Does Age Structure Forecast Economic Growth?

David E. Bloom
David Canning
Günther Fink
Jocelyn Finlay

Harvard School of Public Health

January 2007

Address for correspondence:
Harvard School of Public Health
665 Huntington Avenue
Boston, MA 02115
Phone: 617-432-6336
Fax: 617-495-8231

Email: dcanning@hsph.harvard.edu

David Bloom: dbloom@hsph.harvard.edu
David Canning: dcanning@hsph.harvard.edu
Günther Fink: gfink@hsph.harvard.edu
Jocelyn Finlay: jfinlay@hsph.harvard.edu

Descriptive title:

Does age structure forecast economic growth?

Abstract:

High ratios of working age to dependent population can yield a “demographic dividend” that increases the rate of economic growth. We estimate the parameters of an economic growth model with a cross section of countries over the period 1960 to 1980 and investigate whether the inclusion of age structure improves the model’s forecasts for the period 1980 to 2000. We find that including age structure improves the forecast, although there is evidence of parameter instability between periods with an unexplained growth slowdown in the second period. We use the model to generate growth forecasts for the period 2000–2020.

Key Words: Economic Growth, Demography, Forecast Evaluation, Error Decomposition, Panel Analysis.

Biographical Sketches

David E. Bloom is Clarence James Gamble Professor of Economics and Demography in the Department of Population and International Health, Harvard University. He was awarded a PhD in Economics and Demography from Princeton University in 1981.

David Canning is Professor of Economics and International Health in the Department of Population and International Health, Harvard University. He was awarded a PhD in Economics from Cambridge University in 1984.

Günther Fink is a post-doctoral fellow at the Harvard School of Public Health. He was awarded a PhD in Economics from Bocconi University in 2006.

Jocelyn Finlay is a post-doctoral fellow at the Harvard School of Public Health. She was awarded a PhD in Economics from the Australian National University in 2006.

He who lives by the crystal ball will die from eating broken glass.

–- Chinese proverb

1: Introduction

During the demographic transition, falling death rates set off a population boom that continues until fertility rates decline. In addition to its effect on population size, the transition can have a sizable impact on the age structure of the population. Mortality rate reductions are initially concentrated among young age groups, triggering a surge in the number of children and the youth dependency rate. As this "baby boom" generation enters working age, and as falling fertility rates reduce the total number of children, the ratio of working age population to total population goes up. This increase reverses when the baby boom cohort ages and the old age dependency ratio rises.

Changes in population age structure can have a large impact on economic performance because labor supply and saving rates vary over the life cycle. Increased longevity may also boost savings rates and labor supply. In addition, fertility decline can lead to increased female labor supply (Bailey, 2006) and the resources available to invest in childrens' health and education (Joshi and Schultz, 2006). Several studies emphasize the role of shifting birth and death rates and age structure in explaining cross-country variation in economic growth (Bloom and Canning, 2003; Bloom, Canning and Malaney, 2000; Bloom, Canning and Sevilla, 2003; Bloom and Freeman, 1988; Bloom and Williamson, 1998; Brander and Dowrick, 1994; Kelley and Schmidt, 1995).

This paper investigates whether age structure can be used to forecast long run economic growth. The problem of climate change has created substantial interest in long-run forecasts of economic growth since energy demand is highly income elastic, though these forecasts have to be combined with projections of population, pollution, and global warming as in Nordhaus and Boyer (2000). In addition to the direct interest in forecasts, the ability of a model to forecast can be thought of as a robustness check that guards against specification searches that over-fit models to existing data (Clements and Hendry, 2005).

Starting with a structural model of economic growth (the average annual growth rate in real GDP per capita) we derive a reduced form in which growth over a period depends on factors at the beginning of the period, including the initial level of income per capita and the initial ratio of working age to total population. We estimate the parameters of the model from data for the period 1960–1980 and use the estimated coefficients to predict economic growth in the period 1980–2000. While we are particularly interested in the effect of age structure we need to model the entire conditional convergence process. The other variables in the conditional convergence growth model are taken from Sala-i-Martin, Doppelhofer, and Miller (2004) who use Bayesian methods to find the variables with the highest posterior probabilities (based on the data) of being required in a growth model.

We show that conditional convergence models favored by Sala-i-Martin, Doppelhofer, and Miller (2004) are able to forecast economic growth, but that adding age structure to the growth model significantly improves forecast accuracy based on the root mean squared error (RMSE) criterion. However, we find that all our models for the period 1960-1980 tend to over-predict growth for the period 1980–2000. This prediction bias is due to a worldwide slowdown in economic growth in 1980–2000 not captured by our model. We find that our model is substantially better at forecasting relative economic growth (relative to world average growth) in our cross section of countries than the absolute growth rates. Forecasting world average growth rates presumably is difficult using a cross section model and requires a time series or panel data approach.

There are a variety of alternative approaches to forecasting economic growth. Fully specified structural models (McKibbin and Wilcoxen, 1998) represent one extreme of the forecasting methodology spectrum. Atheoretical models where past trends are used to predict future economic growth exist at the other extreme (Kraay, 1999). Methods that fall between these include reduced form models that incorporate a selected subset of contemporaneous and past characteristics. Short run forecasts of single country growth rates using autoregression or vector autoregression models are common (Brischetto and Voss, 2000; Clements and Hendry, 1998; Fair and Shiller, 1990; Robertson and Tallman, 1999; Stock and Watson, 1998), but forecasts of cross-country variation in economic growth entered the literature only recently (Lee and Mason, 2006; Malmberg and Lindh, 2004; Prskawetz, Kögel, Sanderson and Scherbov, 2004). Kraay (1999) compares the forecasting performance of univariate time series models with that of cross sectional economic growth models for a panel of countries. For the forecast period 1990–1997, he finds that the time series model is a better predictor of growth than forecasts based on a growth model using information from 1960–1990; he finds that the reverse is true for the forecast period 1980–1997. It appears that time series models do well forecasting over a short time horizon, but that the reduced form, conditional convergence growth models perform better when forecasting over longer time horizons.

In the section that follows, we discuss the data used and the forecasting method adopted for our investigation. In section 3 we analyze the forecast performance of the different specifications and present a formal comparison of the forecasting ability of each model. In section 4 we present results for our preferred models of absolute and relative growth and decompose the residual to identify the contributions to forecasting error of noise, parameter instability, and structural breaks. In section 5 we present out-of-sample forecasts of average annual growth rates over the period 2000–2020. We conclude in section 6 with a summary and discussion.

2: Methodology and Data

Bloom, Canning, and Malaney (2000), Bloom, Canning, and Sevilla (2003), and Bloom and Canning (2003) emphasize that labor supply and aggregate output are closely tied to the size of the working age population. In this view, income per capita tends to be higher when the share of working age people in the population is high. Taking income to be Y and population to be P we can express income per capita as

$$\frac{Y}{P} = \frac{Y}{WA}\frac{WA}{P} \tag{1.1}$$

where WA is the number of working-age people. Taking logs

$$y = \log\frac{Y}{P},\ z = \log\frac{Y}{WA},\ w = \log\frac{WA}{P} \tag{1.2}$$

we can express the steady state level of income per capita as

$$y^* = z^* + w = \beta x + w \tag{1.3}$$

where the vector x consists of a set of variables that determines steady state income per working-age person, z*. Following Barro and Sala-i-Martin (2003), economic growth occurs as each country converges from its initial position to its steady state. In our case, this is conditional on the variables x and w. Thus, we have

$$\Delta y = \lambda(y^* - y_{-1}) = \lambda(\beta x + w - y_{-1}) \qquad (1.4)$$

The steady state determines the end of period equilibrium and economic growth reflects transitional dynamics. Let us suppose that we can write a structural model for the evolution of the x variables that affect steady state income per capita, and w the age structure as:

$$x = \alpha_1 x_{-1} + \alpha_2 w + \alpha_3 y, \; w = \gamma_1 x + \gamma_2 w_{-1} + \gamma_3 y \qquad (1.5)$$

Then we can derive the reduced form

$$\Delta y = \lambda(y^* - y_{-1}) = \delta_1 x_{-1} + \delta_2 w_{-1} + \delta_3 y_{-1} \qquad (1.6)$$

where the reduced form coefficients δ are combinations of the structural coefficients from equations (1.4) and (1.5).

We estimate an economic growth model of the type set out in equation (1.6) for the period 1960–1980, and then use the coefficient estimates to forecast economic growth in the period 1980–2000. This prompts consideration of what variables, in addition to the log working age share w, to use to explain economic growth. To choose among the many variables proposed as candidates for factors that influence the rate of economic growth, we use recent work by Sala-i-Martin, Doppelhofer and Miller (2004) (henceforth SDM). They use a large set of potential explanatory variables and calculate the Bayesian posterior probability of each variable being included, given a fixed model size. We focus on models with 5, 9 and 16 regressors, in each case using the variables SDM find have the highest posterior rankings as shown in bold in Table 1 below.

Table 1 here: SDM Rankings

Our main variable of interest for forecasting economic growth is the log of the working age share. In their analysis SDM include as potential explanatory variables the share of the population 15 and younger and the share the population over 65, though neither ranks highly on their selection criterion, rather than the log of the working age share which we employ.

We examine the ability of the SDM models to forecast economic growth and test whether the addition of age structure adds to the models' forecasting performance. For variables that do not change over time we use the same data as SDM. Time varying variables require more attention. SDM examine growth over the period 1960–1996. Our growth periods are 1960–1980 and 1980–2000, and we use data from 2000 to forecast future economic growth. We measure our time-varying variables at 1960, 1980 and 2000 using the sources cited by SDM, or more up-to-date versions of these sources when available. Values for real gross domestic product per capita, investment prices, and government consumption share are from the Penn World Tables 6.2 (Heston, Summers and Aten, 2006). Educational attainment data are from Barro and Lee (2000), and data on life expectancy are from *World Development Indicators* (World Bank, 2006). We restrict our analysis of 1960-2000 to those countries where all series of interest are available for the full sample period, resulting in a balanced panel of 67 countries, though we provide forecasts for the period 2000-2020 for all countries that have data for the year 2000. A full description of the variables is included in the appendix. Summary statistics are provided in Table 2 and the correlation matrix is displayed in Table 3 below.

Table 2: Summary Statistics here

Table 3 here: Correlation Matrix

3: Empirical Results

We start our empirical analysis by estimating each of the SDM models in the period 1960–1980 based on data from 1960 Using the estimated coefficients, we then forecast growth rates from 1980–2000 based on data from 1980 and the time invariant variables. We compare the forecasts with the actual growth rates over the period. We estimate four growth models: a constant (SDM0), and models with 5 (SDM5), 9 (SDM9) and 16 (SDM16) explanatory variables. In each case the variables are shown in bold in Table 1.

Table 4 shows the results for the SDM specifications without the age structure variable. Column 1 of Table 4 provides details of the performance of a naïve model in which growth during the period 1960–1980 depends on a constant only. Columns 2, 3 and 4 show the results for the larger growth model specifications. Each model is estimated using a sample of 67 countries in the period 1960–1980, although the degrees of freedom fall as the number of explanatory variables increases. As expected, the R^2 in the estimation period (1960–1980) increases as the number of explanatory variables increases, rising from zero (with a constant only) to 0.66 with 16 additional regressors. However, the SDM9 model has the largest adjusted R^2, which indicates that the additional variables in SDM16 do not significantly improve the fit.

We assess the forecasts by the root mean squared error (RMSE), both absolute and adjusted for the degrees of freedom in the sample. As shown in the middle section of the table, the (unadjusted) RMSE of the forecast decreases from 2.1 percent to 1.7 percent when the SDM5 variables are added to the constant in the growth regression. Forecast performance worsens as further covariates are included in SMD9 and SDM16.

To assess the performance of these forecasting models we use three tests of model adequacy. The first is bias: we test whether the average forecast error is different from zero. In our sample, the average annual growth rate fell from 2.7 percent during 1960–1980 to 1.3 percent during 1980–2000. None of our forecasting models predicts this slowdown. Our preferred forecasting model, in terms of the RMSE, SDM5, has a bias of -1.1 percent per year, which is significant even at the one percent level.

The failure of growth models to predict the slowdown is not surprising. Growth models explain relative growth rates in a cross section of countries using country specific characteristics. Changes in the world growth rate over time are likely to be due to worldwide shocks. For example, Hamilton (2003) examines the effect of oil price shocks on macroeconomic performance and Easterly (2001) links the slow growth in the developing countries after 1980 to slow growth in the developed world and high world interest rates.

Predictive efficiency tests whether the slope of the relationship between predicted and actual growth is significantly different from one. Failure of this test would suggest that forecasts could be systematically improved by systematically scaling them up or down after controlling for the average growth rate. We cannot reject the null hypothesis that the estimated slope coefficient is one for any model with at least five regressors.

The serial correlation test looks for a correlation between the residuals from the 1960–1980 growth regression and the 1980–2000 forecast errors. A significant correlation would suggest that the growth residuals from 1960–1980, which could be known in 1980, would be useful in constructing forecasts, although they are not used by our forecasting model. One potential explanation for positive serial correlation is the presence of omitted variables that affect economic growth but are fixed in each country over time. The presence of such fixed effects would require the use of panel data forecasting methods as discussed in Baltagi (2006). For the naïve SDM0 (constant only), we reject the null hypothesis of no serial correlation, indicating that a country's growth rate over the period 1960–1980 has predictive power for the period 1980–2000[1]. However, for each of the models with some explanatory variables (SDM5, SDM9 and SDM16), we cannot reject the null hypothesis of no serial correlation, indicating model adequacy with respect to this criterion.

Table 4 here: Absolute Growth SDM Only

To test the forecasting performance of age structure compared with that of the basic SDM specifications, we repeat the previous regressions with the addition of the log of the working age (15 to 64) share of the total population, *w*. The results are summarized in Table 5 below. The forecasting model that minimizes RMSE is SDM5 plus the log of working-age share. Although there is little improvement in the fit of the regression in the period 1960–1980, the inclusion of the working age share improves the RMSE of the forecast.

Table 5 here Absolute Growth SDM plus Demographics

In Table 6 we test if this improvement in forecasting ability is statistically significant. We use the methodology suggested by West (2006). If we have both the estimated gain in RMSE

[1] Easterly, Kremer, Pritchett, and Summers (1993) find little correlation between growth rates at 5 year intervals. However for longer time intervals correlations between successive period's growth rates are higher.

and the statistical distribution of the estimated gain due to sampling error, we can test the null hypothesis that the true gain in average squared forecast error is zero. Given the small sample size, we bootstrap the standard error to calculate the critical values for this test. We use 500 repetitions of the non-parametric bootstrapping method, with replacement, to generate corresponding sampling distributions. Each cell of Table 6 shows the average gain in RMSE when enlarging the model, and the p-value for a test of the null hypothesis of zero gain. The test is one tailed, so that we reject only if there is a significant increase in forecasting ability. Including age structure significantly improves the RMSE in specifications SDM0, SDM5, and SDM9, although not in SDM16. Most important, adding age structure significantly improves the SDM5 specification, our preferred model for forecasting without age structure.

Table 6 here: Nested Model Comparison for Absolute Growth Models

Figure 1 here: Absolute Growth 1980 -2000: Predicted and Actual

Figure 1 shows the actual growth rates over 1980-2000 and the predicted growth rates from SDM5+w. The graph clearly shows the bias in the forecast; we systematically over-predict growth rates. Since our cross country growth models is not designed to predict movements in the average world growth rate we now consider the issue of forecasting relative economic growth. We de-mean each variable by subtracting the sample mean for that period; this gives us growth rates of each country relative to the world average fro the period. We use regression analysis to fit relative growth rates over the period 1960–1980 using the de-meaned explanatory variables from the same period and use de-meaned variables from 1980 to forecast relative growth over 1980–2000. This is equivalent to allowing for a period specific intercept in the growth model. The results for relative growth forecasts with and without age structure are summarized in Tables 7 and 8 below.

Table 7 here: Relative Growth Without Demographics

As shown in table 7 all the models perform better in terms of RMSE when predicting relative growth rather than absolute growth. The bias of the forecast is now zero by construction and the other hypotheses of model adequacy, prediction efficiency and lack of serial correlation, cannot be rejected for any of the models that contain at least the SDM5 set of variables.

Table 8 reports the results of the same relative growth regressions with the addition of age structure. Adding age structure lowers the RSME of the forecast in every case. As shown in Table 9, these improvements in forecast accuracy are significant for the SDM 0, SDM 5 and SDM 9 models. Overall, the best performing forecasting model for relative growth is SDM 9 plus age structure. This model displays prediction efficiency and lack of serial correlation and has the lowest RMSE among all our models.

Table 8 here: Relative Growth Forecast with Demographics

Table 9 here: Relative Growth Models: Nested Model Comparison

The actual and predicted values for relative growth using SDM9 + w are plotted in Figure 2. The plotted points tend to lie along the 45 degree line showing prediction efficiency and no bias.

Figure 2 here: Relative Growth 1980-2000: Predicted and Actual

4: Error Decomposition

Although the predictions of our two preferred models for absolute and relative appear to satisfy our model adequacy criteria, the average errors are considerable: 1.1 percent and 1.7 percent for relative and absolute growth forecasts, respectively. From a theoretical viewpoint, assuming the data generating process is correctly specified, there are three main factors contributing to forecasting errors: random noise in the data generating process, parameter instability between the estimation and forecast period, and imprecision in the coefficient estimation. Provided there is no covariance between these sources of error we can decompose the variance of the growth forecasts as follows

$$V(\Delta y_{t+1} - \hat{\beta}_0 x_1) = V(\Delta y_{t+1} - \beta_1 x_1) + V(\beta_1 x_1 - \beta_0 x_1) + V(\beta_0 x_1 - \hat{\beta}_0 x_1) \qquad (1.7)$$

where the first term on the right hand side is random noise, the second is the effect of parameter instability, and the third is the effect of estimation error of first period parameters. We can estimate the size of the first two error components by replacing the unknown parameter vectors β_0 and β_1 with their estimated values based on regressions for the two sub-periods. The third error component can be calculated using the estimated variance-covariance matrix of the first period coefficient estimates.

We can further decompose the first term, the forecast variance due to random noise, into two parts: the expected noise based on the variance of the noise in the first period, and the change in the variance of the noise term between the two periods.

Table 10 below shows the contribution of each of these factors to the actual forecast error of our two preferred models. The mean squared error in annual average percentage growth rate over the sample period is 1.71 percent for the absolute growth forecast based on the SDM5 + *w* model, and 1.26 percent for the relative growth forecast based on the SDM9 + *w* model. For both models, random noise accounts for roughly half of the forecast error. According to our estimates, total random noise slightly decreases in the second period for the absolute growth variable, but remains fairly steady for relative growth.

Table 10 here: Error Decomposition

The effect of imprecise parameter estimates in the first period is very small, accounting for less than 3 percent of total variance. The most important source of forecast error, when forecasting absolute growth rates, is parameter instability across the two periods. However, for relative growth the parameter instability effect is substantially smaller. This indicates that in the absolute growth model parameter instability is largely due to a shift in the intercept across periods.

Table 11 shows the estimated coefficients of our preferred models for the two sub-samples (1960–1980 and 1980–2000), as well as for the full (pooled) sample for the period 1960–2000. An F-test of parameter stability rejects the null that the parameters are the same in both sub-periods for both the relative and absolute growth models. For absolute growth, Wald tests for each variable reject parameter equality between the two sub-periods at the 5 percent significance level only for the intercept and the log of the working age share of the population. In the case of relative growth, we reject parameter equality over the two periods only for the log of the working age share.

Our age structure variable, the log of the working age proportion of the population, has a small, statistically insignificant coefficient in the 1960–1980 estimation period, and a much larger coefficient in the forecast period. It would have been difficult to justify putting age structure into the model based on the 1960-1980 estimation. *Ex post*, we would have liked to increase the estimated parameter tenfold for forecasting purposes although, as shown, even the estimated coefficient significantly improves the forecast. Our argument for including age structure was primarily theoretical, suggesting that theoretical as well as "goodness of fit" arguments should be considered in the construction of forecasting models.

Table 11 here: Coefficient Estimates in Sub-Samples

5: Forecasts

We now use our preferred models to forecast future economic growth. Given the twenty year horizon used in our analysis, the natural forecast period is 2000–2020. To generate these forecasts, we use estimates from our preferred models of absolute (SDM5 + *w*) and relative (SDM9 + *w*) growth over the pooled sample combining observations from 1960–1980 and 1980-2000. We then use the 2000 values of the relevant explanatory variables to forecast future growth. We forecast growth for all countries that have the relevant data for 2000, even if they are ot in our 1960-2000 sample. Table 12 displays the growth rate for each country over the period 1980-2000 and both our absolute, and relative, growth forecasts for 2000–2020. The absolute growth model predicts growth of 2.05 percent per year on average, and the model predicts positive growth rates for all countries. The countries we expect to fare best in terms of absolute growth are China, South Korea, and the Philippines, with forecasted average growth rates above 4.5 percent. The lowest growth rates are predicted for Mali, Guatemala and Niger.

Table 12 also shows our forecasts for relative growth. These forecasts are based on a larger model (9 variables from SDM rather than 5 in the absolute growth forecast) and make no prediction on the world average growth rate over 2000-2020, which may be wise given the past volatility of average growth. The ranking for the top three countries, China, South Korea, and the Philippines stays the same. However the countries that have the worst forecast when turning to relative growth are now South Africa, Botswana and Zimbabwe. This change in the ranking is due to the inclusion of life expectancy in the SDM 9 model used in forecasting relative economic growth. The HIV/AIDS in Sub-Saharan Africa has substantially reduced life expectancy in these countries and their low life expectancies in 2000 lead to predictions of slow economic growth in most of Sub-Saharan Africa over the next twenty years.

Table 12 here: Predicted Economic Growth 2000 - 2020

6: Conclusion

By looking at forecasts of growth over the period 1980–2000 based on data from the period 1960–1980, we are able to evaluate the forecasting ability of cross-sectional growth models. We show that such models do have forecasting power, though larger growth models are not necessarily better than smaller models for forecasting economic growth. We also show that the addition of age structure significantly improves the forecasts. Much of the forecast error is due to parameter instability between periods. In particular, there is a downward shift of the intercept term in the period 1980–2000, which causes actual outcomes to lie below forecast growth on average. Changing the focus to forecasting relative economic growth (relative to the world average) improves the forecast considerably and removes this bias. We provide forecasts of economic growth for a cross section of countries for the period 2000–2020 to allow *ex post* validation of our model.

Future studies of models for forecasting economic growth should consider how to combine the cross-section approach used in this paper with time series methods that can forecast movements in world growth rates over time. This will require exploitation of the full panel series nature of the data. The nature of parameter instability should also be investigated, to determine whether it reflects shifting parameters or is a symptom of deeper mis-specification.

References:

Bailey, M.J. (2006). More Power to the Pill: The Impact of Contraceptive Freedom on Women's Labor Supply. *Quarterly Journal of Economics,* 121, 289-320. 2006.

Baltagi, B.H. (2006). Forecasting with panel data, Deutsche Bundesbank, Research Centre.Discussion Paper Series 1:25.

Barro, R. & Sala-i-Martin, X. (2003). Economic Growth. Cambridge: MIT Press.

Barro, R.J. & Lee, J.-W. (2000). International Data on Educational Attainment: Updates and Implications, CID Working Paper No. 42.

Bloom, D.E. & Canning, D. (2003). Contraception and the Celtic Tiger, *Economic and Social Review*, 34, 229-247.

Bloom, D.E., Canning, D. & Malaney, P. (2000). Demographic change and economic growth in Asia, *Population and Development Review*, 26(supp.), 257-290.

Bloom, D.E., Canning, D. & Sevilla, J. (2003). The Demographic Dividend: A New Perspective on the Economic Consequences of population Change, Population Matters Monograph MR-1274, RAND, Santa Monica.

Bloom, D.E. & Freeman, R. (1988). Economic Development and the Timing and Components of Population Growth, *Journal of Policy Modeling*, 10.

Bloom, D.E. & Williamson, J.G. (1998). Demographic transitions and economic miracles in emerging Asia, *World Bank Economic Review*, 12(3), 419-455.

Brander, J.A. & Dowrick, S. (1994). The Role of Fertility and Population in Economic Growth, *Journal of Population Economics*, 7(1), 1-25.

Brischetto, A. & Voss, G. (2000). Forecasting Australian economic activity using leading indicators, Reserve Bank of Australia Research Discussion Paper.

Clements, M.P. & Hendry, D.F. (1998). Forecasting Economic Processes, *International Journal of Forecasting*, 14, 111-131.

Clements, M.P. & Hendry, D.F. (2005). Evaluating a Model by Forecasting Performance, *Oxford Bulletin of Economics and Statistics*, 67(supp.), 0305-9049.

Easterly, W. (2001). The Lost Decades: Developing Countries' Stagnation in Spite of Policy Reform 1980-1998, *Journal of Economic Growth*, 6(2), 135-57.

Easterly, W., Kremer, M., Pritchett, L. & Summers, L.H. (1993). Good Policy or Good Luck?, *Journal of Monetary Economics*, 32, 459-483.

Fair, R.C. & Shiller, R.J. (1990). Comparing information in forecasts from econometric models, *American Economic Review*, 80(3), 375-89.

Hamilton, J.D. (2003). What Is an Oil Shock?, *Journal of Econometrics*, 113, 363-398.

Heston, A., Summers, R. & Aten, B. (2006). Penn World Table Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

Joshi S and Schultz P. (2004). Family Planning as an Investment in Development : Evaluation of a Program’s Consequences in Matlab, Bangladesh. Mimeo, Yale University.

Kelley, A.C. & Schmidt, R.M. (1995). Aggregate Population and Economic Growth Correlations: The Role of the Components of Demographic Change, *Demography*, 32(4), 543-555.

Kraay, A. (1999). Growth Forecasts Using Time Series and Growth Models, World Bank Policy Research Working Paper, WPS 2224.

Lee, S.-H. & Mason, A. (2006). Who Gains from the Demographic Dividend? Forecasting Income by Age, University of Hawaii at Manoa Economics Working Paper Series, 06-13.

Malmberg, B. & Lindh, T. (2004). Demographically based global income forecasts up to the year 2050, Stockholm, Institute for Futures Studies, Working Paper No.2004:7.

McKibbin, W. & Wilcoxen, P.J. (1998). The theoretical and empirical structure of the G-Cubed model, *Economic Modelling*, 16(1), 123-48.

Nordhaus, W.D. & Boyer, J. (2000). Warming the World: Economic Modeling of Global Warming. Cambridge, MA: MIT Press.

Prskawetz, A., Kögel, T., Sanderson, W.C. & Scherbov, S. (2004). The Effects of Age Structure on Economic Growth: An Applicaton of Probabilistic Forecasting in India, Vienna Institute of Demography, Working Papers 03/2004.

Robertson, J.C. & Tallman, E.W. (1999). Vector autoregressions: Forecasting and reality, *Federal Reserve of Atlanta Economic Review*, 84(1), 4-18.

Sala-i-Martin, X., Doppelhofer, G. & Miller, R.I. (2004). Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach, *American Economic Review*, 94(4), 813-35.

Stock, J.H. & Watson, M.W. (1998). A comparison of linear and nonlinear univariate models for forecasting macroeconomic time series, NBER Working Paper No. 6607.

World Bank. (2006). World Bank Development Indicators CD-ROM, The World Bank Group.

Appendix
Time-Invariant Variables

East Asia Dummy	Dummy for East Asia Countries
African Dummy	Dummy for Sub-Saharan African countries
Latin American Dummy	Dummy for Latin American countries.
Fraction Buddhist	Fraction of the population that is Buddhist in 1960 (Barro, 1999)
Fraction Muslim	Fraction of the population that is Muslim in 1960 (Barro, 1999)
Fraction Confucian	Fraction of the population that is Confucian (Barro, 1999)
Fraction of Tropical Area	Proportion of the country's land area within geographical tropics (Gallup et al., 1999, p.36; Gallup et al., 2001, datasets)
Population Density Coastal	Proportion of the population in 1994 within 100 km. of the coastline or ocean-navigable river (as defined for Lt100cr). The population data are as for Pop100km. (Gallup et al., 1999, p.36; Gallup et al., 2001, datasets)
Fraction GDP in Mining	Fraction of GDP in mining (Hall and Jones, 1999)
Ethno-linguistic fractionalization	Average of five different indices of ethnolinguistic fractionalization, which is the probability of two random people in a country not speaking the same language. (Easterly and Levine, 1997).
Malaria prevalence	Index of Malaria prevalence in 1966. (Gallup et al., 1999, p.36; Gallup et al., 2001, datasets)

Note: Data are available from Gernot Dopelhofer's website at http://www.econ.cam.ac.uk/faculty/doppelhofer/research/bace.htm#appendix

Time-Variant Variables

Investment price	PPP over investment / exchange rate in Current Prices. Current prices are for the year 2000. Investment price in Uganda in 1980 is recorded as 1738.41, which features as an outlier in that country series and affects the final results. We replace the 1980 price of investment in Uganda with the 1981 price of investment to address the outlier problem. Source: Heston et al. (2006)
Government Consumption Share	We calculate the real government share of GDP using three series from the PWT6.2. Current government share of GDP multiplied by the ratio of the price of government share of GDP and the price of GDP (cg*pg/p). We choose not to use the PWT6.2 Real Government Share of GDP as these series are imputed from the current year, 2000, by multiplying the base year with the real growth rates of the corresponding item of the national accounts. A further note on the PWT6.2 data construction is that each price level has its own PPP measure, so the PPP over government consumption, we denote as PPP(g), will differ from that over GDP, PPP. As a result, the nominal government share, cg, is not a perfect measure of the government consumption share as the numerator and denominator PPP will differ given, cg = (G/PPP(g))/(GDP/PPP). By using our calculation we have the true share of government consumption to GDP, G/GDP = ci*(pg/p) = G/PPP(g))/(GDP/PPP)*((PPP(i)/XRAT)/PPP/XRAT)). Thus we account for the different PPP measures used for GDP and government consumption. Source: Heston et al. (2006), own calculations.
Log(GDP)	As described the PWT6.2 Appendix, "RGDPL is obtained by adding up consumption, investment, government and exports, and subtracting imports in any given year…It is a fixed base index where the reference year is 2000, hence the designation "L" for Laspeyeres." Source: Heston et al. (2006)
Primary Schooling	Primary schooling in the initial periods (1960, 1980, 2000) is the proportion of the population older than 15 who has *at least some* primary schooling. This data series is generated subtracting the proportion who has no schooling from the full population. Source: Barro and Lee (1994), CID website: http://www.cid.harvard.edu/ciddata/ciddata.html
Life Expectancy	Life expectancy at birth, total. Source: World Population Prospects, World Bank (2006a).
Log(Initial Working-Age Share)	Percent of total population between the ages of 15 and 64. Source: World Development Indicators, World Bank (2006).

FIGURES AND TABLES

Table 1: Sala-i-Martin, Doppelhofer, and Miller (2004) Rankings

	Model Size[1]		
Variable	**SDM5**	**SDM9**	**SDM16**
East Asian Dummy	**1**	**4**	**4**
Primary Schooling	**2**	**2**	**3**
Investment price	**3**	**1**	**1**
Log (Initial GDP per Capita)	**4**	**3**	**2**
Fraction of Tropical Area	**5**	**5**	**7**
Population Density Coastal	(6)	**6**	**8**
Malaria Prevalence	(7)	(12)	**16**
Life Expectancy	(8)	**8**	**10**
Fraction Confucian	(9)	**7**	**5**
African Dummy	(10)	**9**	**9**
Latin American Dummy	(11)	(11)	**11**
Fraction GDP in Mining	(12)	(10)	**6**
Spanish Colony	(13)	(18)	(20)
Years Open 1950-1994	(14)	(17)	(17)
Fraction Muslim	(15)	(14)	**13**
Fraction Buddhist	(16)	(13)	**12**
Ethno-linguistic Fractionalization	(17)	(17)	**15**
Government Consumption Share	(18)	(18)	**14**

Notes:
1) Number of regressors included in Bayesian Averaging (BACE).
Figures in parentheses indicate the ranking of variables not included in the respective specifications.

Table 2: Summary Statistics

Variable Factors	1960 - 1980 Mean	1960 - 1980 St.dev.	1980 - 2000 Mean	1980 - 2000 St.Dev.	Cross-Period Correlation
Annual Growth Rate[1)]	2.7	1.6	1.3	1.6	0.468
Primary Schooling[2,3)]	0.606	0.293	0.713	0.249	0.943
Log Working-Age Share [3)]	4.018	0.090	4.033	0.108	0.816
Government Cons. Share[3)]	11.74	5.471	16.001	8.45	0.660
Investment Price[3)]	77.25	63.072	103.83	67.22	0.624
Life expectancy	56.34	11.52	64.04	9.83	0.960
Log (Real GDP per capita)[3)]	7.920	0.943	8.450	1.035	0.952

Time-Invariant Factors	Full Sample Mean	Full Sample St.dev.
African Dummy	0.224	0.420
Coastal Density	118.29	377.98
East Asian Dummy	0.104	0.308
Fraction Buddhist	0.052	0.185
Fraction Confucian	0.011	0.075
Fraction Muslim	0.125	0.262
Fraction of Tropical Area	0.533	0.483
Ethno-linguistic Fractionalization	0.339	0.293
Latin American Dummy	0.299	0.461
Malaria Prevalence	0.254	0.377
Fraction GDP in Mining	0.041	0.050

Notes:

Summary statistics are based on 67 observations.
1) Annual average percentage economic growth in GDP per capita, based on Real GDP per capita, PPP adjusted (PWT, 6.2).
2) Fraction of population with at least some primary education (Barro and Lee (2000)).
3) Values correspond to levels at the beginning of the respective periods.
4) Variable is used in logs. Working-age fraction is defined as population aged 15 to 64 over total population.

Table 3: Correlation Matrix DSM 5, Economic Growth and Working-Age Share

	GDP Growth	Investment Price	Initial GDP	Primary Schooling	East Asia	Fraction Tropical	Working-Age Share
GDP Growth	1						
Investment Price	-0.30	1					
Initial GDP	0.13	-0.22	1				
Primary Schooling	0.36	-0.14	0.76	1			
East Asian Dummy	0.42	-0.17	-0.11	0.01	1		
Fraction Tropical	-0.25	0.02	-0.53	-0.44	0.13	1	
Log (Working-Age Share)	0.28	-0.07	0.63	0.60	-0.05	-0.72	1

Table 4: Absolute Growth Prediction: SDM Variables Only

Regression	SDM 0	SDM 5	SDM 9	SDM16
Number of Observations	67	67	67	67
Degrees of Freedom	66	61	57	50
R^2	0.00	0.43	0.64	0.66
Adjusted R^2	0.00	0.39	0.58	0.55
Forecast Accuracy				
RMSE	2.12	1.73	2.07	2.09
Adjusted-RMSE[1)]	2.14	1.82	2.24	2.42
Model Adequacy				
Mean Prediction Error (bias) [2)]	-1.37	-1.12	-1.62	-1.59
	(0.00)	(0.00)	(0.00)	(0.00)
Prediction Efficiency [3)]	–	0.976	1.001	0.899
	–	(0.910)	(0.995)	(0.545)
Serial Correlation Test (p-value)[4)]	0.000	0.230	0.769	0.379

Notes:

P-values in parentheses.

1) RMSE is adjusted by the degrees of freedom, rather than the number of observations.

2) $E(Y_{t+1} - X_{t+1}\beta_i) = 0$, regress the prediction error on a constant, coefficient reported. Heteroskedastic consistent standard errors, p-values in parentheses.

3) Regress Y_{t+1} on $X_{t+1}\beta^*$ and a constant, coefficient on the predicted growth rate reported. Heteroskedastic consistent standard errors, test the null of coefficient equal to one, p-values in parentheses.

4) $E(Y_{t+1} - X_{t+1}\beta_1^*)(Y_t - X_t\beta_1^*) = 0$

Table 5: Absolute Growth Prediction: Including Age Structure

Regression	SDM 0 + w	SDM 5 + w	SDM 9 + w	SDM16 + w
Number of Observations	67	67	67	67
Degrees of Freedom	65	60	56	49
R^2	0.08	0.44	0.64	0.67
Adjusted R^2	0.06	0.38	0.58	0.55
Forecast Accuracy				
RMSE	2.02	1.71	2.04	2.10
Adjusted-RMSE[1)]	2.05	1.81	2.23	2.45
Model Adequacy				
Mean Prediction Error (bias) [2)]	-1.45	-1.12	-1.61	-1.62
	(0.00)	(0.00)	(0.00)	(0.00)
Prediction Efficiency [3)]	1.665	0.993	1.015	0.888
	(0.018)	(0.971)	(0.925)	(0.469)
Serial Correlation Test (p-value)[4)]	0.014	0.295	0.881	0.426

Notes:

P-values in parentheses.

1) RMSE is adjusted by the degrees of freedom, rather than the number of observations.

2) $E(Y_{t+1} - X_{t+1}\beta_i) = 0$, regress the prediction error on a constant, coefficient reported. Heteroskedastic consistent standard errors, p-values in parentheses.

3) Regress Y_{t+1} on $X_{t+1}\beta^*$ and a constant, coefficient on the predicted growth rate reported. Heteroskedastic consistent standard errors, test the null of coefficient equal to one, p-values in parentheses.

4) $E(Y_{t+1} - X_{t+1}\beta_1^*)(Y_t - X_t\beta_1^*) = 0$

Table 6: Absolute Growth Models: Testing Improvements in Forecasting

X_1 \ X_2	SDM 5	SDM 9	SDM 16	SDM 0 + w	SDM 5 + w	SDM 9 + w	SDM 16 + w
SDM 0	6.02			1.73			
	(0.001)			(0.047)			
SDM 5		-5.09			0.33		
		(1.000)			(0.008)		
SDM 9			-0.40			0.44	
			(0.763)			(0.006)	
SDM 16							-0.05
							(0.564)

Notes:
We test $E(Y_{1,t+1} - X_{1,t+1}\beta_1^*)^2$ -- $E(Y_{2,t+1} - X_{2,t+1}\beta_2^*)^2 = 0$ by regressing the error squared difference on a constant. Reported coefficient is the estimated constant, p-values of a one tail test for a positive coefficient are in parentheses. Standard errors (not reported) were estimated using non-parametric bootstrapping method with replacement over 500 repetitions of the difference of the expected residual squares regressed on a constant.

Table 7: Relative Growth Prediction: SDM Variables Only

Regression	SDM 0	SDM 5	SDM 9	SDM16
Number of Observations	67	67	67	67
Degrees of Freedom	66	61	57	50
R^2	0.00	0.43	0.64	0.66
Adjusted R^2	0.00	0.39	0.58	0.55
Forecast Accuracy				
RMSE	1.62	1.32	1.29	1.36
Adjusted-RMSE[1)]	1.64	1.38	1.39	1.57
Model Adequacy				
Mean Prediction Error (bias) [2)]	0.00	0.00	0.00	0.00
	(1.00)	(1.00)	(1.00)	(1.00)
Prediction Efficiency [3)]		0.976	1.001	0.899
		(0.910)	(0.995)	(0.545)
Serial Correlation Test (p-value)[4)]	0.000	0.230	0.769	0.379

Notes:

P-values in parentheses.

1) RMSE is adjusted by the degrees of freedom, rather than the number of observations.

2) $E(Y_{t+1} - X_{t+1}\beta_i) = 0$, regress the prediction error on a constant, coefficient reported. Heteroskedastic consistent standard errors, p-values in parentheses.

3) Regress Y_{t+1} on $X_{t+1}\beta^*$ and a constant, coefficient on the predicted growth rate reported. Heteroskedastic consistent standard errors, test the null of coefficient equal to one, p-values in parentheses.

4) $E(Y_{t+1} - X_{t+1}\beta_1^*)(Y_t - X_t\beta_1^*) = 0$

Table 8: Relative Growth Forecast: Including Age Structure

Regression	SDM 0 + w	SDM 5 + w	SDM 9 + w	SDM16 + w
Number of Observations	67	67	67	67
Degrees of Freedom	65	60	56	49
R^2	0.08	0.44	0.64	0.67
Adjusted R^2	0.06	0.38	0.58	0.55
Forecast Accuracy				
RMSE	1.41	1.29	1.26	1.33
Adjusted-RMSE[1)]	1.43	1.37	1.38	1.56
Model Adequacy				
Mean Prediction Error (bias) [2)]	0.00	0.00	0.00	0.00
	(1.00)	(1.00)	(1.00)	(1.00)
Prediction Efficiency [3)]	1.665	0.993	1.015	0.888
	(0.018)	(0.971)	(0.925)	(0.469)
Serial Correlation Test (p-value)[4)]	0.014	0.295	0.881	0.426

Notes:

P-values in parentheses.

1) RMSE is adjusted by the degrees of freedom, rather than the number of observations.

2) $E(Y_{t+1} - X_{t+1}\beta_i) = 0$, regress the prediction error on a constant, coefficient reported. Heteroskedastic consistent standard errors, p-values in parentheses.

3) Regress Y_{t+1} on $X_{t+1}\beta^*$ and a constant, coefficient on the predicted growth rate reported. Heteroskedastic consistent standard errors, test the null of coefficient equal to one, p-values in parentheses.

4) $E(Y_{t+1} - X_{t+1}\beta_1^*)(Y_t - X_t\beta_1^*) = 0$

Table 9: Relative Growth Models: Testing Improvements in Forecasting

X_1 \ X_2	SDM 5	SDM 9	SDM 16	SDM 0 + w	SDM 5 + w	SDM 9 + w	SDM 16 + w
SDM 0	3.58 (0.018)			2.60 (0.000)			
SDM 5		0.36 (0.327)			0.31 (0.003)		
SDM 9			-0.73 (0.988)			0.28 (0.002)	
SDM 16							0.24 (0.103)

Notes:
We test $E(Y_{1,t+1} - X_{1,t+1}\beta_1^*)^2$ -- $E(Y_{2,t+1} - X_{2,t+1}\beta_2^*)^2 = 0$ by regressing the error squared difference on a constant. Reported coefficient is the estimated constant, p-values of a one tail test for a positive coefficient are in parentheses. Standard errors (not reported) were estimated using non-parametric bootstrapping method with replacement over 500 repetitions of the difference of the expected residual squares regressed on a constant.

Table 10: Forecast Error Decomposition

Dependent Variable:	Absolute Growth	Relative Growth
Model Specification:	SDM 5 + w	SDM 9 + w
Variance due to:		
Parameter Estimates	0.036	0.016
Parameter Instability	1.803	0.657
Expected Residual Variance	1.414	0.895
Change in Residual Variance	-0.290	0.033
Total Attributed Variance	2.963	1.601
Total Attributed RMSE	1.721	1.265
Actual RMSE	1.71	1.26

Table 11: Coefficient Estimates in Sub-Samples and Full Sample

Dependent Variable	Absolute Growth Rate			Relative Growth Rate		
Model Specification	SDM 5 plus w			SDM 9 plus w		
Sample Period	1960-1980	1980-2000	1960-2000	1960-1980	1980-2000	1960-2000
Constant	0.516	-6.210***	-2.898**			
	(0.24)	(4.13)	(2.12)			
East Asian Dummy	0.378***	0.382***	0.379***	0.222**	0.260*	0.252***
	(3.48)	(2.88)	(4.15)	(2.07)	(1.81)	(3.26)
Primary Schooling	0.555***	0.316	0.413***	-0.177	-0.006	-0.125
	(3.45)	(1.50)	(2.95)	(0.91)	(0.01)	(0.65)
Investment price	-0.001**	-0.000	-0.001***	-0.001*	0.000	-0.000
	(2.20)	(0.27)	(3.30)	(1.71)	(0.20)	(1.30)
Log (Initial GDP)	-0.150***	-0.223***	-0.215***	-0.276***	-0.307***	-0.267***
	(2.74)	(4.23)	(5.46)	(5.24)	(6.03)	(7.43)
Fraction Tropical	-0.165*	-0.220***	-0.215***	-0.040	-0.159*	-0.080
	(1.69)	(3.36)	(3.77)	(0.41)	(1.80)	(1.29)
Density Coastal				0.000	0.000	0.000
				(0.92)	(0.51)	(1.42)
Fraction Confucian				0.280	0.666***	0.533**
				(1.45)	(2.86)	(2.03)
African Dummy				-0.090	-0.114	-0.100
				(0.87)	(0.92)	(1.35)
Life Expectancy				0.031***	0.017	0.024***
				(3.95)	(1.47)	(3.83)
Log (Working-Age Share)	0.252	2.037***	1.231***	0.212	1.913***	1.050***
	(0.45)	(4.88)	(3.35)	(0.48)	(4.40)	(3.49)
F test[1]: (p-value)			0.000			0.000
Observations	67	67	134	67	67	134
R-squared	0.44	0.57	0.44	0.64	0.65	0.58

Notes:

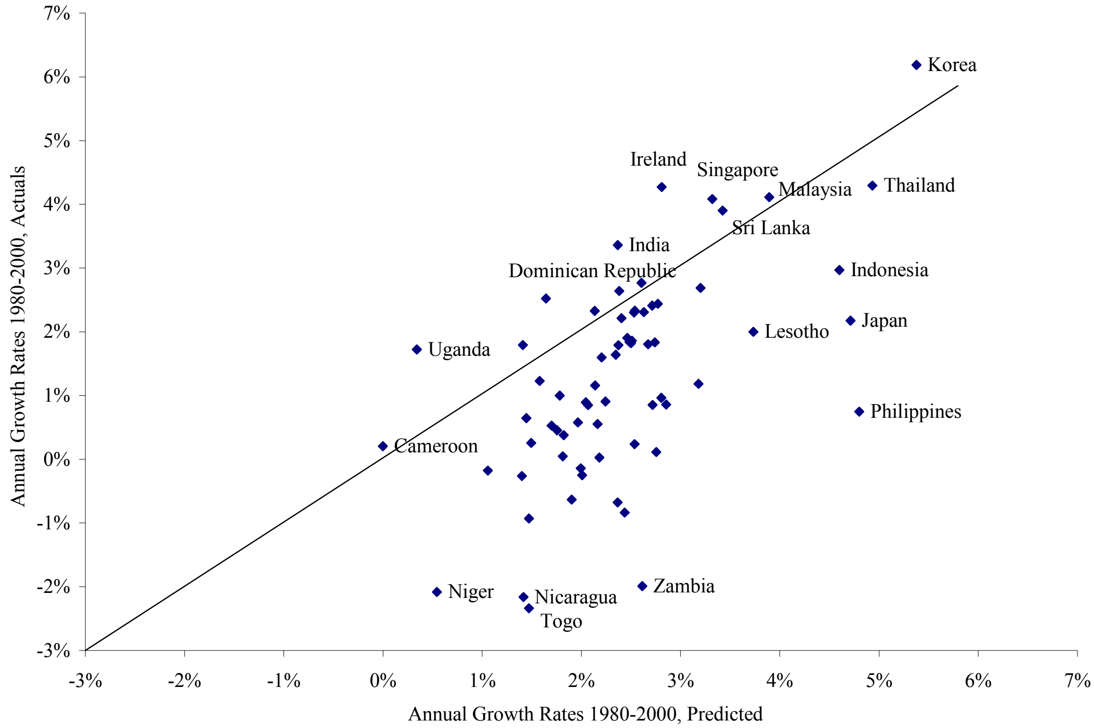
1) Null hypothesis: All coefficients are the same in the two sub-samples 1960-1980 and 1980 - 2000.
Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 12: Predicted Economic Growth 2000 – 2020 ##sort on relative#

Rank	Country	Growth Rate 1980- 2000	Forecast 2000-2020		Rank	Country	Growth Rate 1980- 2000	Forecast 2000-2020	
			Absolute	Relative				Absolute	Relative
1	China*	8.4%	5.9%	4.8%	46	France	1.8%	1.9%	0.2%
2	Korea, Rep.	6.2%	4.9%	3.8%	47	Netherlands	1.9%	1.9%	0.2%
3	Philippines	0.7%	4.6%	2.6%	48	Iran*	0.5%	1.9%	0.5%
4	Japan	2.2%	4.3%	1.5%	49	Ireland	4.3%	1.9%	-0.1%
5	Thailand	4.3%	4.3%	2.3%	50	Ecuador	-0.7%	1.9%	1.6%
6	Indonesia	3.0%	4.0%	2.4%	51	Zimbabwe	0.0%	1.8%	-2.5%
7	Poland*	1.6%	3.3%	1.9%	52	UK	2.3%	1.8%	0.1%
8	Syria	0.3%	3.3%	2.5%	53	Belgium	1.8%	1.8%	0.3%
9	Lesotho	2.0%	3.2%	-1.1%	54	Italy	1.8%	1.8%	0.5%
10	Malaysia	4.1%	3.1%	1.0%	55	Sweden	1.6%	1.8%	0.0%
11	Hungary*	1.5%	3.0%	1.2%	56	Switzerland	0.9%	1.7%	-0.1%
12	Turkey	2.3%	2.8%	1.4%	57	Sierra Leone*	-3.4%	1.7%	-0.2%
13	Zambia	-2.0%	2.8%	-0.7%	58	Ghana	1.0%	1.7%	0.2%
14	P. N. Guinea*	0.9%	2.7%	0.0%	59	Brazil	0.4%	1.6%	0.6%
15	Jordan	-0.6%	2.7%	1.6%	60	United States	2.3%	1.6%	-0.6%
16	Nepal	2.4%	2.6%	2.2%	61	Sudan*	0.0%	1.6%	0.7%
17	Congo, P.R.*	-5.8%	2.6%	0.6%	62	CAF Rep.*	-0.6%	1.6%	-1.0%
18	Singapore	4.1%	2.6%	2.8%	63	Bolivia	-0.2%	1.5%	0.6%
19	Greece	0.9%	2.6%	1.2%	64	Norway	2.6%	1.5%	-0.5%
20	Uruguay	1.2%	2.5%	1.0%	65	Panama	1.6%	1.5%	0.7%
21	Argentina	0.2%	2.5%	0.7%	66	Congo, Rep.*	-2.4%	1.5%	-1.2%
22	Sri Lanka	3.9%	2.4%	2.3%	67	Rwanda*	-1.0%	1.5%	-1.2%
23	Chile	2.7%	2.4%	1.3%	68	Israel	2.3%	1.5%	0.1%
24	Spain	2.4%	2.3%	0.9%	69	Venezuela	-0.9%	1.5%	0.4%
25	Paraguay	0.1%	2.3%	1.1%	70	Australia*	2.0%	1.5%	0.0%
26	Bangladesh*	1.6%	2.3%	2.1%	71	Gambia*	0.4%	1.4%	0.6%
27	South Africa	0.5%	2.2%	-1.9%	72	Uganda	1.7%	1.4%	-1.3%
28	Tunisia*	2.5%	2.2%	1.4%	73	Colombia	1.2%	1.4%	0.8%
29	Kenya	0.0%	2.2%	-0.4%	74	Costa Rica	0.9%	1.4%	0.7%
30	Pakistan	2.2%	2.1%	1.4%	75	Trin. & Tobago	0.6%	1.3%	-0.3%
31	Portugal	2.8%	2.1%	0.7%	76	Nicaragua	-2.2%	1.2%	0.8%
32	Finland	1.8%	2.1%	0.3%	77	El Salvador	0.8%	1.2%	0.7%
33	Togo	-2.3%	2.1%	0.7%	78	Mozambique	-0.2%	1.2%	-1.3%
34	India	3.4%	2.1%	1.6%	79	Botswana*	4.8%	1.2%	-3.7%
35	Malawi	0.9%	2.1%	-0.7%	80	Cameroon	0.2%	1.1%	-1.9%
36	Honduras	-0.1%	2.1%	1.4%	81	G. Bissau*	2.1%	1.1%	-0.6%
37	Algeria	0.6%	2.1%	1.1%	82	Kuwait*	-0.8%	1.1%	-0.2%
38	Mexico	0.6%	2.0%	0.9%	83	Mauritius*	4.4%	1.0%	-0.6%
39	Canada	1.8%	2.0%	0.3%	84	Senegal	0.5%	0.9%	-0.8%
40	Jamaica	1.0%	2.0%	0.9%	85	Dom. Rep.	2.5%	0.9%	-0.1%
41	Liberia*	-6.4%	2.0%	-0.1%	86	Benin*	0.5%	0.9%	-0.4%
42	Peru	-0.8%	2.0%	1.2%	87	Haiti*	-1.2%	0.9%	-0.3%
43	Tanzania	1.8%	2.0%	-0.6%	88	Niger	-2.1%	0.6%	-0.8%
44	Egypt	2.8%	2.0%	1.0%	89	Guatemala	-0.3%	0.4%	-0.3%
45	Austria*	2.1%	1.9%	0.1%	90	Mali	1.2%	0.2%	-1.3%

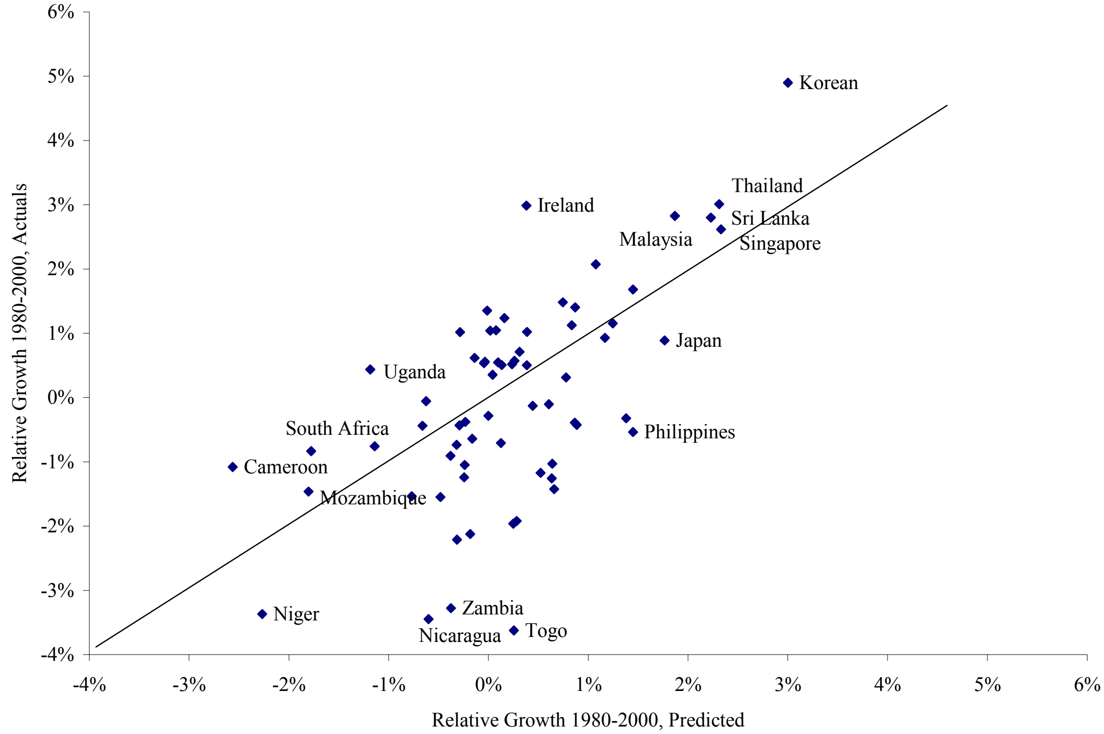
* Countries marked with an asterisk are not included in the estimation sample.

Figure 1. Absolute Growth 1980 -2000: Predicted and Actual



Notes: Predictions are based on the SDM 5 plus Demographics specification.

Figure 2. Relative Growth 1980-2000: Predicted and Actual



Notes: Predictions are based on the SDM 9 plus Demographics specification.