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The Role of Age-Structured Education Data for Economic Growth Forecasts

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Abstract

This paper utilizes for the first time age-structured human capital data for economic growth forecasting. We concentrate on pooled cross-country data from 58 countries over six five-year periods between 1970 and 2000. We consider specifications chosen by model selection criteria, Bayesian model averaging methodologies based on in-sample and out-of-sample goodness of fit, and on adaptive regression by mixing. The results indicate that forecast averaging and exploiting the demographic dimension of education data improve economic growth forecasts significantly.

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Contents

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1 Introduction

Recent theoretical (e.g., Boucekkine et al. 2002) and empirical (e.g., Birdsal et al. 2001; Azomahou and Mishra 2007) advances in the economic growth literature decisively demonstrate that age-structure variations exert discernible effects on long-term economic growth (measured as growth rates of GDP per capita). Due to its appealing advantage for minimizing forecast uncertainty, age-structure dynamics have been used in the recent studies of economic growth forecasts (see in particular the special issue of the *International Journal of Forecasting*, Vol 23, No. 4, 2007 on "Global Income Growth in the 21st Century: Determinants and Forecast").

At least two possible reasons explain the surging interests in the demographic determinants of economic growth. Lindh and Malmberg (2007) argue that embedding age-structure information in economic growth models improves income forecasts over long time horizons. Lindh and Malmberg (2007) claim that the production function approach to income forecasting involves a great deal of parameter uncertainty, and suggest exploiting the correlations between age structure and GDP growth in the framework of demography-based models for long-run predictions. Due to their relative stability, demography-based forecasts of GDP have caught the attention of forecasters recently. In line with the research of Lindh and Malmberg (2007), Bloom et al. (2007), for instance, examine whether age structure improves forecasts of economic growth. The authors find that including a simple variable summarizing the age structure improves income growth forecasts. While the size and differential dynamics of each age group for a country are commonly interpreted in this literature as a gross indicator of aggregate productivity effects, no study hitherto, to the knowledge of the authors, explicitly considers differential effects of human capital (in the form of education) across age groups.

Indeed, the importance of human capital on economic growth has been highlighted systematically in the theoretical literature on the determinants of long-run income growth. However, the empirical evidence of human capital's impact on economic growth has yielded ambiguous results (see, for instance, Benhabib and Spiegel 1994; Pritchett 2001; Krueger and Lindahl 1999). Data quality has been deemed at least partly responsible for the lack of a significant positive correlation between GDP per capita growth and human capital variables (see De la Fuente and Domenech 2006; Cohen and Soto 2007). Recently, a new data base has been developed which for the first time summarizes educational attainment figures in different age groups (IIASA-VID dataset, see Lutz et al. 2007).[1] While the relative size of age groups can contain information

[1]Description of the dataset and its qualities can be found in Lutz et al. (2007). Crespo Cuaresma and Lutz

which is good for economic growth forecasts, age-structured human capital information, by disentangling "quantity" and "quality" effects, can lead to further improvements.[2]

An important reason illustrating the possible performance differential is that while age-structure demographic information can be argued to render *level effects* on GDP per capita, age-structured human capital may induce both *level* and *growth effects* (through its effect on technology adoption, see Benhabib and Spiegel 1994, 2005) on the latter. Age-structured human capital introduces the role of first, demographic change (age-structured population change and its direct impact on resources) and second, a productivity change (via the stock of human capital that directly contributes to technological changes and initiates a shift in production function due to radical and induced innovation).

In this paper, we make use of the new age-structured education data base by IIASA-VID and document its usefulness for growth forecasts for the period 1970-2000 by comparing its forecasting performance with that of the widely used Barro-Lee data (Barro and Lee 1996). Bayesian model averaging (BMA) methods are utilized in the paper to explicitly assess the issue of model uncertainty.

The paper is organized as follows. Section 2 describes the demographic dimension of the education data and its role in economic growth forecasts and summarizes the quality of the new human capital data. Section 3 describes the Bayesian model averaging technique and the related forecasting issues. Section 4 discusses the forecasting results and finally, concluding remarks are presented in Section 5.

2 Explaining economic growth: The role of age structure and human capital

Theoretical models of economic growth have studied the long-run effects of human capital on economic growth for a very long time. Lucas (1988) and Mankiw et al. (1992), for instance, use human capital as an accumulable input of production and thus establish that accumulation of human capital drives economic growth. Nelson and Phelps (1966) argue that education drives innovation and thus technological improvement and adoption, and Benhabib and Spiegel (1994, 2005) are good examples of the empirical interpretation of the arguments in Nelson and Phelps (1966). Cross-country growth regressions, however, tend to show that changes in educational attainment are not robustly related to economic growth (see, for example, Benhabib and Spiegel 1994; Pritchett 1997). Several reasons can be found in the literature to explain this counterintuitive and surprising result. Outliers are deemed responsible by Temple (1999) and most of the literature attributes the existence of the puzzle to deficiencies in the human capital data (see Krueger and Lindahl 2001; De la Fuente and Domenech 2006; Cohen and Soto 2007).

(2007) show that the age-structured education data can explain differences in income per capita across countries better than standard data bases.

[2]In a recent study, Castelló-Climent (2007) showed that educational distribution is positively related to democracy, which is a strong indicator of political stability in the economy. It can be argued that political stability allows for better forecasts of income growth by minimizing the probability of structural breaks in the relationship between economic growth and institutional and structural variables.

A clearly differentiated stream of literature has established the importance of demographic factors and age structure on economic growth processes. Lindh and Malmberg (2007) and Bloom et al. (2007) are recent examples of empirical studies that have established the importance of age-structure information for better growth forecasts (see also Lindh and Malmberg 1999 for growth regressions in the spirit of Mankiw et al. 1992).

Recently, Lutz et al. (2007) constructed a new dataset of educational attainment by age groups for most countries in the world at five-year intervals for the period 1970-2000. Demographic back-projection methods were used in order to recover the age/education pyramid of each country, taking into account differential mortality and migration by both age groups and educational attainment. The back-projection exercise was carried out as a joint effort by the International Institute for Applied Systems Analysis (IIASA) and the Vienna Institute of Demography (VID) of the Austrian Academy of Sciences, so we refer to this dataset as the IIASA-VID data. Lutz et al. (2007) provide a detailed account of all the specific assumptions that had to be made as part of this reconstruction exercise, discuss their plausibility and provide sensitivity analysis. The back-projection method starts with an empirical distribution of the population by age, sex and four categories of educational attainment (no formal education, some primary, completed lower secondary, completed first level of tertiary) for each country in the year 2000. These data mostly stem from national censuses or Demographic and Health Surveys (DHS). The proportions with different education levels in five-year age groups of men and women for the past decades were recovered by imposing several assumptions on the differences in mortality and migration across age groups and educational levels, and matching the data with the historical data from United Nations (2005), which provides estimates of the age and sex structure in five-year intervals since 1950 for every country in the world. Lutz et al. (2007) provide a detailed analysis on the reconstruction of the dataset.

This new dataset allows us to assess the importance of the interaction of the demographic and educational characteristics of a society on income growth at the macroeconomic level. The results of Crespo Cuaresma and Lutz (2007) and Crespo Cuaresma and Mishra (2007) point at the capital importance of assessing the demographic dimension of education data when explaining cross-country differences in income, income growth and economic growth externalities.

3 Growth regressions: Model uncertainty, selection and averaging

When constructing empirical models of economic growth, the issue of model uncertainty is of singular importance, due to what Brock and Durlauf (2001) dub the "open-endedness" of the theories of economic growth. Based on different theoretical models, many different economic, social and political variables have been proposed as important determinants of economic growth. Durlauf and Quah (1999), for instance, name more than 80 variables that have been included at least once in a cross-country growth regression. Durlauf et al. (2005) update this list using more recent references, leading to over 150 variables which have been used as potential determinants of economic growth in empirical studies.

Recent developments in model averaging allow to assess the robustness of different competing variables as robust determinants of economic growth. The methods used to assess the robustness of covariates in growth regressions used by Levine and Renelt (1992) and Sala-i-Martin (1997a, 1997b) rely on models of a given size. More sophisticated (Bayesian) model averaging methods allow to account for model uncertainty both in the size of the model and in the choice of explanatory variables (for applications to economic growth, see, for example, Fernández et al. 2001; Sala-i-Martin et al. 2004; Crespo Cuaresma and Doppelhofer 2007).

Ignoring model uncertainty can result in strong biases in parameter estimates and incorrect standard errors (see Draper 1995). Model averaging techniques consider model specification itself to be an unobservable that needs to be estimated, and therefore it is treated as an extra parameter whose distribution can be obtained based on data (and prior information, if the approached used is Bayesian, as here).

The idea behind BMA can be easily put forward in a linear setting. Consider a set of $\bar{N}$ variables, $\mathbf{X}_{it}$, evaluated at time t for country i, which are potentially (linearly) related to economic growth in country i for the period t to $t+\tau$, so that the stylized specification considered is

$$y_{it+\tau} - y_{it} = \alpha + \sum_{k=1}^{n} \beta_k x_{k,it} + \varepsilon_{it}, \tag{1}$$

where y_{it} refers to the log of GDP per capita in country i at time t, $x_1, \ldots, x_n$ are n variables which belong to the set $\mathbf{X}$ and ε is an error term assumed uncorrelated across cross-sectional units and in time, with constant variance σ^2. When dealing with model uncertainty, the size of the model, n and the identity of the regressors in (1) are not assumed to be known, and are treated as objects to be estimated.

In the situation put forward above, there are $2^{\bar{N}}$ possible combinations of the variables, each one defining a model M_i. Assuming a diffuse prior with respect to σ and the usual multivariate normal priors on the β parameter vector, the odds ratio for two competing models, M_0 and M_1, can be approximated when the priors on β approach a diffuse prior (see Leamer 1978; Schwarz 1978) as

$$\frac{P(M_0|Y)}{P(M_1|Y)} = \frac{P(M_0)}{P(M_1)} T^{(k_0-k_1)/2} \left(\frac{SSE_0}{SSE_1}\right)^{-T/2}, \tag{2}$$

where k_i is the size of model i, T is the sample size, $P(\cdot|Y)$ refers to posterior probabilities and SSE_i is the sum of squared residuals from the estimation of model i. Therefore, given our model space $\mathcal{M}$ the posterior probability of model i can be computed as

$$P(M_i|Y) = \frac{P(M_i) T^{-k_i/2} SSE_i^{-T/2}}{\sum_{j=1}^{card(\mathcal{M})} P(M_j) T^{-k_j/2} SSE_j^{-T/2}}. \tag{3}$$

The posterior model probabilities allow us to easily compute the first and second moment of the posterior densities of the parameters in (1), given by

$$E(\beta_j|Y) = \sum_{l=1}^{card(\mathcal{M})} P(M_l|Y) E(\beta_j|Y, M_l) \tag{4}$$

and

$$
\begin{aligned}
\mathrm{var}(\beta_j|Y) \quad = & \sum_{l=1}^{card(\mathcal{M})} P(M_l|Y)\mathrm{var}(\beta_j|Y, M_l) + \\
& + \sum_{l=1}^{card(\mathcal{M})} P(M_l|Y)(E(\beta_j|Y, M_l) - E(\beta_j|Y))^2
\end{aligned} \tag{5}
$$

where β_j is the parameter of interest and $E(\beta_j|Y, M_l)$ is the OLS estimator of β_j for the constellation of **X**- variables implied by model M_l. The unconditional expectation of β_j is thus given by the weighted average of the estimates conditional in a model, where the weights are the posterior probabilities that the model is the right one. The posterior probability that a given **X**-variable is part of the true regression model can be computed as the sum of posterior model probabilities of those models containing the variable of interest.

Alternatively, instead of averaging over the whole model space, the model with the highest posterior probability could be selected and inference and prediction could be based on this single model. Assuming equal prior probabilities over models, this implies choosing the model which minimizes the Schwarz information criterion (Bayesian information criterion, Schwarz 1978) among all models in $\mathcal{M}$. The chosen model is thus the one that maximizes

$$BIC_i = T^{-k_i/2} SSE_i^{-T/2}.$$

Recently, some alternative strategies have been put forward to obtain weights for model averaging. In particular, model averaging based on the out-of-sample (OS) predictive likelihood instead of in-sample fit has been recently proposed by Kapetanios et al. (2006) and Crespo Cuaresma (2007), for instance. In practice, this amounts to replacing the in-sample residuals by out-of-sample forecasting errors in (2) and (3) when computing the corresponding sum of squared errors. The forecasting errors are obtained from the estimation of each model on a sub-sample of the available data, which is used in order to predict the remaining sample.

Yang (2001, 2003) presents a method called *adaptive regression by mixing* (ARM) for combining models. Applied to forecasts, the weights assigned to predictions from each model are computed as follows: (a) The dataset is split in two parts (assumed of equal size), and the different models are estimated for the first part of the sample; (b) for each of the fitted models, predictive accuracy is measured based on forecasts for the second part of the sample as the sum of squared prediction errors ($SSPE$); and (c) the weight for the prediction of model i is given by

$$w_i = \frac{\hat{\sigma}_i^{-T/2} \exp(-\hat{\sigma}_i^{-2} SSPE_i/2)}{\sum_{j=1}^{card(\mathcal{M})} \hat{\sigma}_j^{-T/2} \exp(-\hat{\sigma}_j^{-2} SSPE_j/2)}, \tag{6}$$

where $\hat{\sigma}_i$ is the estimate of σ under model i.

In many applications, the cardinality of the model space poses a severe limit to the computational feasability of the expressions above. Several methods can be used in order to approximate the expressions when the size of the model space makes the problem intractable. The *leaps and bounds* algorithm, the use of Markov chain Monte Carlo model composite (MC^3) methods or the use of Occam's window are possible methods of setting bounds to the number of models to be evaluated when computing the posterior objects (see, for example, Madigan and York 1995; Raftery 1995; Raftery et al. 1997). In the empirical application put forward in this study, however, the size of the model space allows us to compute all models in the model space in a relatively short time.

4 Forecasting exercise

In this section we assess the potential improvement from using age-structured education data in forecasting economic growth. We will consider the additional set of (time-varying) covariates found to be robust (in-sample) determinants of economic growth by Sala-i-Martin et al. (2004) as potential (extra) predictors of growth in a linear regression setting.[3] The set has been augmented by data on fertility rates, so as to control for pure demographic factors when assessing the role of the demographic dimension of human capital data. We will consider panel regressions where the dependent variable is the growth rate of GDP per capita over a five-year period and the explanatory variables are evaluated at the first year of the sub-period. The models considered include in all cases country-specific fixed effects and common period effects. This implies that we are concentrating on the forecasting abilities of *within-country* changes in the variables considered; that is, we consider the predictive content of differences in the time dimension, and not in the cross-country dimension. The countries included in the sample are given in Table 1. Table 2 presents the description of the (non human capital) variables which are included in the exercise and their respective sources. Table 3 shows the mean and standard deviation across countries in the sample for each five-year subperiod.

Table 4 presents the different education variables considered in this study. The benchmarks are given by the Barro-Lee schooling variables (Barro and Lee 1996). The IIASA-VID dataset allows us to construct variables taking into account the demographic dimension of human capital. The variables which are considered as potential predictors for income growth are the following: the proportion of the working-age population in the age group g with primary education ($\mathbf{E}_1^g$); the proportion of the working-age population in the age group g with secondary education ($\mathbf{E}_2^g$); and the proportion of the working-age population in the age group g with tertiary education ($\mathbf{E}_3^g$).[4] These variables are evaluated for the age groups g=15-20, 20-25, 25-30, 30-35, 35-40, 40-45, 45-50, 50-55, 55-60, 60-65.

Descriptive statistics of these variables and the Barro-Lee schooling variable are presented in Table 5. The difficulties reported in empirical applications in finding a robust correlation between additions to the human capital stock and growth in GDP per capita have led other authors to rely on the Nelson and Phelps (1966) paradigm and model human capital as a variable that affects the creation and adoption of new technologies (and therefore tends to be included as a determinant of total factor productivity), instead of a traditional input of production.[5] Therefore, apart from including the human capital variable as a potential determinant of eco-

[3] Similar variables were used by Bloom et al. (2007) in a similar setting (albeit without explicitly considering model uncertainty and fixed effects) to assess the forecasting ability of demographic variables for economic growth.

[4] The group with primary schooling corresponds to the population with uncompleted primary to uncompleted lower secondary schooling (corresponding to ISCED - International Standard Classification of Education - 1); the group with secondary education refers to those with completed lower secondary to uncompleted first level of tertiary (ISCED 2, 3 and 4); tertiary refers to those with at least the first level of tertiary education completed (ISCED 5, 6).

[5] See Benhabib and Spiegel (1994, 2005) for empirical examples of this branch of research.

nomic growth, the interaction between education measures and the level of development of the economy (as a proxy of the distance to the technological frontier) will also be considered as an extra regressor in the forecasting exercise.

The specification for a given combination of variables is thus given by the expression in (1), where the error term ε_{it} is assumed to be formed by a fixed cross-sectional (country) effect, a fixed time effect (common to all countries) and a random shock, assumed uncorrelated across countries and time periods. Our forecasting exercise considers eight potential variables for each education measure (the six variables of Table 2 plus a human capital variable from Table 4 and its interaction with initial GDP per capita - GDPCL). This implies that 2^8=256 models are evaluated for each one of the education variables. We will assume equal prior probability for each model, which means that the posterior model probabilities only depend on the sum of squared errors (in-sample or out-of-sample, depending on the method used) and the corresponding model size. The first five subperiods (1970-1975, 1975-1980, 1980-1985, 1985-1990 and 1990-1995) are used to obtain model-averaging weights using the different methods outlined above. The subperiod corresponding to 1995-2000 is used to evaluate the forecasts of the different methods and education variables. For the methods requiring the evaluation of out-of-sample forecasts in order to obtain model weights (BMA based on the out-of-sample predictive likelihood and ARM), the subperiod 1990-1995 is used to evaluate the predictions based on models estimated using data for the period 1970-1990.

Table 6 presents the evaluation of the different methods and human capital variables in terms of mean square forecast errors for the period 1995-2000, defined as

$$MSFE_k = \sum_{i=1}^{58}[(y_{i2000} - y_{i1995})^{f,k} - (y_{i2000} - y_{i1995})]^2/65,$$

where $(y_{i2000} - y_{i1995})^{f,k}$ is the growth forecast for the period 1995-2000 for country i using method k. The mean square forecast error is shown in the first column of Table 6 for models estimated using the Barro-Lee dataset and chosen by the Bayesian Information Criterion (BIC), for the forecasts obtained using in-sample BMA (BMA), for the forecasts obtained using BMA with out-of-sample errors instead of residuals (BMA, OS) and for the forecasts obtained using ARM (ARM). The columns corresponding to IIASA-VID variables present the ratio of the mean square forecast error of the predictions obtained using Barro-Lee data to the mean square forecast error of the predictions obtained using IIASA-VID data for each method. Values below one thus indicate a lower average forecast error of the model with IIASA-VID compared to the Barro-Lee data. The corresponding significance level of the difference between prediction errors is also presented in Table 6 for each variable and model selection/averaging method.

Analyzing the results in Table 6, some interesting features can be highlighted. If we concentrate on the column referring to Barro-Lee data, it can be noted that BMA forecasts based on in-sample residuals improve systematically over the predictions based on the choice of a single model and on BMA forecasts based on out-of-sample forecast errors (both using weights based on BIC and on ARM). It is only the case of models estimated on data for tertiary education that out-of-sample BMA improves over the single model chosen by BIC, although the standard BMA performs best in terms of prediction accuracy. Given the relatively short time dimension of the panel used, the out-of-sample prediction-based weights are only based in a subperiod and may thus lead to weighting schemes which are "noisy" compared to those constructed upon in-sample fit.

Comparing the results of age-detailed and aggregated (Barro-Lee) data for each education category, some differences appear. In the case of primary education, there is no relevant improvement from using data for education of different age groups. The only case of significant better forecasting ability by using age detail corresponds to the ARM method (age group 45-50), which tends to perform worse than all other methods for this education category. This result is reinforced by the fact that the method with the best forecasting ability in this education category is BMA for Barro-Lee data without age structure. For secondary education, the results indicate that the use of age-structured education data significantly improves economic growth forecasts.

The best forecasting ability in this education category is achieved by BMA forecasts with secondary education data corresponding to the age group 35-40. For this averaging method, significant improvements appear when data for the age groups in the interval 30-55 are used. This result reinforces the conclusions in Lutz et al. (2008), who find secondary education in older age groups (over 40) to be a robust determinant of economic growth using a production function approach. This result can be interpreted (see also Lutz et al. 2008) as highlighting the channel of technological progress based on imitation and adoption of new foreign technologies, for which secondary education can be thought of as the most relevant education level. Statistically significant improvements are also found for other model averaging methods by using age-disaggregated information in the case of secondary education. Similarly, significant improvements are found in forecasting ability when using age-disaggregated data for tertiary education attainment ratios.

Overall, the results eke out the importance of considering the demographic dimension of human capital (in particular, education) when forecasting income growth in the framework of techniques which assess model uncertainty in economic growth regressions.

5 Conclusion

In this paper we exploit for the first time age-structured educational attainment data for economic growth forecasting. Using pooled cross-country data from 58 countries over the period 1970-2000, divided into five-year subperiods, we explicitly assess the issue of model uncertainty by considering model-averaged predictions. From a theoretical point of view, the differences across countries and in time of age-structured educational attainment should affect economic growth, on the one hand, because of different productivity patterns across age groups, and on the other hand, by affecting technology adoption and convergence to the global technological frontier.

Our results indicate that forecast averaging and exploiting the demographic dimension of education data improve economic growth forecasts significantly. In particular, the effects are significant and systematic when using data on secondary and tertiary education by age groups.

These results enlarge and complement those obtained hitherto concerning the importance of demographic variables as predictors of income growth and the differential effect of educational attainment across age groups on economic growth. The characteristics of the new IIASA-VID dataset make it an extremely useful instrument to identify and exploit such effects in estimation and prediction in the framework of economic growth models.

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Table 1: Countries in the sample

Argentina	Jordan
Australia	Kenya
Austria	Malawi
Bahrain	Malaysia
Belgium	Mali
Benin	Mauritius
Bolivia	Mexico
Brazil	Mozambique
Cameroon	Nepal
Canada	Netherlands
Central African Republic	New Zealand
Chile	Nicaragua
Colombia	Niger
Costa Rica	Norway
Cyprus	Pakistan
Denmark	Panama
Dominican Republic	Paraguay
Ecuador	Peru
El Salvador	Philippines
Finland	Poland
France	Portugal
Germany	Rwanda
Ghana	Singapore
Greece	South Africa
Guatemala	Spain
Haiti	Sri Lanka
Honduras	Sweden
Hungary	Switzerland
India	Thailand
Indonesia	Togo
Ireland	Turkey
Italy	Zimbabwe
Japan	

Table 2: Description of regressors: Common variables

Short Name	Variable Description	Source
GROWTH	Growth of GDP per capita	Penn World Table 6.2 (Heston et al. 2006)
at PPP (five-year subperiod)		
IPRICE	Investment Price	Penn World Table 6.2 (Heston et al. 2006)
GDPCL	Log GDP per capita	Penn World Table 6.2 (Heston et al. 2006)
OPEN	Trade over GDP	Penn World Table 6.2 (Heston et al. 2006)
FERT	Fertility Rate	World Development Indicators 2006 (World Bank 2006)
LIFE	Life Expectancy	World Development Indicators 2006 (World Bank 2006)
GVR	Government Consumption Share	Penn World Table 6.2 (Heston et al. 2006)

Table 3: Descriptive statistics: Common variables

Variable	Mean (std. dev.) 1970-1975	Mean (std. dev.) 1975-1980	Mean (std. dev.) 1980-1985	Mean (std. dev.) 1985-1990	Mean (std. dev.) 1990-1995	Mean (std. dev.) 1995-2000
GROWTH	0.025	0.027	0.003	0.014	0.012	0.022
	(0.027)	(0.025)	(0.026)	(0.029)	(0.026)	(0.017)
IPRICE	69.375	87.614	95.330	71.175	83.120	83.347
	(44.770)	(43.233)	(49.929)	(33.210)	(33.115)	(29.666)
GDPCL	8.288	8.412	8.546	8.563	8.633	8.691
	(0.981)	(1.011)	(1.011)	(1.046)	(1.085)	(1.124)
OPEN	52.027	52.745	58.276	53.517	62.792	73.514
	(42.034)	(38.315)	(41.717)	(36.370)	(46.339)	(52.452)
FERT	4.837	4.464	4.173	3.854	3.568	3.252
	(2.030)	(2.079)	(2.093)	(2.035)	(1.859)	(1.737)
LIFE	59.849	61.735	63.591	65.193	66.279	67.033
	(10.896)	(10.539)	(10.221)	(10.110)	(10.776)	(11.460)
GVR	13.255	14.239	14.607	15.412	15.087	14.753
	(4.958)	(5.463)	(5.468)	(5.983)	(5.675)	(5.257)

The descriptive statistics for GROWTH refer to the corresponding subperiod. All other variables are evaluated in the first year of the subperiod.

Table 4: Description of regressors: Human capital variables

Short Name	Variable Description	Source
LP15	Percentage of "primary school attained" (persons over 15) in total population	Barro-Lee dataset (Barro and Lee 2001)
$\mathbf{E}_1^g$	Percentage of "primary school attained" in age group g in working age population (ISCED 1), g=15-20, 20-25,...,60-65	IIASA-VID dataset (Lutz et al. 2007)
LS15	Percentage of "secondary school attained" (persons over 15) in total population	Barro-Lee dataset (Barro and Lee 2001)
$\mathbf{E}_2^g$	Percentage of "secondary school attained" in age group g in working age population (ISCED 2,3,4), g=15-20, 20-25,...,60-65	IIASA-VID dataset (Lutz et al. 2007)
LH15	Percentage of "tertiary school attained" (persons over 15) in total population	Barro-Lee dataset (Barro and Lee 2001)
$\mathbf{E}_3^g$	Percentage of "tertiary school attained" in age group g in working age population (ISCED 5,6), g= 20-25,...,60-65	IIASA-VID dataset (Lutz et al. 2007)

Table 5: **Descriptive statistics: Human capital variables**

Variable	Mean (std. dev.) 1970-1975	Mean (std. dev.) 1975-1980	Mean (std. dev.) 1980-1985	Mean (std. dev.) 1985-1990	Mean (std. dev.) 1990-1995	Mean (std. dev.) 1995-2000
LP15	0.415	0.412	0.391	0.393	0.379	0.366
	(0.203)	(0.185)	(0.165)	(0.154)	(0.141)	(0.132)
LS15	0.200	0.214	0.254	0.266	0.292	0.302
	(0.170)	(0.165)	(0.165)	(0.167)	(0.166)	(0.163)
LH15	0.034	0.048	0.060	0.072	0.087	0.105
	(0.040)	(0.055)	(0.067)	(0.072)	(0.083)	(0.092)
$\mathbf{E}_1^{15-20}$	0.071	0.068	0.064	0.060	0.056	0.053
	(0.044)	(0.043)	(0.042)	(0.042)	(0.042)	(0.042)
$\mathbf{E}_1^{20-25}$	0.052	0.052	0.049	0.045	0.041	0.038
	(0.034)	(0.035)	(0.034)	(0.033)	(0.032)	(0.031)
$\mathbf{E}_1^{25-30}$	0.045	0.045	0.044	0.041	0.038	0.035
	(0.028)	(0.028)	(0.029)	(0.028)	(0.027)	(0.026)
$\mathbf{E}_1^{30-35}$	0.039	0.038	0.038	0.038	0.035	0.033
	(0.024)	(0.023)	(0.023)	(0.024)	(0.024)	(0.023)
$\mathbf{E}_1^{35-40}$	0.035	0.034	0.033	0.033	0.032	0.031
	(0.022)	(0.020)	(0.019)	(0.019)	(0.020)	(0.020)
$\mathbf{E}_1^{40-45}$	0.031	0.030	0.029	0.028	0.028	0.028
	(0.022)	(0.019)	(0.018)	(0.017)	(0.017)	(0.018)
$\mathbf{E}_1^{45-50}$	0.028	0.027	0.026	0.025	0.024	0.025
	(0.022)	(0.020)	(0.017)	(0.016)	(0.015)	(0.015)
$\mathbf{E}_1^{50-55}$	0.022	0.024	0.024	0.022	0.022	0.021
	(0.020)	(0.020)	(0.018)	(0.015)	(0.014)	(0.013)
$\mathbf{E}_1^{55-60}$	0.020	0.019	0.021	0.020	0.019	0.019
	(0.022)	(0.018)	(0.019)	(0.016)	(0.014)	(0.013)
$\mathbf{E}_1^{60-65}$	0.017	0.017	0.016	0.018	0.018	0.017
	(0.021)	(0.020)	(0.016)	(0.017)	(0.015)	(0.013)
$\mathbf{E}_2^{15-20}$	0.070	0.077	0.083	0.085	0.085	0.086
	(0.039)	(0.040)	(0.039)	(0.037)	(0.035)	(0.033)
$\mathbf{E}_2^{20-25}$	0.058	0.067	0.074	0.079	0.082	0.080
	(0.037)	(0.035)	(0.034)	(0.031)	(0.029)	(0.026)
$\mathbf{E}_2^{25-30}$	0.038	0.047	0.053	0.059	0.064	0.066
	(0.028)	(0.032)	(0.030)	(0.029)	(0.028)	(0.026)
$\mathbf{E}_2^{30-35}$	0.028	0.032	0.039	0.043	0.049	0.053
	(0.025)	(0.026)	(0.028)	(0.027)	(0.027)	(0.026)
$\mathbf{E}_2^{35-40}$	0.023	0.025	0.029	0.035	0.040	0.045
	(0.024)	(0.024)	(0.025)	(0.028)	(0.026)	(0.027)
$\mathbf{E}_2^{40-45}$	0.020	0.021	0.023	0.027	0.033	0.037
	(0.025)	(0.023)	(0.024)	(0.024)	(0.027)	(0.026)
$\mathbf{E}_2^{45-50}$	0.017	0.018	0.019	0.021	0.025	0.030
	(0.026)	(0.024)	(0.022)	(0.023)	(0.024)	(0.027)
$\mathbf{E}_2^{50-55}$	0.013	0.016	0.017	0.018	0.020	0.023
	(0.022)	(0.024)	(0.023)	(0.021)	(0.022)	(0.023)
$\mathbf{E}_2^{55-60}$	0.012	0.011	0.014	0.015	0.016	0.018
	(0.024)	(0.020)	(0.023)	(0.021)	(0.020)	(0.021)
$\mathbf{E}_2^{60-65}$	0.011	0.011	0.010	0.013	0.014	0.015
	(0.023)	(0.022)	(0.019)	(0.020)	(0.019)	(0.019)

$\mathbf{E}_3^{20-25}$	0.003	0.004	0.004	0.005	0.005	0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
$\mathbf{E}_3^{25-30}$	0.007	0.009	0.011	0.012	0.013	0.013
	(0.006)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
$\mathbf{E}_3^{30-35}$	0.007	0.010	0.013	0.015	0.016	0.018
	(0.006)	(0.008)	(0.011)	(0.012)	(0.012)	(0.013)
$\mathbf{E}_3^{35-40}$	0.005	0.007	0.009	0.012	0.014	0.015
	(0.005)	(0.006)	(0.008)	(0.010)	(0.011)	(0.012)
$\mathbf{E}_3^{40-45}$	0.004	0.005	0.006	0.008	0.011	0.013
	(0.005)	(0.005)	(0.006)	(0.008)	(0.010)	(0.011)
$\mathbf{E}_3^{45-50}$	0.003	0.004	0.005	0.006	0.007	0.010
	(0.004)	(0.004)	(0.005)	(0.006)	(0.007)	(0.010)
$\mathbf{E}_3^{50-55}$	0.002	0.003	0.004	0.004	0.005	0.007
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)
$\mathbf{E}_3^{55-60}$	0.002	0.002	0.003	0.003	0.004	0.005
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
$\mathbf{E}_3^{60-65}$	0.001	0.002	0.002	0.002	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)

Table 6: Forecasting results

	$MSFE$	Ratio of $MSFE$ with Barro-Lee data to $MSFE$ with IIASA-VID data									
	LP15	$\mathbf{E}_1^{15-20}$	$\mathbf{E}_1^{20-25}$	$\mathbf{E}_1^{25-30}$	$\mathbf{E}_1^{30-35}$	$\mathbf{E}_1^{35-40}$	$\mathbf{E}_1^{40-45}$	$\mathbf{E}_1^{45-50}$	$\mathbf{E}_1^{50-55}$	$\mathbf{E}_1^{55-60}$	$\mathbf{E}_1^{60-65}$
$MSFE_{BIC}$	4.36	1.14	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06
$MSFE_{BMA}$	*4.26*	1.13	1.01	1.01	1.01	1.01	1.00	1.01	1.01	1.02	1.01
$MSFE_{BMA,OS}$	4.61	1.02*	1.00	1.00	0.99	0.99	0.99	0.99	0.99	1	0.99
$MSFE_{ARM}$	5.4	1.11**	1.04***	1.03**	1.02*	1.02	0.97	0.98*	0.98	0.99	0.96
		Ratio of $MSFE$ with Barro-Lee data to $MSFE$ with IIASA-VID data									
	LS15	$\mathbf{E}_2^{15-20}$	$\mathbf{E}_2^{20-25}$	$\mathbf{E}_2^{25-30}$	$\mathbf{E}_2^{30-35}$	$\mathbf{E}_2^{35-40}$	$\mathbf{E}_2^{40-45}$	$\mathbf{E}_2^{45-50}$	$\mathbf{E}_2^{50-55}$	$\mathbf{E}_2^{55-60}$	$\mathbf{E}_2^{60-65}$
$MSFE_{BIC}$	4.65	1.00	1.20	1.16	1.00	1.00	1.00	1.00	1.00	1.00	1.00
$MSFE_{BMA}$	4.36	1.02	1.27	1.12	0.99*	*0.93**	0.97**	0.99***	0.99***	0.99	1
$MSFE_{BMA,OS}$	4.83	0.95**	0.95**	0.96*	0.95**	0.95**	0.95**	0.97	0.95**	0.95**	0.96**
$MSFE_{ARM}$	5.73	0.94**	1.04	1.03	0.89**	0.91***	0.94	0.99	0.96	0.95*	0.97
		Ratio of $MSFE$ with Barro-Lee data to $MSFE$ with IIASA-VID data									
	LH15	$\mathbf{E}_3^{15-20}$	$\mathbf{E}_3^{20-25}$	$\mathbf{E}_3^{25-30}$	$\mathbf{E}_3^{30-35}$	$\mathbf{E}_3^{35-40}$	$\mathbf{E}_3^{40-45}$	$\mathbf{E}_3^{45-50}$	$\mathbf{E}_3^{50-55}$	$\mathbf{E}_3^{55-60}$	$\mathbf{E}_3^{60-65}$
$MSFE_{BIC}$	4.65	-	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00
$MSFE_{BMA}$	4.30	-	*0.94*	1.01**	0.97	0.97	0.95	0.96**	0.97**	0.96	0.98
$MSFE_{BMA,OS}$	4.58	-	1.00	1.01	1.00***	1.00*	1.00*	1.00	1.00	1.00*	1.00*
$MSFE_{ARM}$	5.46	-	0.98	1.02	1.00	0.97	1.02*	1.00	0.98	1.00	1.00

Mean square forecast errors multiplied by 10^4. *[**](***) indicates that the forecast error measures are significantly different at the 10% [5%] (1%) level. Figures in italics correspond to the minimum forecast error in each category.