact? In J. Krishnakumar and E. Ronchetti (eds) Festschrift for Pietro Balestra. Amsterdam: North Holland.

39. **Neyman J, Scott E** (1948). Consistent estimates based on partially consistent observations. *Econometrica*, 16, 1-32.

40. **Preston S H** (1976). Mortality patterns in national populations. New York: Academic Press.

41. **Quah D** (1996). Twin peaks: Growth and convergence in models of income dynamics. *Economic Journal*, 106, 1045-1055.

42. **Sala-i-Martin X** (1996). The classical approach to convergence analysis. *Economic Journal*, 106, 1019-1036.

43. **Sargan JD** (1964). Wages and prices in the U.K.: A study in econometric methodology. In P. Hart, G. Mills, J.K. Whitaker (eds) Econometric analysis for national economic planning. London: Butterworths, pp.25-54.

44. **Sargan JD** (1971). Production functions. Part 5 in Qualified manpower and economic performance. Edited by Layard, P.R.G., Sargan, J.D., Ager, M.E., and Jones, D.J. London: Allen Lane.

45. **Sargan JD** (1983). Identification and the lack of identification. *Econometrica*, 51, 1605-1634.

46. **Scrimshaw NS** (1996). Nutrition and health from womb to tomb. *Nutrition Today*, 31, 55-67.

47. **Scrimshaw NS, Taylor CE, Gordon JE** (1959). Interactions of nutrition and infection. *American Journal of Medical Science*, 237, 367-403.

48. **Solow R** (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70, 65-94.

49. **Spurr GB** (1983). Nutritional status and physical work capacity. Yearbook of Physical Anthropology, 1-35.

50. **Stronks K, van de Mheen H, van den Bos J, Makenbach JP** (1997). The interrelationship between income, health and employment status. International Journal of Epidemiology, 26, 592-599. Strauss, J. and Thomas, D. (1998). Health, nutrition and economic development. *Journal of Economic Literature*, 36, 766-817.

51. **Summers R, Heston A** (1991). The Penn World Table (Mark 5): An expanded set of international comparisons, 1950-88. *Quarterly Journal of Economics*, 06, 327-368.

52. **von Neumann J** (1941). Distribution of the ratio of mean square successive difference to the variance. *Annals of Mathematical Statistics* 12, 367-95.

53. **World Bank** (1993). Investing in health: World Development Report 1993. Washington: The World Bank.

54. **World Bank** (1998). World Development Indicators 1998 CD-ROM. Washington: The World Bank.

List of Tables and Figures

TABLE 1

Maximum likelihood estimates of the first order non-stationary random effects model for the logarithm of percapita GDP and GDP growth rates at 5-year intervals using the data from Penn World Table (PWT) and World Development Indicators (WDI) [1,2]

	P W T		W D I	
Variable	Levels	Growth Rates	Levels	Growth Rates
Constant	-0.294 (0.352)	0.027 (0.004)	-1.062 (0.430)	0.026 (0.004)
Time Dummy 3	-0.001 (0.018)	-	0.001 (0.022)	-
Time Dummy 4	-0.050 (0.021)	-0.010 (0.004)	-0.026 (0.024)	-0.003 (0.004)
Time Dummy 5	-0.147 (0.025)	-0.027 (0.004)	-0.153 (0.029)	-0.025 (0.004)
Time Dummy 6	-0.150 (0.048)	-0.034 (0.004)	-0.103 (0.030)	-0.011 (0.005)
Lagged Dependent Variable	1.060 (0.048)	0.298 (0.079)	1.167 (0.061)	0.154 (0.078)
Between/Within variance ratio	0.343 (0.343)	0.090 (0.085)	2.633 (1.671)	0.220 (0.117)
Within Variance	0.0152	0.0008	0.0193	0.0009
Likelihood ratio [3] test for nonstationary random effects model	48.11	10.78	51.40	15.66
No. of Countries	125	125	107	107
No. of Time Periods	6	5	6	5

Notes:

1. The GDP series from the PWT (1965-90) is in "international prices" whereas the series from WDI (1966-90) is in constant 1987 dollars using exchange rates.
2. Asymptotic standard errors are in parentheses.
3. Degrees of freedom are 17 for Levels and 11 for Growth Rates models.

TABLE 2

Maximum likelihood estimates of the stationary first order autoregression for the logarithm of percapita GDP and GDP growth rates at 5-year intervals using the data from Penn World Table (PWT) and World Development Indicators (WDI) [1,2]

	P W T		W D I	
Variable	Levels	Growth Rates	Levels	Growth Rates
Constant	0.224 (0.017)	0.028 (0.003)	0.146 (0.017)	0.027 (0.003)
Time Dummy 3	0.010 (0.018)	-	0.019 (0.022)	-
Time Dummy 4	-0.028 (0.018)	-0.010 (0.003)	0.013 (0.025)	-0.003 (0.004)
Time Dummy 5	-0.118 (0.018)	-0.027 (0.003)	-0.093 (0.022)	-0.025 (0.004)
Time Dummy 6	-0.118 (0.018)	-0.023 (0.004)	-0.041 (0.023)	-0.012 (0.004)
Lagged Dependent Variable	0.990 (0.001)	0.253 (0.062)	0.994 (0.001)	0.108 (0.062)
Between/Within variance ratio	0.0[3] (0.0)	0.138 (0.071)	0.0[3] (0.0)	0.286 (0.103)
Within Variance	0.0200	0.0007	0.0233	0.0008
Likelihood ratio[4] test for stationary random effects model	146.87	18.66	130.86	41.06
No. of Countries	125	125	107	107
No. of Time Periods	6	5	6	5

Notes:

1. The GDP series from the PWT (1965-90) is in "international prices" whereas the series from WDI (1966-90) is in constant 1987 dollars using exchange rates.
2. Asymptotic standard errors are in parentheses.
3. Boundary solution.
4. Degrees of freedom are 18 for Levels and 12 for Growth Rates models.

TABLE 3

Stochastic properties of the unconstrained estimated serial covariance matrix of the first order autoregression for the logarithm of GDP using the data from the Penn World Table and World Development Indicators [1]

Penn World Table

Robust Wald statistics for moving average error specification [2]

	Homoscedastic variances over time		
Order of the moving average	3	2	1
Wald statistic	24.45	24.48	25.68
Degrees of freedom	10	11	12
	Heteroscedastic variances over time [3]		
Order of the moving average	3	2	1
Wald statistic	8.34	15.16	24.21
Degrees of freedom	8	9	10

World Development Indicators

Robust Wald statistics for moving average error specification

	Homoscedastic variances over time		
Order of the moving average	3	2	1
Wald statistic	26.81	31.61	43.77
Degrees of freedom	10	11	12
	Heteroscedastic variances over time		
Order of the moving average	3	2	1
Wald statistic	9.05	15.93	33.59
Degrees of freedom	8	9	10

Notes:

1. There are 125 countries in the Penn World Table and 107 countries in the World Development Indicators with 6 time observations.
2. The statistics are robust with respect to distributional misspecification.
3. Error variances are assumed to follow a linear pattern over time.

TABLE 4

Estimated slope coefficients from static random effects models for real per capita GDP growth rates 1965-90 at 5 year intervals using data from Penn World Tables [1]

Variable	Specification 1	Specification 2 [2]
Constant	0.291 (0.051)	0.479 (0.079)
Tropics	-0.012 (0.005)	-0.012 (0.005)
Openness	0.026 (0.006)	0.026 (0.006)
Log Fertility Rate lagged 5 years	-0.012 (0.007)	-0.027 (0.010)
Log Investment/GDP ratio lagged 5 years	0.014 (0.003)	0.020 (0.003)
Log Adult Survival Rate Lagged 5 years	0.190 (0.091)	0.294 (0.144)
Interaction between lagged Adult Survival Rate and GDP	-0.024 (0.012)	-0.036 (0.020)
Log GDP lagged 5 years	-0.029 (0.005)	-0.048 (0.009)
GDP at which partial derivative of GDP growth rate with respect to lagged Adult Survival Rate is zero	2,474	3,554
Chi-square (80) test for exogeneity of lagged GDP/Investment ratio, Adult Survival rate, interaction with GDP, and GDP	315.66	
Number of countries	92	92
Number of time observations	5	5

Notes:
1. Asymptotic standard errors are in parentheses.
2. Specification 1 treats log Investment/GDP ratio, log Adult Survival Rates, log lagged GDP and interaction between Adult Survival Rate and GDP as exogenous variables; Specification 2 treats them as endogenous.

TABLE 5

Slope coefficients from estimating static random effects models for real per capita GDP growth rates 1965-90 at 5 year intervals using data from World Development Indicators [1]

Variable	Specification 1	Specification 2 [2]
Constant	0.191 (0.040)	0.288 (0.056)
Tropics	-0.012 (0.005)	-0.014 (0.006)
Openness	0.034 (0.007)	0.040 (0.008)
Log Fertility Rate lagged 5 years	-0.019 (0.008)	-0.031 (0.009)
Log Investment/GDP ratio lagged 5 years	0.007 (0.003)	0.007 (0.003)
Log Adult Survival Rate Lagged 5 years	0.158 (0.075)	0.301 (0.104)
Interaction between lagged Adult Survival Rate and GDP	-0.023 (0.012)	-0.046 (0.017)
Log GDP lagged 5 years	-0.019 (0.005)	-0.031 (0.007)
GDP at which partial derivative of GDP growth rate with respect to lagged Adult Survival Rate is zero	938	690
Chi-square(80) test for exogeneity of lagged Investment/GDP ratio, Adult Survival rate, interaction with GDP, and GDP	202.00	
Number of countries	73	73
Number of time observations	5	5

Notes:
1. Asymptotic standard errors are in parentheses.
2. Specification 1 treats log Investment/GDP ratio, Adult Survival Rates, log lagged GDP and interaction between Adult Survival Rate and GDP as exogenous variables; Specification 2 treats them as endogenous.

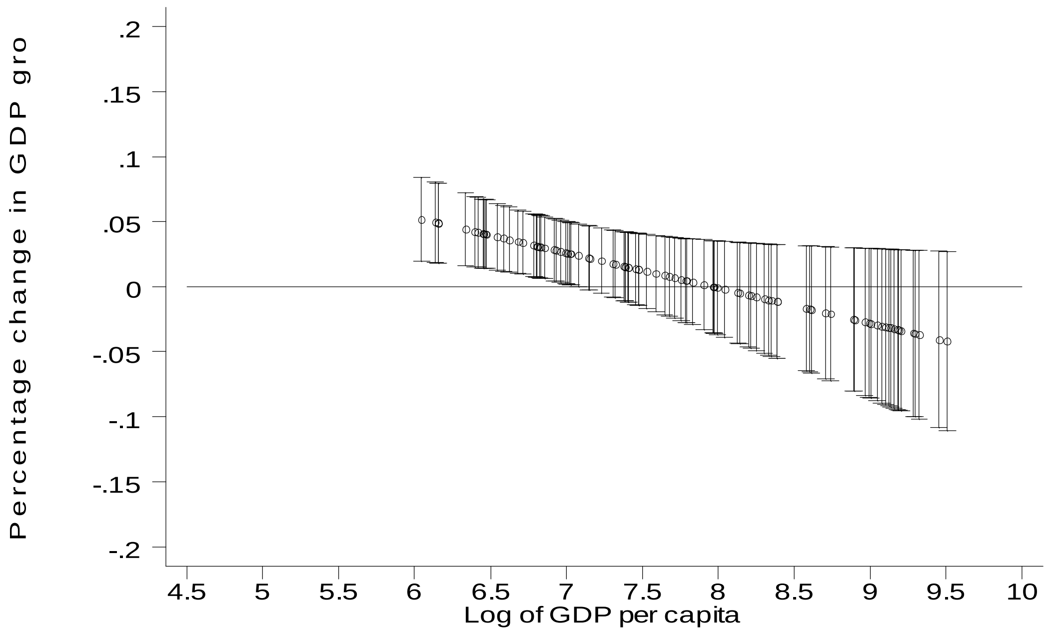

Figure 1. Net Effect of a Percentage Change in Adult Survival Rate on GDP Growth Rate at Different Values of Mean Log GDP per Capita Using GDP Data from Penn World Tables (Exogenous Explanatory Variables).

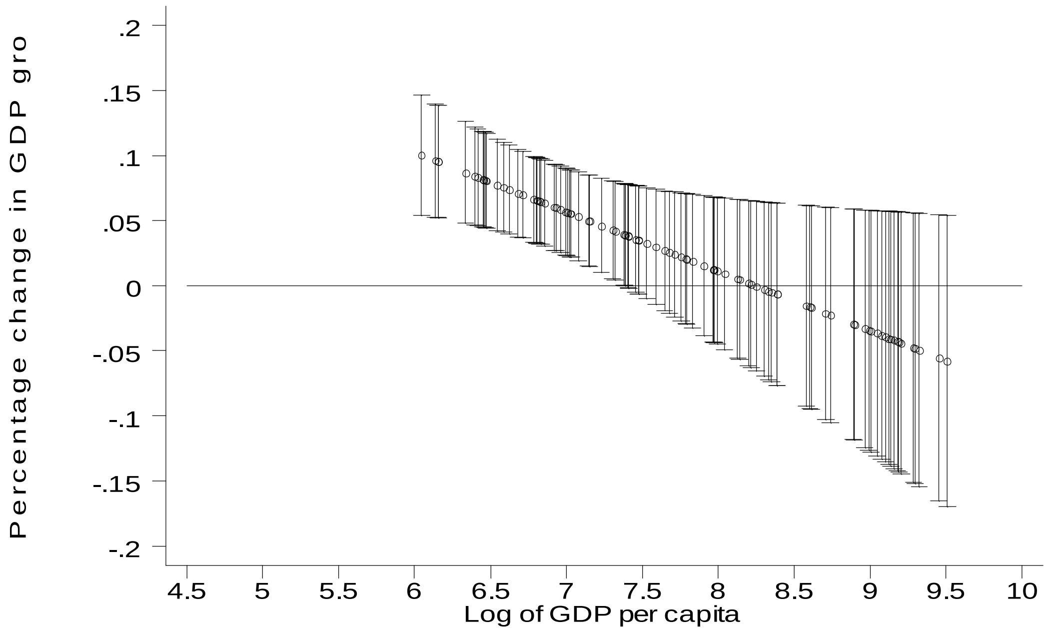

Figure 2. Net Effect of a Percentage Change in Adult Survival Rate on GDP Growth Rate at Different Values of Mean Log GDP per Capita Using GDP Data from Penn World Tables (Endogenous Explanatory Variables).

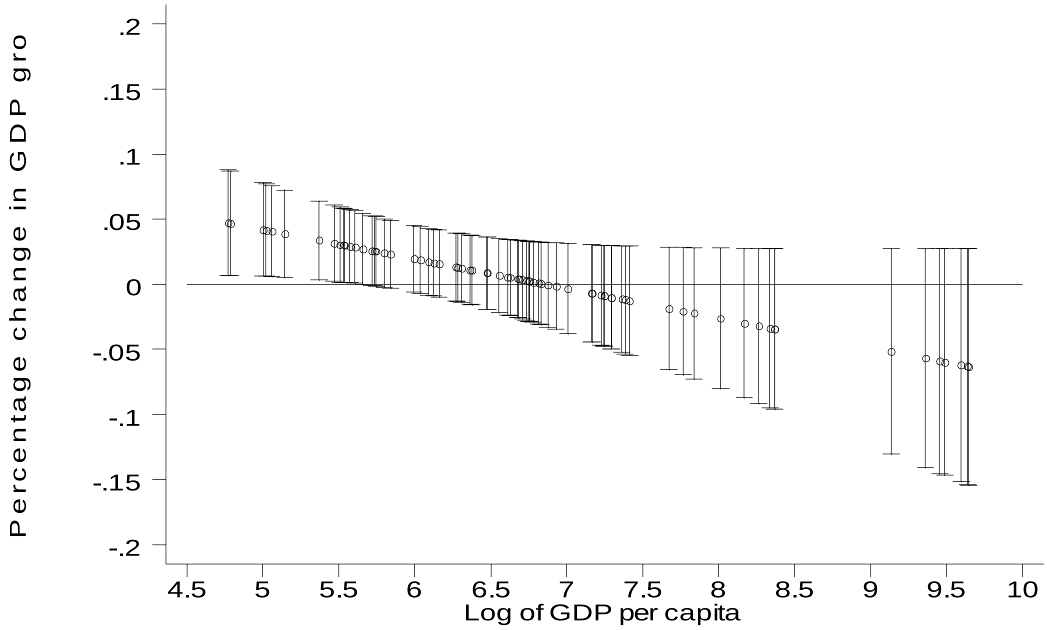

Figure 3. Net Effect of a Percentage Change in Adult Survival Rate on GDP Growth Rate at Different Values of Mean Log GDP per Capita Using GDP Data from World Development Indicators (Exogenous Explanatory Variables).

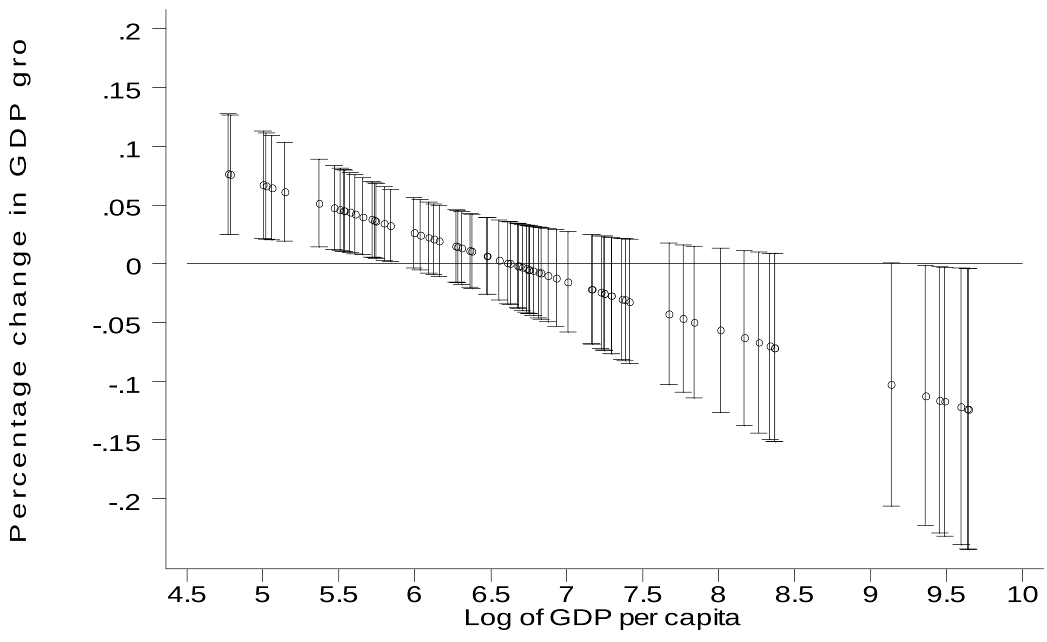

Figure 4. Net Effect of a Percentage Change in Adult Survival Rate on GDP Growth Rate at Different Values of Mean Log GDP per Capita Using GDP Data from World Development Indicators (Endogenous Explanatory Variables).