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Does Age Structure Forecast Economic Growth?[1]

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Abstract:
Increases in the proportion of the working age population can yield a "demographic dividend" that enhances 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 to 2020.

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

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Does age structure forecast economic growth?

Biographical Sketches

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

–- Chinese proverb

1: Introduction

During a demographic transition, falling death rates set off a population boom that continues until fertility rates decline. In addition to its effect on population size, a 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 labor supply and saving rates. In addition, a decline in fertility increases female labor supply (Bailey, 2006) and the resources available to invest in children's health and education (Joshi & Schultz, 2007). Several studies emphasize the role of shifting birth and death rates and age structure in explaining cross-country variation in economic growth (Bloom & Canning, 2003; Bloom, Canning, & Malaney, 2000; Bloom, Canning, & Sevilla, 2003; Bloom & Freeman, 1988; Bloom & Williamson, 1998; Brander & Dowrick, 1994; Kelley & Schmidt, 1995).

This paper investigates whether age structure can be used to forecast long-run economic growth. Such forecasts may be of interest in their own right or in the investigation of other topics. For example, the problem of forecasting climate change has created a need for long-run forecasts of economic growth because energy demand is highly income elastic; to be useful, these economic growth forecasts have to be combined with projections of population, pollution, and global warming (for example, see Nordhaus & Boyer, 2000). In addition to direct interest in the forecasts produced by a model, the ability of a model to forecast can serve as a robustness check, guarding against specification searches that over-fit models to existing data (Clements & Hendry, 2005).

To forecast economic growth we adopt a reduced form conditional convergence framework. Our main variable of interest is the average annual growth rate in real GDP per capita ("growth" or "economic growth" hereafter). Starting with a structural model 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. We estimate the model on data from the period 1960–1980 and use the estimated coefficients to predict economic growth in the period 1980–2000. The specification for the growth model is 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 add the log of the initial ratio of working age to total population ("age structure") as an explanatory variable.

We show that economic growth models perform well in forecasting growth when analyzing twenty-year periods; we also show that adding age structure to the growth model significantly improves forecast accuracy. However, we find that all models tend to predict higher growth for the period 1980–2000 than actually occurred. This prediction bias is due to a worldwide slow down in economic growth in the period 1980–2000 not captured by the model.

There are a variety of approaches to forecasting economic growth. Fully specified structural models (McKibbin & Wilcoxen, 1998) represent one extreme of the spectrum of forecasting methodologies. 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 & Voss, 2000; Clements & Hendry, 1998; Fair & Shiller, 1990; Robertson & Tallman, 1999; Stock & Watson, 1998), but forecasts of cross-country variation in economic growth have entered the literature only recently (Lee & Mason, 2006; Malmberg & Lindh, 2004; Prskawetz, Kögel, Sanderson, & 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 the period 1960–1990, but that the reverse is true for the forecast period 1980–1997. It appears that time series models may 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 next section 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 estimation error. 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

$$\frac{Y}{P} = \frac{Y}{WA}\frac{WA}{P} \tag{1}$$

where WA is the number of working age people. We assume that the working age population measures the workforce, which implies a constant participation rate. In fact, participation is not constant, with female participation rates varying widely in developing countries and schooling and early retirement depressing participation rates in developed economies. Taking logs

$$y = \log\frac{Y}{P},\ z = \log\frac{Y}{WA},\ w = \log\frac{WA}{P} \tag{2}$$

We assume that there is a steady state level of income working age person, z^*, given by $z^* = \beta x$ where the vector x consists of a set of variables that determines steady state income per working age person. We can express the steady state level of income per capita y^* as

$$y^* = z^* + w = \beta x + w \tag{3}$$

As in Barro and Sala-i-Martin (2003), economic growth occurs as each country converges from its initial position to its steady state.[2] Thus, we can derive

$$\Delta y = \lambda(y^* - y_{-1}) = \lambda(\beta x + w - y_{-1}) \tag{4}$$

The steady state determines the long-run equilibrium and economic growth reflects transitional dynamics. Let us suppose that we can write a structural model for the factors that affect the long-run equilibrium as

$$x = \alpha_1 x_{-1} + \alpha_2 w + \alpha_3 y,\ w = \gamma_1 x + \gamma_2 w_{-1} + \gamma_3 y \tag{5}$$

Then we can derive the reduced form

$$\Delta y = \lambda(y^* - y_{-1}) = \delta_1 x_{-1} + \delta_2 w_{-1} + \delta_3 y_{-1} \tag{6}$$

where the reduced form coefficients δ are combinations of the structural coefficients from equations (4) and (5). The advantage of the reduced form is that all of the variables on the right-hand side of the equation are measured at the beginning of the growth period under consideration. Thus, they are plausibly exogenous with respect to growth shocks.

We estimate an economic growth model of the type set out in equation (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 the variables, in addition to the log working age share w, that should be used to explain economic growth. Many variables have been suggested as factors that can potentially affect economic growth. Rather than propose our own specification, we use the results of recent work by Sala-i-Martin,

[2] This representation of the economic growth equation can be derived from the neoclassical Cobb-Douglas production function and is used widely in empirical applications aimed to explain cross country differences in economic growth. See for example Acemoglu & Johnson (2006), Bloom, Canning & Sevilla (2004), Dowrick and Rogers (2002), Sachs and Warner (1997).

Doppelhofer, and Miller (2004) (henceforth, SDM). They use a large set of potential explanatory variables for economic growth and calculate the Bayesian posterior probability of each variable being included in the specification, given a fixed model size. We focus on models with 5, 9, and 16 regressors, in each case using the variables with the highest posterior rankings as shown in bold in Table 1 below.

Table 1 here: SDM Rankings

Although the posterior rankings of the variables differ across the 5, 9, and 16 regressor specifications, smaller models are strict subsets of larger models. The rankings differ across the different-sized specifications as some variables, like mining, require more "conditioning variables in order to display its full importance" (Sala-i-Martin *et al*., 2004, p.831). Our main variable of interest is the log of the working age share, which our theory above predicts will be important for economic growth. We assume that the working age population measures the workforce, which implies a constant participation rate, which as discussed above does not hold in fact. Age structure has a mechanical effect on income per capita. It may also act a proxy for other variables, such as work experience. Bloom, Canning, and Sevilla (2004) investigate the effect of adding detailed data on age structure to a growth model to find if worker age, and work experience, matter; however, they find little impact. SDM do not include the log of working age share among their candidate variables, and instead include both the fraction of the population 15 and younger and the fraction of the population over 65. Neither of these variables performs well according to the SDM selection criteria. Although it would be interesting to know how the log of the working age share performs in a SDM-type analysis of the variables that best explain past economic growth, our focus is somewhat different. We ask if the log of the working age share can help predict future economic growth. We use the SDM analysis only to find a reasonable specification for the rest of the growth regression. We show that augmenting the SDM specification with the log of the working age share improves forecasting ability.

We examine the ability of SDM models with 5, 9, and 16 regressors to forecast economic growth and test whether the addition of age structure adds to the models' forecasting performances. 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 the periods 1960–1980 and 1980–2000, and we use data from 2000 to forecast future economic growth.[3] 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, & Aten, 2006). Educational attainment data are from Barro and Lee (2000), and data on life expectancy are from the United Nations World Population Prospects (United Nations, 2004). We restrict our analysis of the period 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; we provide forecasts for the period 2000–2020 for all countries that have data for the year 2000. A full description of

[3] Later we also undertake a pooled regression using a 10-year panel for 1960–1990 to forecast 1990–2000. This time split also yields the same key result: the addition of the log of the working age share improves the forecast ability of the model over specifications that only include the SDM-ranked variables. See Tables 12 and 13 for the forecast error measure summary of this sample split.

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 explanatory variables from 1960. Using the estimated coefficients, we then forecast growth rates for the period 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 five growth models. Our first two models provide a baseline: we start with a naive model where we use growth in each country over the period 1960–1980 as the forecast for the period 1980–2000. The second baseline model uses average growth across countries in the period 1960–1980 (SDM0) as the forecast for all countries in the period 1980–2000. We then estimate three reduced form models, with 5 (SDM5), 9 (SDM9), and 16 (SDM16) explanatory variables respectively. 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 shows the results using a country's growth for the period 1960–1980 as a forecast for the period 1980–2000. Column 2 of Table 4 provides details of the forecast performance of a model in which growth during the period 1960–1980 depends on a constant only. Columns 3, 4, and 5 show the results for the larger growth model specifications. Each model is estimated using data from a sample of 67 countries for the period 1960–1980, with the degrees of freedom declining 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 use each of the models estimated over the period 1960–1980 to produce forecasts for the period 1980–2000. There is a debate as to the best measure for assessing the goodness of fit of forecasts (Ahlburg, 1992; Armstrong & Collopy, 1992; Clements & Hendry, 1998; Fair & Shiller, 1990; Fildes, 1992; Hendry & Hubrich, 2006; Hyndman & Koehler, 2005). We assess the forecasts using five measures: the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Geometric Mean Relative Absolute Error (GMRAE), the Arithmetic Mean Relative Absolute Error (AMRAE), and the Mean Absolute Scaled Error (MASE). These measures are calculated as follows

$$RMSE = \left[N^{-1} \sum_{j=1}^{N} \left(\Delta y_j - \Delta \hat{y}_j \right)^2 \right]^{1/2}, \quad MAE = N^{-1} \sum_{j=1}^{N} \left| \Delta y_j - \Delta \hat{y}_j \right| \tag{7}$$

$$GMRAE = \prod_{j=1}^{N} \left[\frac{\left| \Delta y_j - \Delta \hat{y}_j \right|}{\left| \Delta y_j - \Delta y_j^* \right|} \right]^{1/N}, \quad AMRAE = N^{-1} \sum_{j=1}^{N} \frac{\left| \Delta y_j - \Delta \hat{y}_j \right|}{\left| \Delta y_j - \Delta y_j^* \right|} \tag{8}$$

$$MASE = N^{-1} \sum_{j=1}^{N} \frac{\left| \Delta y_j - \Delta \hat{y}_j \right|}{N^{-1} \sum_{j=1}^{N} \left| \Delta y_j - \Delta y_j^* \right|} \tag{9}$$

where Δy_j is the actual growth rate in country j, $\Delta \hat{y}_j$ is our forecast growth rate, Δy_j^* is a naive forecast, and N is the number of countries. RMSE is the natural forecasting counterpart to minimizing the residual sum of squares in fitting the model in the first period. However RMSE is very sensitive to outliers and the mean absolute error (MAE) may be a more robust measure. These measures have been criticized for being dependent on the unit of measurement. This is mitigated in our case by noting that the growth rate at time t can be written as $\Delta y_t = \log(y_t / y_{t-1})$ and is therefore invariant to the scale used to measure income per capita. In addition, the percentage-error measures proposed to overcome scale dependence are very sensitive to errors when the actual outcome is close to zero, which occurs frequently in our data.

Another approach to measuring the accuracy of forecasts is to compare the goodness of fit of the forecasts relative to the performance of a baseline naive forecast. This gives us the relative forecast measures GMRAE and AMRAE. These measures are averages (either geometric or arithmetic) of each forecast error relative to the naive forecast. Note that these averages can become very large if the naive model predicts one observation almost exactly because it creates a number close to zero in the denominator. Our final measure is MASE, which scales our forecast error by the average forecast error in the naive model and has a natural metric: zero is perfect forecasting, less than one improves over the naive model, and greater than one is worse than the naive model. For the naive forecast we use the simple extrapolation of the last period's growth rate for the country reported in column 1 of Table 4.

As shown in the middle section of the table, the forecasts of the model SDM5 with 5 explanatory variables outperforms the simple lagged forecast and constant forecast models on most criteria. The only criterion on which it fails is AMRAE, where the lagged growth rate appears to be a better forecast. This is because the naive forecast, lagged growth, is almost exactly right for Chile. This produces a very large error relative to the lagged forecast for all our other models, which dominates the arithmetic average. In what follows we focus on RMSE, MAE, and MASE as our preferred measures of forecast error to avoid this problem. Note that forecast performance on all measures worsens relative to SDM5 as further covariates are included in SMD9 and SDM16.

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 the period 1960–1980 to 1.3 percent during the period 1980–2000. None of our forecasting models predicts this slowdown. Our preferred forecasting model SDM5, has a bias of -1.1 percent per year, which is significant even at the one percent level.

The predictive efficiency test checks whether the slope of the relationship between predicted and actual growth is significantly different from one. Failure of this test would suggest that forecasts are systematically biased even when controlling for changes in the global macroeconomic environment. We cannot reject the null hypothesis that the estimated slope coefficient equals one for any SDM model. We do find a coefficient significantly less than one for lagged growth. This suggests lagged growth contains both a permanent component that is predictive, and a temporary component that does not help forecast.

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 the period 1960–1980, which could be known in 1980, would be useful in constructing forecasts, although our forecasting model does not use them. 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 could be addressed by the use of panel data forecasting methods as discussed in Baltagi (2006). For the naive SDM0 (constant only), we reject the null hypothesis of no serial correlation, indicating that a country's relative growth rate over the period 1960–1980 has predictive power for the period 1980–2000.[4] 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 (aged 15–64) share of the total population, *w*. The results are summarized in Table 5 below. Although there is little improvement in the fit of the regression in the period 1960–1980, the inclusion of the working age share improves forecasting accuracy on a number of measures. In our best performing model, SDM5,

[4] Easterly *et al*. (1993) find little correlation between growth rates at 5 year intervals. For longer time intervals, however, correlations between successive periods' growth rates are higher.

adding the log working age share improves the RMSE, MAE, and MASE measures of forecast accuracy.

Table 5 here: Absolute Growth SDM plus Demographics

We test if this improvement in RMSE forecasting ability is statistically significant; the results are shown in Table 6. We use the methodology suggested by (West, 2006). If we have both the estimated gain in RMSE and the statistical distribution of the estimated gain under the null due to sampling error, we can test the null hypothesis that the expected 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 for the period 1980–2000 and our forecasts using SDM5 and the log working age share. Figure 1 shows that actual outcomes are systematically below the forecasts, which is in line with the prediction bias reported in Tables 4 and 5. Growth slowed around the world in the period 1980–2000 and our model fails to predict this. The failure of cross-country growth models to predict the worldwide slowdown is not surprising. Such models explain relative growth rates in a cross section of countries using country-specific characteristics, while 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. Cross-country growth models lack these worldwide time series variables.

To avoid this problem we consider a forecast of relative economic growth. This shifts the question from how fast each country will grow to how fast it will grow relative to the world average; cross-country growth models seem better suited to this second question. We de-mean each variable by subtracting the sample mean for that 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. Accordingly, we take de-meaned variables from 1980 to forecast relative growth over the period 1980–2000. This approach allows for a period-specific intercept that changes arbitrarily between periods. We leave open the question of what causes these worldwide changes to growth rates. 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

All the models shown in Table 7 perform better in predicting relative growth than in predicting absolute growth, and the bias of the forecast is now zero by construction. The 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. In terms of RMSE, MAE, and MASE, our preferred model is now SDM9.

Table 8 reports the results of the same relative growth regressions with the addition of age structure. Adding age structure lowers the RSME, MAE, and MASE of the forecast in every case. As shown in Table 9, these improvements in RMSE forecast accuracy are significant for the SDM0, SDM5, and SDM9 models. Overall, the best performing forecasting model for relative growth is SDM9 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 (SDM5 + *w* for absolute growth and SDM9 + *w* for relative growth) appear to satisfy our model adequacy criteria, the average errors are considerable: the RMSE are 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, three main factors contribute 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

$$V(\Delta y_1 - \hat{\beta}_0 x_1) = V(\Delta y_1 - \beta_1 x_1) + V(\beta_1 x_1 - \beta_0 x_1) + V(\beta_0 x_1 - \hat{\beta}_0 x_1) \quad (10)$$

where we make a forecast in period 1 based on estimates from period 0. The first term on the right-hand side of equation (10) is random noise, the second is the effect of parameter instability over time, and the third is the effect of estimation error. 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 RMSE 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 small 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

We have focused on 20-year periods for both estimation and forecasts. In Tables 12 and 13 we report forecasts of the relative growth model based on estimating for three 10-year time periods between 1960 and 1990 and using these estimates to forecast for the period 1990–2000. As before our preferred model in Table 12 is SDM9, which outperforms the other models in terms of MAE and MASE (though SDM16 performs best in terms of RMSE).

Table 12 here: Relative Growth Forecast 1990-2000 From Pooled Regression 1960-1990

Table 13 here: Relative Growth Forecast 1990-2000 From Pooled Regression 1960-1990 Including Age Structure

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 the period 1960–1980 and the period 1980-2000. We then use the year 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 not in the sample for the period 1960–2000. Table 14 displays the growth rate for each country over the period 1980–2000 and both our absolute and relative growth forecasts for the period 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[5] (all of which are classified as East Asian by Sala-i-Martin *et al.* (2004)), with forecasted average growth rates above 4.5 percent. The lowest growth rate is predicted for Mali, followed by Guatemala and Niger.

Table 14 also shows our forecasts for relative growth. These forecasts are based on a larger model (9 variables from SDM rather than 5 as in the absolute growth forecast) and make no prediction on the world average growth rate over the period 2000–2020,

[5] The high primary school enrollment in the Philippines, in addition to being classified as an East Asian country, gives this country a high predicted growth rate. India, on the other hand, might be expected to perform well over the next two decades, but has very low primary school enrollment and is not classified as East Asian.

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 South Africa, Botswana, and Zimbabwe. This change results from the inclusion of life expectancy in the SDM9 model we use for forecasting relative economic growth. The HIV/AIDS epidemic in Sub-Saharan Africa has substantially reduced life expectancy in these countries; 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 do not necessarily perform better than smaller models in forecasting future 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.

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Appendix
Variables That Are Treated as Time-Invariant

East Asian Dummy	Dummy for East Asian 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 in 1960 (Barro, 1999)
Fraction of Tropical Area	Proportion of the country's land area within geographical tropics (Gallup, Mellinger, & Sachs, 2001; Gallup, Sachs, & Mellinger, 1999)
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., 2001; Gallup et al., 1999)
Fraction GDP in Mining	Fraction of GDP in mining (Hall & Jones, 1999)
Ethno-linguistic fractionalization	Average of five different indices of ethno-linguistic fractionalization, which is the probability of two random people in a country not speaking the same language. (Easterly & Levine, 1997)
Malaria prevalence	Index of Malaria prevalence in 1966. (Gallup et al., 2001; Gallup et al., 1999)

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 = cg*(pg/p) = G/PPP(g))/(GDP/PPP)*((PPP(g)/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 by subtracting the proportion that has no schooling from the full population. Source: Barro & Lee (2000)
Life Expectancy	Life expectancy at birth, total. Source: United Nations (2004)
Log(Initial Working-Age Share)	Percent of total population between the ages of 15 and 64. Source: 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.

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	Lagged Growth	SDM 0	SDM 5	SDM 9	SDM16
Number of Observations	67	67	67	67	67
Degrees of Freedom	66	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)]	2.1471	2.1245	1.7347	2.0691	2.0933
MAE[2)]	1.7718	1.7302	1.3820	1.6820	1.6722
GMRAE[3)]	1.0000	0.8957	0.7594	0.8456	0.8412
AMRAE[4)]	1.0000	1.6615	1.2068	1.6186	1.4578
MASE[5)]	1.0000	0.9765	0.7800	0.9493	0.9438
Model Adequacy					
Mean Prediction Error (bias) [6)]	-1.37	-1.37	-1.12	-1.62	-1.59
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Prediction Efficiency [7)]	0.481	-	0.976	1.001	0.899
	(0.00)	-	(0.910)	(0.995)	(0.545)
Serial Correlation Test[8)]	-	0.000	0.230	0.769	0.379

Notes:

1) Root Mean Squared Error, see text for the formula

2) Mean Absolute Error, see text for the formula

3) Geometric Mean Relative Absolute Error, see text for the formula

4) Mean Relative Absolute Error, see text for the formula

5) Mean Absolute Scaled Error, see text for the formula

6) Regress prediction error on a constant, coefficient reported. Heteroskedastic consistent standard errors, p-values in parentheses.

7) Regress outcome on the forecast and a constant, coefficient on the forecast reported. Heteroskedastic consistent standard errors, test the null of coefficient equal to one, p-values in parentheses.

8) Regress the forcast error on the residual of the baseline regression and a constant, p-value reported.

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	2.0204	1.7110	2.0424	2.0963
MAE	1.7233	1.3667	1.6720	1.6987
GMRAE	0.9983	0.7604	0.8865	0.9225
AMRAE	1.6245	1.2278	1.5947	1.4705
MASE	0.9726	0.7713	0.9437	0.9587
Model Adequacy				
Mean Prediction Error (bias)	-1.45	-1.12	-1.61	-1.62
	(0.00)	(0.00)	(0.00)	(0.00)
Prediction Efficiency	1.665	0.993	1.015	0.888
	(0.018)	(0.971)	(0.925)	(0.469)
Serial Correlation Test	0.014	0.295	0.881	0.426

Notes:
For technical descriptions see footnotes in Table 4.

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 (0.001)			1.73 (0.047)			
SDM 5		-5.09 (1.000)			0.33 (0.008)		
SDM 9			-0.40 (0.763)			0.44 (0.006)	
SDM 16							-0.05 (0.564)

Notes:

We test $E(\Delta y - \Delta\hat{y}_1)^2 - E(\Delta y - \Delta\hat{y}_2)^2 = 0$ 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	Lagged Growth	SDM 0	SDM 5	SDM 9	SDM16
Number of Observations	67	67	67	67	67
Degrees of Freedom	66	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	1.6541	1.6246	1.3211	1.2863	1.3559
MAE	1.2775	1.2774	1.0627	1.0524	1.1152
GMRAE	1.0000	1.2648	1.0240	1.0410	1.0379
AMRAE	1.0000	5.9739	4.0579	3.4609	5.0058
MASE	1.0000	1.0000	0.8319	0.8238	0.8730
Model Adequacy					
Mean Prediction Error (bias)	0.00	0.00	0.00	0.00	0.00
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Prediction Efficiency	0.481	-	0.976	1.001	0.899
	(0.0001)	-	(0.910)	(0.995)	(0.545)
Serial Correlation Test	-	0.000	0.230	0.769	0.379

Notes:

For technical descriptions see footnotes in Table 4.

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	1.4109	1.2918	1.2589	1.3331
MAE	1.0508	1.0299	1.0275	1.1009
GMRAE	0.7928	0.9702	0.9646	1.1474
AMRAE	11.6220	4.5586	3.0016	4.9461
MASE	0.8226	0.8062	0.8043	0.8618
Model Adequacy				
Mean Prediction Error (bias)	0.00	0.00	0.00	0.00
	(1.00)	(1.00)	(1.00)	(1.00)
Prediction Efficiency	1.665	0.993	1.015	0.888
	(0.018)	(0.971)	(0.925)	(0.469)
Serial Correlation Test	0.014	0.295	0.881	0.426

Notes:

For technical descriptions see footnotes in Table 4.

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 $E(\Delta y - \Delta\hat{y}_1)^2 - E(\Delta y - \Delta\hat{y}_2)^2 = 0$ 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: Relative Growth Forecast 1990-2000 From Pooled Regression 1960-1990

Regression	Lagged Growth	SDM 0	SDM 5	SDM 9	SDM16
Number of Observations	195	195	195	195	195
Degrees of Freedom	192	192	177	165	144
R^2	-	0.00	0.26	0.32	0.39
Adjusted R^2	-	0.00	0.24	0.28	0.33
Forecast Accuracy					
RMSE	2.3085	1.8078	1.6643	1.5809	1.5413
MAE	1.8667	1.4149	1.2884	1.1961	1.1990
GMRAE	1.0000	0.5408	0.5969	0.5234	0.5102
AMRAE	1.0000	1.4484	1.3284	1.4025	1.3745
MASE	1.0000	0.7451	0.6785	0.6299	0.6314

Notes:
See text for error measure details.

Table 13: Relative Growth Forecast 1990-2000 From Pooled Regression 1960-1990 Including Age Structure

Regression	SDM 0 + w	SDM 5 + w	SDM 9 + w	SDM16 + w
Number of Observations	195	195	195	195
Degrees of Freedom	189	174	162	141
R^2	0.08	0.28	0.34	0.39
Adjusted R^2	0.07	0.26	0.30	0.33
Forecast Accuracy				
RMSE	1.6513	1.5892	1.5485	1.5480
MAE	1.3409	1.2354	1.1523	1.2061
GMRAE	0.6607	0.5600	0.4255	0.5411
AMRAE	1.3161	1.3288	1.4316	1.3850
MASE	0.7061	0.6506	0.6068	0.6352

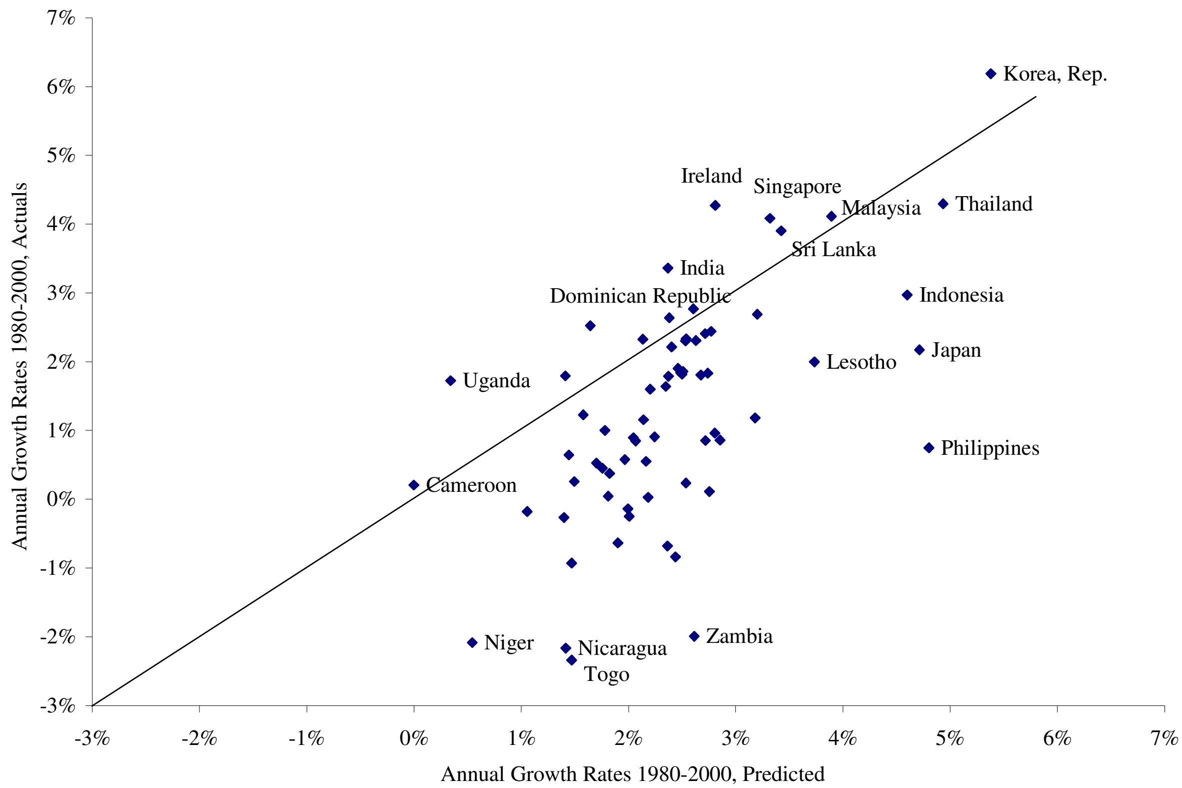
Notes:
See text for error measure details.

Table 14: Predicted Economic Growth 2000 - 2020

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%

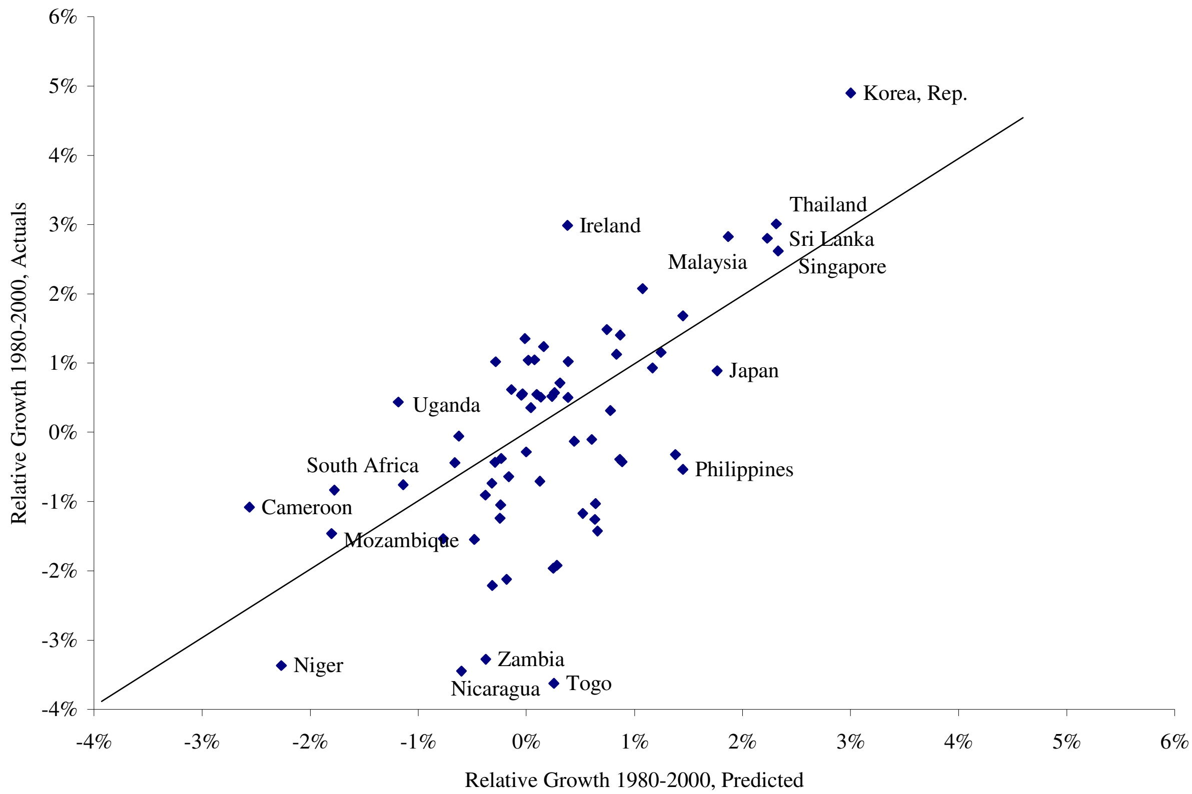
* Countries marked with an asterisk are not included in the estimation sample.

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



Notes: Predictions are based on the SDM 5 specification plus log working age share.

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



Notes: Predictions are based on the SDM 9 plus specification plus log working age share.