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 of 65 countries over six five-year periods (1970-2000) and 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 improves economic growth forecasts significantly.

Keywords: Economic growth, education data, forecasting, adaptive regression, Bayesian model averaging.

JEL classification: C11, C23, C52, C53, O50.

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1 Introduction

Recent theoretical (e.g., Boucekkine et al., 2002) and empirical (e.g., Birdsal, et al. 2001, and Azoamhou and Mishra, 2007) advances in the economic growth literature decisively demonstrates that age-structure variations exert discernible effect 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 Benhabib and Spiegel, 1994, Pritchett, 2001 and Krueger and Lindahl, 1999, for instance). 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 and 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 which is useful for economic growth forecasts, age-structured human capital information, by disentangling "quantity" and "quality" effects, can lead to further improvements.[2]

[1] Description of the dataset and its qualities can be found in Lutz et al (2007). Lutz and Crespo-Cuaresma (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, Castello-Climent (2008) 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.

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 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 in-sample model averaged parameter estimates. 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 since long ago studied the long-run effects of human capital on economic growth. 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 or Pritchett, 1997). Several reasons have been put forward in the literature in order 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, and Cohen and Soto, 2007).

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-years 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 will 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 each age group 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 a capital importance of assessing the demographic dimension of education data when explaining cross-country differences in income, income growth and economic growth externalities.

We aim at evaluating the role of age-structured education data as an economic growth predictor. At a fundamental level, it is clearly understood in the literature that disaggregates provide more micro and dynamic information than the aggregate. For instance Granger (1980) and Hosking (1981), among others showed that aggregation smoothes out individual dynamics and very often the specific observed pattern of an aggregate series renders hard interpretation due to inherent mix of complexity. In our case, significance of education level for adult population can be better understood if interpreted at the level of individual age group than at the aggregate level.

It follows from two well-grounded economic theoretic reasons. The first one concerns the enhanced efficiency in labor due to the introduction of education at various ages or life cycle of the adult population. The whole adult population reflects only the aggregate characteristics of the impacts of education on economic growth while the dynamics can be distinctly observed at disaggregated adult population, i.e., at education levels of various age groups of the whole adult population. The second reason concerns the fact that certain individual adult age groups tend to contribute more to economic growth by way of gaining efficiency through education at earlier stage, accumulating them overtime and being able to innovate at later stage. It also enables faster diffusion of a new idea/technology through evolution of twin processes of adaptability and adoptability. On the whole, the significance education level at certain individual adult population reflects the required delay in productive ability contributing to economic growth. In general it is understood that the introduction of education at earlier stages of adulthood contributes more to economic growth than at later stage simply because the role of education to economic growth requires completion of certain necessary stages. That is, once an adult receives education, it takes time to create resources because of the requirement of assimilation and adaptation time of an adult population. This micro dynamic effect of education on the adult population may turn to be statistically insignificant due to the common problem of aggregation.

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.

While the typical approach to forecasting extracts a single model (or a small group of models) from the set of regressors, this implies ignoring uncertainty about the nature of the model itself in terms of choice of variables. Especially in empirical economic growth models, uncertainty is severe enough as for different models to be sensible choices in terms of fit and diagnostic checks. 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 (see for example Fernández et al., 2001, Sala-i-Martin et al., 2004, or Crespo Cuaresma and Doppelhofer, 2007, for applications to economic growth).

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, and Schwarz, 1978)[3] 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

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

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 $\mathbf{X}$- 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 $\mathbf{X}$-variable is part of the true regression model can be computed as

[3] Fernández et al. (2001) show that even if the shocks of the true model are not normally distributed, the posterior distribution of Bayesian model averaged statistics derived on the basis of Bayes factor is still consistent.

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 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, and Raftery et al., 1997). In the empirical application put forward in this study, however, the size of the model space is tractable and allows us to compute all models in the model space in a relatively short time.

To sum up, we assess the issue of model uncertainty in economic growth regressions in four different ways: model selection, BMA using in-sample explanatory power, BMA using out-of-sample explanatory power and ARM. In this last case, the predictions from different models are weighted using statistics which rely on both in-sample and out-of-sample measures of fit. The use of such a range of techniques allows us to investigate the role of model uncertainty in economic growth predictions.

4 Forecasting exercise: Do age-structured education data matter?

4.1 Out-of-sample prediction: The role of education and demography

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.[4] 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 and Table 3 shows the mean and standard deviation across the 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).[5] The IIASA/VID dataset allows us to construct variables taking into account the age dimension of human capital. The variables which are considered as potential predictors for income growth are the following: proportion of working age population in the age group g with primary education ($\mathbf{E}_1^g$), proportion of working age population in the age group g with secondary education ($\mathbf{E}_2^g$) and proportion of working age population in the age group g

[4] Similar variables were used by Bloom et al. (2007) in a comparable setting (albeit without explicitly considering model uncertainty and fixed effects) to assess the forecasting ability of demographic variables for economic growth. It should be noticed that the setting in Sala-i-Martin et al. (2004) is based on cross-country regressions (without time dimension). In our case, where the data is a panel based on five-year intervals, we are therefore able to use country fixed effects which account for time-invariant unobserved heterogeneity. This means that we concentrate on variables with time variation (some other variables which appear robust in Sala-i-Martin et al., 2004, are dummy variables or covariates which proxy initial conditions, for instance, which in our case are captured by the fixed effects).

[5] Admittedly, the Barro-Lee dataset has been shown to contain serious errors (see De la Fuente and Domenech, 2006). We decided to use it as a benchmark in our analysis instead of the Cohen-Soto or De la Fuente-Domenech datasets for several reasons. First of all, it has been the most widely used education dataset in economic growth studies. Furthermore, its five-year periodicity (as compared to Cohen and Soto's 10-year periods) makes it suitable for our prediction purposes, where constraints in the time dimension of the dataset play an important role concerning the type of model averaging that can be implemented. Although the de la Fuente-Domenech dataset is clearly superior in quality to the Barro-Lee data, it is only available for OECD countries, and our aim is to assess also the degree of heterogeneity between high and low-income countries.

with tertiary education ($\mathbf{E}_3^g$).[6] 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.[7] Therefore, apart from including the human capital variable as a potential determinant of economic 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.

On the other hand, the effect of improvements in educational attainment in a given cohort is necessarily modulated by the relative size of the cohort with respect to the working age population. We thus add also a variable measuring the ratio of the corresponding cohort whose educational attainment is being measured, as well as the interaction between the size and educational attainment of the age group. This implies that four different variables related to human capital accumulation are considered in the forecasting exercise: the educational attainment of a given age group, the relative size of the age group with respect to working age population, the interaction of educational attainment with the income level of the respective country and the interaction of educational attainment with the size of the age group. For the exercises including Barro-Lee variables which span the whole working age population, we use the ratio of working age population (15 to 64) over total population over 15 as the age-group size variable.

The specification for a given combination of variables is thus given by the expression in (1). The error term ε_{it} is assumed to have the form

$$\varepsilon_{it} = \rho_i + \lambda_t + \nu_{it},$$

where ρ_i is a fixed cross-sectional (country) effect, λ_t is a fixed time effect (common to all countries) and ν_{it} is a random shock, assumed uncorrelated across countries and time periods.[8] Our forecasting exercise considers 10 potential variables for each education measure (the 6 variables of Table 2 plus the 4 variables related to human capital accumulation described above, namely educational attainment, relative age-group size and the interactions between attainment and size, as well as between attainment and income). This implies that 2^10=1024 models are evaluated for each one of the education variables. Different alternatives to the specification of model size priors have been proposed in the literature

[6]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) and "tertiary" refers to those with at least first level of tertiary education completed (ISCED 5, 6).

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

[8]In-sample tests systematically support the use of this two-way fixed effects structure in the error.

(see Ley and Steel, 2008, for a recent assessment of the issue). Sala i Martin et al. (2004), for instance, specify prior inclusion probabilities for the variables, which are set so as to ensure a particular expected model size, while Ley and Steel (2008) propose a more flexible prior Binomial-Beta distribution on model size. In order not to subjectivize the choice of the mode in the prior distribution of model size, 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 and 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.

We first present the evaluation of the different methods and human capital variables in terms of mean square forecast errors for the period 1995-2000, defined as

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

where $(y_{i2000} - y_{i1995})^{f,k}$ is the growth forecast for the period 1995-2000 for country i using method k. Figure 1 presents, for each educational attainment level (primary, secondary and tertiary education) the ratio of the mean square forecast error of the predictions obtained using IIASA-VID data for each age group to the mean square forecast error of the predictions obtained using Barro-Lee data for each method. Values below one indicate thus a lower average forecast error of the model with IIASA-VID compared to the Barro-Lee data. The results are presented for the full sample as well as for subsamples formed by OECD and non-OECD countries. We present results for each one of the methods of dealing with model uncertainty: single model chosen by minimizing BIC (BIC), in-sample BMA (BMA), BMA with out-of-sample errors instead of residuals (BMA, OS) and mixing by ARM (ARM).

The results in Figure 1 for the full sample including developed and developing countries reveals a series of interesting features. First of all, there are sizable returns to the use of age-structured data in terms of predictive performance, in particular for secondary and tertiary education. On the other hand, the improvements tend to be concentrated on predictions based on forecast averaging, which highlights the importance of dealing with model uncertainty in economic growth regressions. The results, however, are rather different across educational attainment levels: while exploiting age-structured human capital data using BMA based on past predictive ability and ARM tend to lead to very satisfactory predictive performance for secondary school attainment data, for tertiary education the improvement is best in settings using standard BMA and inference based on a single model.

For the full sample, the best forecasts overall are obtained with the proportion of individuals with tertiary education in the age group 20-25 using BMA with weights based on in-sample explanatory power. The root mean square forecast error is roughly equal to 1.5 %, with a median root mean square error of 1.2 %. The actual average growth of the period was around 2.25 %, and the highest errors are for the usual growth miracles (Rwanda, Ireland) and disasters (Togo, Paraguay). If we exclude the 5 best and worst performers in terms of growth in the period being forecast, the root mean square error falls below 1.3 % and the median error below 0.9 %. However, a test of equality of predictive performance against models using aggregated measures of human capital is not able to reject the null hypothesis of similar forecasting accuracy. The heterogeneous group of countries in the sample being analyzed is partly responsible for this, so an analysis based on subsamples of more homogenous economies appears necessary in the context of income growth forecasting.

The second part of Figure 1 presents the results for the subsample formed by the 20 OECD economies. The differences in predictive accuracy between models with and without age detail in the educational variable are much larger in this subsample, and the improvements using primary and secondary education are concentrated in the method of BMA based on past predictive performace. This is in contrast with the results we obtained for the full sample, where BMA with weights based on out-of-sample predictive likelihoods led to systematic improvements only using data on secondary schooling. 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" in heterogeneous panels such as the one we are dealing with, so it is not surprising that the results for this method are better in a more homogeneous subsample of countries. The best predictive performance is obtained using the proportion of the 50-55 age group with tertiary education and using ARM. This method delivers an average root mean square error in this subsample which is roughly equal to 1%, significantly lower than in the full sample, compared to an average growth rate of GDP per capita in this period for the OECD economies in the sample of 2.3%, thus higher than in the full set of countries, and a standard deviation of 1.7%.

The results for non-OECD economies, presented in the third row of Figure 1, reveal systematic and widespread improvements in prediction for practically all age groups and all attainment levels. The relative improvement with respect to the aggregated data is particularly large for forecasts based on single models and in-sample standard BMA, while BMA based on predictive accuracy tends to beat the aggregated data only when using primary school attainment as a human capital variable. The global minimum in forecasting error for this subsample corresponds to standard BMA using the proportion of individuals with secondary school in the age group 50-55. The root mean squared error of the predictions using this method and variable is 2%, and a test of equality of prediction error with respect to the aggregated secondary schooling variable strongly rejects the null hypothesis of equal predictive ability, thus delivering robust evidence that for developing countries age-structured data predicts economic growth better than aggregated measures of human capital.

As an extra robustness exercise, we also performed the out-of-sample forecasting exercise without including the initial level of income as a potential explanatory variable. This should avoid possible biases based on the potential endogeneity induced by the lagged endogenous variable in the specification (see Lee et al., 1998, and Bond et al., 2001 for a detailed exposition of the problem). The results present higher forecast errors than in the design put forward above and show that the improvements in forecasting ability induced by the use of model averaging are not dependent on the inclusion of the variable that may cause endogeneity.[9]

The results of the forecasting exercise lead to a set of interesting conclusions concerning modelling economic growth with the aim of out-of-sample prediction. First, the systematic assessment of model uncertainty in growth regressions leads to sizable improvements in forecasting ability. The best predictions in the settings presented above all correspond to model-averaged forecasts, and the way in which averaging should take place appears data-dependent, with BMA and ARM being particularly promising methods for pooling of forecasts. Second, our results show that the use of disaggregated, age-structured education data improves forecasts over using aggregated education data. For industrialized countries, tertiary education of middle-aged individuals appears as a better predictor of economic growth than the corresponding aggregate measure, namely the proportion of individuals with tertiary education in the adult population. For developing countries, age-structured information on secondary school attainment of middle-aged persons are the most relevant human capital variable for economic growth forecasts.

4.2 The effect of education on growth: model-averaged estimates

The design of the forecasting exercise allows us also to obtain in-sample results about the relationship between human capital and economic growth. In particular, we can compute the posterior inclusion probability of each one of the variables in the model averaging design, which is defined as the posterior model probabilities of all specifications including a given variable. This statistic can thus be interpreted as the probability that a given variable belongs to the true model. We also compute the posterior expected value of the parameter attached to each one of the variables, as well as the posterior variance (see equations (4) and (5) above). Table 6 presents the corresponding inclusion probabilities and the ratios of posterior expectation to posterior standard deviation for the parameters, which can be interpreted as a measure of precision of the estimates, both for the OECD and non-OECD subsamples. For the interpretation of the posterior inclusion probabilities, notice that the prior inclusion probability of any variables in our setting is 0.5, since equal prior inclusion probability is assumed across all model specifications. Therefore, posterior inclusion probabilities above 0.5 imply that, after observing the data, our believe that the variable belongs in the true model has increased. In order to interpret the standarized posterior estimates of the parameter, a rule-of-thumb threshold is given by Masanjala and Papageorgiou (2008), who define those variables where the ratio of posterior mean to posterior standard deviation is above 1.3 in absolute value as "effective" covariates.

The statistics in Table 6 correspond to the settings including the educational attainment

[9] Detailed results are available from the authors upon request.

variables with best predictive performance in the forecasting exercise. For the OECD subsample, the variable is the proportion of 50-55 year-olds with tertiary education and for the non-OECD subsample it is the proportion of individuals in the age group 50-55 with secondary school. The results concerning the robustness of the estimates in Table 6 show important differences across subsamples. Convergence dynamics (parametrized by including the level of income at the beginning of the subperiod) and openness to trade appear extremely important in both subsamples as robust determinants of economic growth. The quantitative effect of openness on income growth is however only estimated with high precision in the subsample of non-OECD economies. Improvements in health, approximated by life expectancy changes, also appear as a robust growth determinant in developing countries, albeit non-effective.

The results concerning the human capital variables for OECD economies indicate that the effect of tertiary education of the 50-55 age group is modulated by the level of income, with richer economies obtaining larger returns in terms of economic growth. This result is consistent with the role of education as an engine of technological innovation in countries which are at the technological frontier, in the vein of the Nelson-Phelps hypothesis. This result concerning the role of education in the process of economic growth is further reinforced by the results in the non-OECD subsample, where the effect of education is also modulated by income in the sense that countries which are further away from the technological frontier profit more of the human capital accumulated in form of secondary education by middle-aged cohorts. This effect can be interpreted in the framework of technology adoption by developing countries which is also embodied in the Nelson-Phelps framework (see the analytical framework in Benhabib and Spiegel, 1994, 2005). Our results concerning the interaction of education and cohort size indicate that the technology adoption effect is larger in countries at early stages of progress in secondary education, where older educated cohorts are relatively small. The set of results summarized in Table 6 reinforces the conclusions in Lutz et al. (2008), who, also with the aid of age-structured data, find secondary and tertiary education to be a robust determinant of economic growth using a production function approach.

5 Conclusion

In this piece of research we exploit for the first time age-structured educational attainment data for economic growth forecasting. Using a panel comprising 65 countries over the period 1970-2000, divided in 5-year subperiods, we also asess the issue of model uncertainty explicitly by considering model-averaged predictions. From a theoretical point of view, 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 improves economic growth forecasts significantly. In particular, the effects are systematic when using data on the educational attainment of middle-aged individuals in terms of secondary and tertiary schooling. The improvements are furthermore more significant for developing economies.

The model-averaged estimates of the parameters in the specification give support to the role of education in economic growth postulated by the Nelson-Phelps hypothesis. While in highly developed countries tertiary education acts as an engine of technology innovation, secondary schooling is the key variable to technology adoption in developing countries. The distance to the technology frontier appears thus a robust determinant of the returns to education in terms of economic growth.

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)

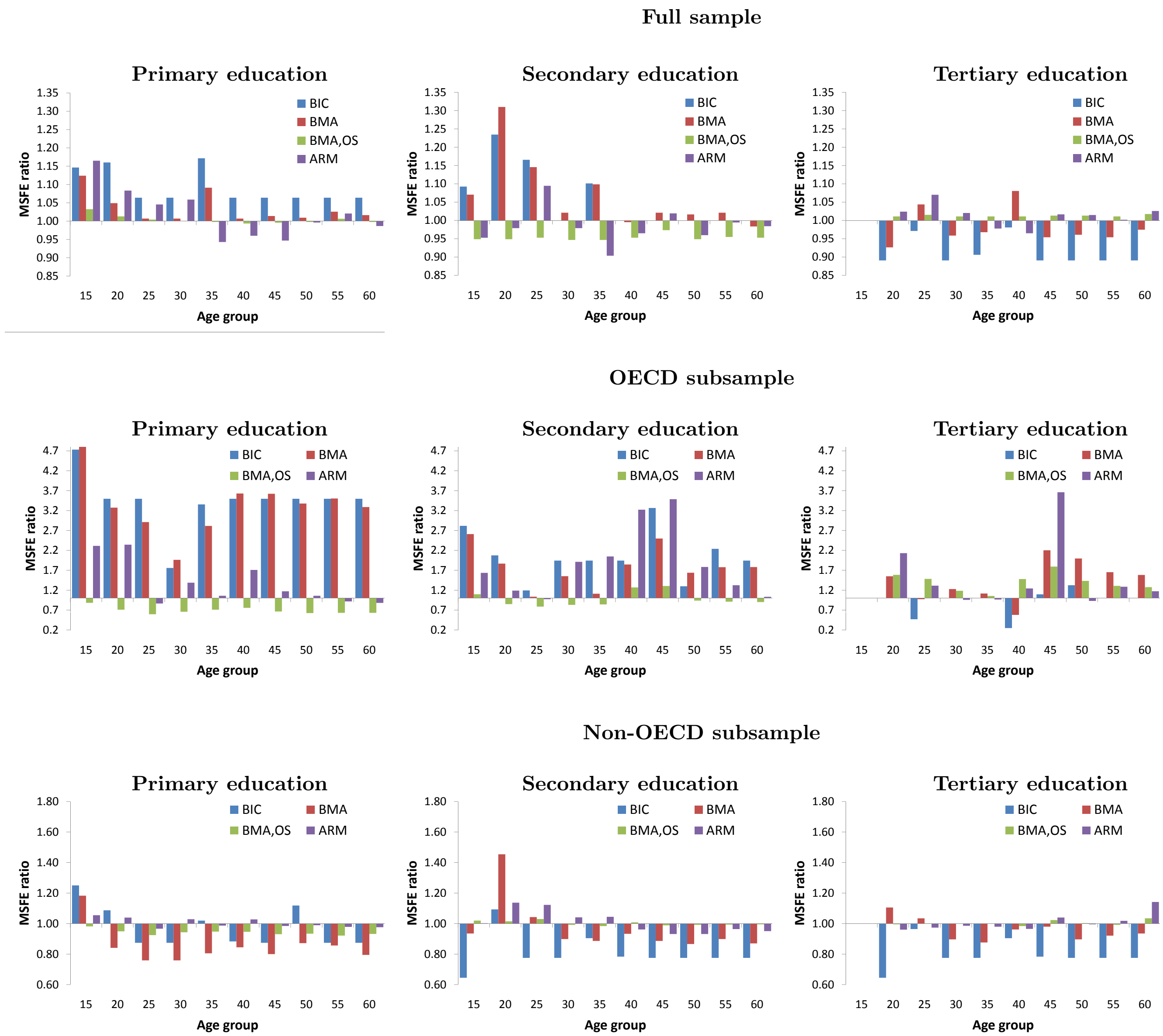

Figure 1: Mean square forecast error ratios, models without to models with age-structured data. BIC stands for "Model chosen by minimizing BIC", BMA stands for "Bayesian model averaged forecasts based on in-sample fit", BMA-OS stands for "Bayesian model averaged forecasts based on out-of-sample fit", ARM stands for "Averaged forecasts using Adaptive Regression by Mixing"

Table 6: Posterior inclusion probabilities and posterior mean-to-standard deviation ratios

	OECD sample		Non-OECD sample	
	Post. Inc. Prob.	$E(\beta_j \mid Y)/\sqrt{var(\beta_j \mid Y)}$	Post. Inc. Prob.	$E(\beta_j \mid Y)/\sqrt{var(\beta_j \mid Y)}$
IPRICE	0.131	0.137	0.480	1.099
GDPCL	1.000	-7.093	1.000	-6.712
OPEN	0.911	0.911	0.685	2.064
FERT	0.272	-0.558	0.079	-0.058
LIFE	0.166	0.581	0.686	0.646
GVR	0.167	-0.055	0.226	-0.300
Share of age group in working age pop.	0.248	0.755	0.187	-0.449
Educational attainment of age group	0.572	-2.933	0.897	3.763
Educational attainment of age group × Share of age group in working age pop.	0.198	-0.150	0.895	-4.251
Educational attainment of age group × GDPCL	0.574	3.025	0.839	-3.332

The posterior inclusion probability of each variable is computed as the sum of posterior probabilities of models including that variable. The educational attainment variable used is $\mathbf{E}_3^{50-55}$ for the OECD sample and $\mathbf{E}_2^{50-55}$ for the non-OECD sample.