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Sources of Economic Growth: A Global Perspective

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Abstract: The main goal of this paper is to determine the factors responsible for economic growth at the global level. The indication of the sources of economic growth may be an important element of the sustainable economic policy for development. The novelty of this research lies in employing an analysis based on data, which consist of an average growth rate of the Gross Domestic Product (GDP) for 168 countries for the years 2002–2013. The Bayesian model averaging approach is used to identify potential factors responsible for differences in countries' GDPs. Additionally, a jointness analysis is performed to assess the potential independence, substitutability, and complementarity of the factors of economic growth. The robustness of the results is confirmed by Bayesian averaging of classical estimates. We identify the most probable factors of economic growth, and we find that the most important determinants are variables associated with the so-called "Asian development model".

Keywords: sustainable economic policy; Bayesian model averaging; gretl; BACE

JEL Classification: C11; E17; O40

1. Introduction

This paper contributes to this important issue by examining the sources of economic growth at the global level, primarily because it is essential to understand its nature. Economic growth has been one of the most important economic issues in the literature since the 1980s (Barro and Sala-i-Martin [1], Barro and Sala-i-Martin [2], Sala-i-Martin [3], Sala-i-Martin [4], Sala-i-Martin and Snowdon [5]). The knowledge about which factors account for economic growth would make it possible to form efficient and sustainable economic policies (Armeanu et al. [6], Tvaronavičienė et al. [7], Manso et al. [8], Brock et al. [9], Kraay and Tawara [10], Musai and Mehrara [11], Bergh and Henrekson [12]). Furthermore, it could facilitate the economic growth of currently underdeveloped regions (Milczarek [13], Thomas and Brycz [14], Comes et al. [15], Sala-i-Martin [16]).

Fernández et al. [17], Fernández et al. [18] (FLS), and Sala-i-Martin et al. [19] (SDM) contributed significantly to modeling the sources of economic growth in the Bayesian approach for cross-sectional data. The FLS dataset (which covers 41 variables for 72 countries between 1960 and 1992) and SDM dataset (which covers 67 variables for 88 countries between 1960 and 1996) were later used by many authors in both replication and research papers: Eicher et al. [20] replicated FLS results by the iterative Bayesian model averaging approach; Ley and Steel [21] and Doppelhofer and Weeks [22] used FLS and SDM datasets in developing the jointness measures; Ley and Steel [23], Eicher et al. [24], and Ley and Steel [25] replicated original results with different prior assumptions; Ciccone and Jarociński [26] and Feldkircher and Zeugner [27] replicated original results by a general-to-specific approach; Dobra et al. [28] replicated FLS results using Gaussian graphical models; Magnus et al. [29] compared

SDM results with results obtained by a weighted-average least squares; Horvath [30] extended the FLS dataset by the number of Nobel prizes indicator as a potential growth determinant; Moral-Benito [31] used these datasets in a panel-data approach using Bayesian averaging of maximum likelihood estimates. Masanjala and Papageorgiou [32], Crespo-Cuaresma [33], Papageorgiou [34], and Moser and Hofmarcher [35] used 25 variables for 37 Sub-Saharan African countries from the FLS dataset to indicate determinants of growth in Africa. Their results differed from the results conducted for the entire FLS dataset. Crespo-Cuaresma et al. [36], Kwiatkowski et al. [37], Cuaresma et al. [38], and Błażejowski et al. [39] used the BMA approach in modeling sources of economic growth in European regions. León-González and Montolio [40] investigated determinants of economic growth in Spanish regions using BMA. Ali et al. [41] and Osiewalski et al. [42] used a Cobb–Douglas-type production function in modeling economic growth. León-González and Montolio [43] used BMA for panel-data to investigate the effect of foreign aid on per capita economic growth. Jones and Schneider [44] showed that human capital plays an important role in the theory of economic growth. Deller et al. [45] used BMA and estimated a neoclassical growth model using data for U.S. counties. Man [46] used 30 (mostly financial) variables for 187 countries between 1988 and 2007 to indicate determinants of economic growth. León-González and Vinayagathasan [47] used a Bayesian panel-data model averaging approach to investigate the determinants of growth in developing Asian economies. Essardi and Razzouk [48] used different approaches to investigate the relationship between human capital and economic growth in Morocco.

The main contribution of our research is an analysis of the 30 potential determinants of global economic growth in a cross-section of 168 economies with the use of the Bayesian model averaging approach. We extend the previous results presented in seminal papers written by Sala-i-Martin [3] and Fernández et al. [18], where data from 72 countries were used. Moreover, our data cover a relatively up-to-date period, from 2002–2013, while the above-mentioned research spanned the period from 1960–1992. This research is a significant extension of our previous studies presented in Błażejowski et al. [39] and Kwiatkowski et al. [37]. Our research is in line with the mainstream of studies on economic growth. We try to answer the significant question: What are the determinants of economic growth at the global level?

The analyzed period is characteristic and significant in a global economy (Pegkas [49]). Its extension generates two types of risk that could impact the results of our study. Firstly, the longer period of analysis could cause problems with comparison of the dynamic growth among a large number of economies (Puziak [50], Soylu et al. [51]). Secondly, the longer time span of the study limits the access to some of the data, potentially reducing the number of growth determinants (Capello and Perucca [52], Fazio and Piacentino [53]). Although this research may be considered "incomplete" because of its shorter time span in comparison to that used in Sala-i-Martin [3], it can still provide valuable information about the nature of the contemporary processes of economic growth (Barro et al. [54], Arvanitidis et al. [55]).

Since the explanatory power of the available theoretical framework is limited (Mankiw et al. [56], Sala-i-Martin [57]), researchers are inclined to adopt an atheoretical approach. Moreover, the high volatility of individual economic aggregates can cause difficulties in inference when employing classical econometric methods (Florax et al. [58]). To omit above-mentioned problems and to take into account a considerable number of the potential sources of economic growth, Bayesian Model Averaging (BMA) is applied. The principal role of BMA is to focus on the most probable determinants of economic growth, while ignoring those with low influence (Fernández et al. [18]).

We use the BMA code by Błażejowski and Kwiatkowski [59], which also allows the use of a jointness measure to identify relations between variables.

2. Materials and Methods

Undoubtedly, there are some specific factors responsible for the dynamics of GDP in individual economies associated with specific characteristics.

One of the questions that has to be asked is whether it is possible to identify such determinants. The MC^3 algorithm used in the BMA method, presented in the following section, makes it possible to "capture" the models and variables with the greatest explanatory power.

2.1. Data

The database developed by the authors for the purpose of this study combines statistics from several sources, namely the International Monetary Fund, the Joshua Project, the Stockholm International Peace Research Institute, and the Human Development Report. The survey takes into account a group of independent variables that represent potential factors responsible for the dynamics of GDP in 168 global economies for 2002–2013 (see Table 1). Initially, the authors attempted to develop a dataset for all economies, but due to the lack of some specific information, this task turned out to be feasible only for a limited number of countries.

Table 1. The list of economies analyzed.

Albania	Czech Republic	Korea	Russia
Algeria	Denmark	Kuwait	Rwanda
Angola	Djibouti	Kyrgyz Republic	São Tomé and Príncipe
Antigua and Barbuda	Dominica	Latvia	Saudi Arabia
Argentina	Dominican Republic	Lebanon	Senegal
Armenia	Ecuador	Lesotho	Serbia
Australia	Egypt	Libya	Seychelles
Austria	El Salvador	Lithuania	Sierra Leone
Azerbaijan	Equatorial Guinea	Luxembourg	Singapore
Bahamas	Eritrea	Madagascar	Slovak Republic
Bahrain	Estonia	Malawi	Slovenia
Bangladesh	Ethiopia	Malaysia	Solomon Islands
Barbados	Fiji	Maldives	South Africa
Belarus	Finland	Mali	Spain
Belgium	France	Malta	Sri Lanka
Belize	Gabon	Mauritania	St. Kitts and Nevis
Benin	Gambia	Mauritius	St. Lucia
Bhutan	Georgia	Mexico	St. Vincent and the Grenadines
Bolivia	Germany	Moldova	Sudan
Bosnia and Herzegovina	Ghana	Mongolia	Swaziland
Botswana	Greece	Morocco	Sweden
Brazil	Grenada	Mozambique	Switzerland
Brunei Darussalam	Guatemala	Myanmar	Tajikistan
Bulgaria	Guinea	Namibia	Tanzania
Burkina Faso	Guinea-Bissau	Nepal	Thailand
Burundi	Guyana	Netherlands	Togo
Cabo Verde	Haiti	New Zealand	Trinidad and Tobago
Cambodia	Honduras	Nicaragua	Tunisia
Cameroon	Hong Kong SAR	Niger	Turkey
Canada	Hungary	Nigeria	Uganda
Central African Republic	Iceland	Norway	Ukraine
Chad	India	Oman	United Arab Emirates
Chile	Indonesia	Pakistan	United Kingdom
China	Iran	Panama	United States
Colombia	Ireland	Papua New Guinea	Uruguay
Comoros	Israel	Paraguay	Uzbekistan
Democratic Republic of the Congo	Italy	Peru	Vanuatu
Republic of Congo	Jamaica	Philippines	Venezuela
Costa Rica	Japan	Poland	Vietnam
Côte d'Ivoire	Jordan	Portugal	Yemen
Croatia	Kazakhstan	Qatar	Zambia
Cyprus	Kenya	Romania	Zimbabwe

Economic growth may be driven by a large number of factors. A simple attempt to enumerate them may face problems with classification and indication due to the ambiguity of criteria. The explanatory variables suggested here are chosen after many stages of selection. Firstly, the selection is made on the basis of a review of the literature on economic growth and convergence by Sala-i-Martin et al. [19], as well as earlier empirical studies by Gazda and Puziak [60]. Secondly, the dataset is limited due to the accessibility of statistical data. Thirdly, the authors propose factors that may potentially explain differentiated growth rates in the European regions similar to previous research (Cuaresma et al. [38]). Finally, the dataset also included dummy variables associated with geographic locations and dominant religions. Table 2 enumerates all the variables used in the research together with detailed explanations.

Table 2. Variables and their definitions.

Variable	Definition
Y	Average growth rate of GDP 2002–2013
X_1	Total investment (% of GDP). Average 2002–2013
X_2	Gross national savings (% of GDP). Average 2002–2013
X_3	Military expenditure (% of GDP). Average 2002–2013
X_4	Population in 2002
X_5	Rate of natural increase in 2002
X_6	Infant mortality rate in 2002
X_7	Area of countries in 2002 (square miles)
X_8	Population per square mile in 2002
X_9	Natural logarithm of GDP per capita in 2002
X_{10}	General government revenue (% of GDP). Average 2002–2013
X_{11}	Current account balance (% of GDP). Average 2002–2013
X_{12}	Gross fixed capital formation (% of GDP). Average 2005–2012
X_{13}	General government final consumption expenditure. (% of GDP). Average 2005–2012
X_{14}	Shares of agriculture, hunting, forestry, and fisheries (% of GDP) in 2012
X_{15}	Unemployment rate (15 years and older). Average 2002–2013
X_{16}	Homicide rate (per 100,000). Average 2008–2011
X_{17}	Stock of immigrants (% of population) in 2013
X_{18}	Years of schooling. Female. Average 2002–2013
X_{19}	Years of schooling. Male. Average 2002–2013
X_{20}	Pre-primary education (% of children of pre-school age). Average 2003–2012
X_{21}	Primary education (% of primary school-age population). Average 2003–2012
X_{22}	Secondary education (% of primary school-age population). Average 2003–2012
X_{23}	Tertiary education (% of primary school-age population). Average 2003–2012
X_{24}	Expenditure on education (% of GDP). Average 2005–2013
D_1	Country located in Europe
D_3	Country located in South America
D_4	Country located in North America
D_5	Country located in Asia and Oceania
D_7	Islamic majority
D_8	Majority other than Islamic or Christian

Source: International Monetary Fund, The Joshua Project, Stockholm International Peace Research Institute, and the Human Development Report. Variables D_2 (country located in Africa) and D_6 (christian majority) are omitted due to possible multicollinearity.

Given the above, the potential factors of economic growth in the regions were divided into three groups.

1. The first group involved variables that describe the condition of the region at the beginning of the research period. They describe the initial condition of a given country. These variables were derived from the literature on economic growth, in particular from a broad range of studies based on the neoclassical model of economic growth, assuming that the initial conditions determine the subsequent growth rate.
2. Another group of factors involved variables presented as averages for the analyzed period. Taking these determinants into account is justified by the necessity of examining the correlations between the rate of economic growth and other processes that occurred in the analyzed period. The data

required to calculate the averages for selected years were not always available. In the case of stock of immigrants, only the data from 2013 were available. Nevertheless, this variable was included in the dataset due to its current importance.

3. The last group consisted of dummy variables. In this study, we examined the potential factors influencing the dynamics of economic growth related to the geographical location and the religious denomination of the majority of citizens of a given country.

2.2. Bayesian Methods Used in Study

Model-building strategies based on theoretical and statistical assumptions always include elements of uncertainty about the determinants. One of the most significant challenges of contemporary theory of economics and economic policy is accurately identifying the factors determining the economic growth. The economic growth literature, e.g., Sala-i-Martin et al. [19] and Cuaresma et al. [38], encompasses a range of studies that refer to various factors and groups of factors responsible for the processes of economic growth. These studies provide the foundation for the considerations below. There is consensus in the literature that methods developed on the basis of Bayesian econometrics are generally applicable in the analysis of the complex economic phenomenon of the determination of the sources of economic growth.

From a statistical point of view, one has to face problems about using the proper set of independent variables during model construction, and the goodness of fit of a statistical model has to be evaluated. Moreover, with a large number of variables and different selection procedures, it is difficult to decide which model and variables are the most appropriate to use in the analysis of the dependencies. For example, if we take into account a set of twenty independent variables, we will get more than one million linear combinations of determinants in a simple regression model. Therefore, it is really hard to find the optimal set of variables in terms of goodness of fit measures. Additionally, Raftery et al. [61] showed that process modeling approaches lead to different estimates and conflicting conclusions about the estimates. From a Bayesian point of view, model uncertainty is a natural aspect of building a strategy and can be incorporated in the construction process. For example, Zellner [62] showed that we can calculate the posterior odds ratio between two competitive models and obtain a posterior probability of every one of them. Using Bayesian inference, we can also obtain not only the posterior probability of the model, but also the posterior characteristics of the parameters, such as the mean, variance, and quantiles (see Koop [63]). Since we have characteristics for all models, we can calculate some interesting measures across the whole model space instead of making inferences based on a single model.

Consider the normal linear regression M_j for a dependent variable y:

$$y = \alpha l_N + X_j \beta_j + \varepsilon, \tag{1}$$

where α is a constant, l_N denotes an $N \times 1$ vector of ones, X_j is an $N \times k_j$ matrix of regressors in model M_j $(j = 1, 2, \ldots, K)$, and β_j is a $k_j \times 1$ vector of parameters. ε is a vector of dimensions $N \times 1$ with a normal distribution $N(0, \sigma^2 I_N)$, where σ^2 is the variance of random error ε and I_N is an identity matrix of size N. Data are taken from $i = 1, 2, \ldots, N$ objects.

To illustrate Bayesian model averaging, we can calculate a posterior mean of regression parameters across the whole model space using the following equations:

$$E\left(\beta|y\right) = \sum_{j=1}^{2^K} E\left(\beta_j|y, M_j\right) Pr\left(M_j|y\right) \text{ for } j = 1, 2, \ldots, 2^K, \tag{2}$$

with the variance:

$$Var\left(\beta|y\right) = \sum_{j=1}^{2^K} \left[V\left(\beta_j|y, M_j\right) + E\left(\beta_j|y, M_j\right)^2\right] Pr\left(M_j|y\right) + E\left(\beta|y\right)^2, \tag{3}$$

where $Pr(M_r|y)$ denotes the posterior probability of model M_j, $\sum_{j=1}^{2^K} Pr(M_j|y) = 1$, $E(\cdot)$ and $Var(\cdot)$ are the expected value and the variance of the parameters, and 2^K is the total number of all linear combinations in the regression model. From Equations (2) and (3), it is clear that the posterior mean and variance calculated across the whole model space are weighted averages of the posterior means and variances of the individual models.

The calculation of the posterior model probability and estimation of parameters in the linear regression model is a well-known topic in the Bayesian statistic literature, so here, we just provide a common overview of the main steps used, especially those related to the model averaging framework.

For computational simplicity, we use a natural conjugate normal-Gamma prior of the regression parameters (see DeGroot [64], Koop [63]); thus, we assume standard noninformative priors for σ^2 and intercept α, which are common parameters in all regression models:

$$p\left(\alpha, \sigma^2|M_j\right) \propto \sigma^{-2}, \tag{4}$$

and for regression coefficient β_j, we assume a normal prior distribution with mean 0_{k_j} and covariance matrix $\sigma^2[g_j X^T X]^{-1}$:

$$p\left(\beta_j|\sigma^2, M_j\right) \propto \frac{1}{\sigma}\left\{\exp\left[-\frac{\beta_j^T g_j X_j^T X_j \beta_j}{2\sigma^2}\right]\right\}. \tag{5}$$

From Equation (5), it is clear that the covariance of the prior distribution of β_j depends on σ^2. Additionally, note that the prior covariance matrix is proportional to the data-based covariance matrix and g-prior (here, g_j). The basic idea, underlined by Zellner [65], of the g-prior is to assume a common prior distribution for the regression coefficients due to the computational speed required for posterior distributions and convenience in the model selection framework. In this case, we used the "benchmark" prior, which is popular in the Bayesian model averaging framework and was recommended by Fernández et al. [17] and Ley and Steel [23]. In our approach, we use $g_j = 1/K^2$ for a large number of regressors, i.e., $N \leq K^2$ and $g_j = 1/N$ when $N > K$.

We assume that the residuals in the regression model are normally distributed; therefore, the likelihood function has the following form:

$$p\left(y|\alpha, \beta_j, \sigma^2, M_j\right) \propto \frac{1}{\sigma^N}\left\{\exp\left[-\frac{\left(y - \alpha I_N - X_j\beta_j\right)^T \left(y - \alpha I_N - X_j\beta_j\right)}{2\sigma^2}\right]\right\}. \tag{6}$$

It is well known from the Bayesian literature that with a natural conjugate framework and integrating out intercept α, the posterior for β_j follows a multivariate Student-t distribution, where the posterior mean and covariance matrix of regression coefficients can be written as follows (see Fernández et al. [17], Koop [63]):

$$E\left(\beta_j|y, M_j\right) = \left[\left(1+g_j\right) X_j^T X_j\right]^{-1} X_j^T y, \tag{7}$$

$$Var\left(\beta_j|y, M_j\right) = \frac{N s_j^2}{N-2}\left[\left(1+g_j\right) X_j^T X_j\right]^{-1}, \tag{8}$$

where:

$$s_j^2 = \frac{\frac{1}{g_j+1} y^T P_{X_j} y + \frac{g_j}{g_j+1}\left(y - \bar{y} I_N\right)^T \left(y - \bar{y} I_N\right)}{N}. \tag{9}$$

and $P_{X_r} = I_N - X_j(X_j^T X_j)^{-1} X_j^T$. After integrating out all parameters, we know that the density of the marginal distribution of the vector y is given by:

$$p\left(y|M_j\right) \propto \left(\frac{g_j}{g_j+1}\right)^{\frac{k_j}{2}} \left[\frac{1}{g_j+1} y^T P_{X_j} y + \frac{g_j}{g_j+1}\left(y - \bar{y} I_N\right)^T \left(y - \bar{y} I_N\right)\right]^{-\frac{N-1}{2}}. \tag{10}$$

Since we have the marginal data density $p(y|M_j)$ in Equation (10), the posterior probability of any variant of regression model M_j can be calculated by the following formula, which is essential for Bayesian model averaging:

$$Pr\left(M_j|y\right) = \frac{Pr\left(M_j\right) p\left(y|M_j\right)}{\sum_{j=1}^{2^K} Pr\left(M_j\right) p\left(y|M_j\right)}, \tag{11}$$

where expressions $Pr(M_1), Pr(M_2), \ldots, Pr(M_K)$ denote the prior probabilities of competitive models. In our work, we take the very simple assumption that all linear combinations are equally probable: $Pr(M_j) = \frac{1}{2^K}$ and $\sum_{r=1}^{m} Pr(M_r) = 1$. Therefore, Equation (11) can be simplified to:

$$Pr\left(M_j|y\right) = \frac{p\left(y \mid M_j\right)}{\sum_{j=1}^{2^K} p\left(y|M_j\right)}. \tag{12}$$

The estimation of parameters in the linear regression model and the computation of marginal data density is a very well-known issue in the Bayesian literature, and it does not require, in most cases, advanced computation techniques Koop [63]. On the other hand, we have to face the problem of obtaining posterior quantities for a large set of exogenous regressors. For example, if we consider $K = 20$ independent variables, we have to estimate 2^{20}, i.e., more than one million linear combinations, which requires tremendous computational CPU time. Both from a practical and computational point of view, this does not seem reasonable. If we decide to choose only the "best" model, we will probably neglect much information from the other potentially interesting competitive models. On the other hand, if we need information based on the whole model space, we will have to estimate a tremendous number of combinations, some of them with very low posterior probability. Moreover, we will have to spend much CPU time obtaining all estimation results for all linear combinations. A much better idea is to use a "smart" algorithm that finds the most probable models and ignores low probability models with a reasonable CPU time.

One of such procedures is the MC^3 algorithm, which was developed by Madigan et al. [66] based on the Markov chain Monte Carlo method. This method facilitates easy "capturing" of the models with the greatest explanatory power. This means that we focus on the most probable variables and models, while neglecting the least likely ones. We use an atheoretical approach for a large number of combinations of determinants, which is why the usage of BMA with MC^3 is crucial for our study. The candidate model M^* is accepted with the probability:

$$\alpha\left(M^{(i-1)}, M^*\right) = \min\left\{\frac{p\left(y|M^*\right) Pr\left(M^*\right)}{p\left(y|M^{(i-1)}\right) Pr\left(M^{(i-1)}\right)}, 1\right\}, \tag{13}$$

where $M^{(i-1)}$ denotes the previously-accepted model in the Markov chain of models.

After a sufficient number of iterations, we get an equilibrium distribution $Pr(M_j|y)$ of the posterior model probabilities, and the posterior mean and variance are calculated across the whole model space. Using Monte Carlo simulation, we can also derive additional posterior characteristics that are useful for the Bayesian averaging approach. One of them is the posterior inclusion probability $(PIP,\ Pr(i|y))$, i.e., the probability that, conditional on the data, but unconditional with respect to the model space, the independent variable x_i is relevant for explaining the dependent variable y. The value of the posterior inclusion probability indicates the importance of an independent variable in the regression model. Another useful posterior characteristic is the jointness measure defined by Ley and Steel [21], which is the posterior odds ratio of the models including both x_i and x_j versus the models that include them only individually. It has the following form:

$$J = \ln\left\{\frac{Pr\left(i \cap j|y\right)}{Pr\left(i|y\right) + Pr\left(j|y\right) - 2Pr\left(i \cap j|y\right)}\right\}, \tag{14}$$

where $Pr(i \cap j|y)$ denotes the sum of the posterior probabilities of those models that contain both variables x_i and x_j. Using the jointness measure, we can identify three types of variable in the regression model: independent, substitute, and complementary. Using the interpretation of the posterior odds ratio, we can classify the strength of jointness, namely, strong substitutes $J \leq -2$, significant substitutes $2 < J \leq 1$, not significantly related $-1 < J < 1$, significant complements $1 \geq J < 2$, and strong complements $J \geq 2$ (Doppelhofer and Weeks [22], Madigan and Raftery [67]).

3. Results and Discussion

We specified the following prior assumptions: a uniform prior over the model space (the prior average model size was 15) and the benchmark g-prior by Fernández et al. [18]. In order to obtain the results, we ran 10,000,000 Monte Carlo simulations with the first 10% burned-in draws to eliminate the influence of the starting (initial) values. The number of iterations was considered sufficient because the correlation coefficient between numerical and analytical model probabilities was above 0.99. We assumed an equal prior probability for all potential growth determinants. This means that we did not give preference to any variables associated with economic growth theory, and the BMA approach helped us to find the most probable ones. All calculations were performed in the BMA 2.01 package by Błażejowski and Kwiatkowski [59] (The BMA 2.01 package is available at http://ricardo.ecn.wfu.edu/gretl/cgi-bin/gretldata.cgi?opt=SHOW_FUNCS) for the gretl program (see Cottrell and Lucchetti [68]). The most probable variables were defined as those with the highest Posterior Inclusion Probabilities (PIPs). The posterior means of regression parameters and the posterior standard deviations, as well as the PIPs are included in Table 3.

The most probable variable among all growth determinants was X_9, i.e., the natural logarithm of GDP per capita in 2002.This is in line with convergence theory. It can therefore be concluded that the initially lower level of development is conducive to higher dynamics of GDP growth. The variables found in the second and third positions of the ranking, that is, X_2, gross national savings, and X_{12}, gross fixed capital formation, respectively, refer to a similar subject, which can have a considerable impact on the dynamics of economic growth, both theoretically and in practice (Matuzeviciute and Butkus [69], Daniloviciene and Lace [70]). Gross fixed capital formation directly demonstrates the proportion of GDP that is further invested, and the gross national savings, understood in the Keynesian approach, can be also ultimately treated as an investment, which is axiomatic in closed economies. The fourth position in the ranking was taken by the D_5 variable indicating a country location in Asia or Oceania regions. This suggests that conditions similar to those in Asia or Oceania (in the period from 2002–2013) may determine the most likely positive economic growth (Lv et al. [71]).

In general, all of the above-mentioned variables, i.e., generally low initial level of development (GDP per capita) and a high level of investment and savings, are typical of the "Asian development model", suggesting that it is the scenario responsible for the high economic growth in recent years. The next two variables in the ranking, i.e., X_{17} and X_{24}, refer to the stock of immigrants and expenditure on education. This suggests that migration should be monitored at the global level since it could soon have a significant impact on the dynamics of economic growth. Moreover, in surveys conducted exclusively for developed economies, expenditure on education had a considerably higher position in the probability rankings of economic determinants (Gazda and Puziak [60]). Despite the fact that this variable achieved the sixth position in the ranking among all analyzed countries, it suggests the need to monitor this variable in the future, so expenditure on education should be taken into account when planning sustainable economic policies to stimulate economic growth (Armeanu et al. [6], Tvaronavičienė et al. [7]). All the posterior results were consistent with growth and convergence theory (Barro and Sala-i-Martin [2], Gazda and Puziak [60]) and general economic empirics (Sala-i-Martin et al. [19]).

Table 3. Posterior estimates of economic growth determinants.

Variable	PIP	Mean	Standard Deviation
X_9	0.999972	−0.863438	0.164274
X_2	0.962024	0.069984	0.020736
X_{12}	0.817661	0.956173	0.557132
D_5	0.931593	0.064148	0.025899
X_{17}	0.390386	0.013865	0.019658
X_{24}	0.190910	−0.030891	0.073117
X_{18}	0.106176	0.012986	0.048070
X_{11}	0.082089	0.003369	0.01532
X_1	0.075268	0.003317	0.016843
D_3	0.062444	0.039613	0.205555
X_5	0.058103	0.012122	0.071737
X_6	0.051441	0.000318	0.002283
D_1	0.050491	−0.020439	0.141528
X_{19}	0.050038	0.001313	0.029461
X_{20}	0.043789	0.000178	0.001445
X_{15}	0.043468	−0.000574	0.004884
X_{21}	0.043003	0.000318	0.002522
X_4	0.042943	3.4×10^{-5}	0.000298
D_7	0.042026	−0.009718	0.089532
D_8	0.041857	−0.00633	0.121322
X_{16}	0.040749	−0.000304	0.002885
X_{14}	0.038122	−0.000388	0.004428
X_{10}	0.038027	−0.000207	0.003546
X_{23}	0.037664	-6.4×10^{-5}	0.001608
X_7	0.036988	3.0×10^{-6}	3.9×10^{-5}
D_4	0.036591	−0.006912	0.097756
X_3	0.035887	−0.123499	2.110139
X_{13}	0.035264	0.001776	0.042313
X_8	0.034702	1.0×10^{-6}	1.5×10^{-5}
X_{22}	0.034011	4.7×10^{-5}	0.001728

Table 4 includes the top five models according to their posterior probabilities. The total probability of the presented models was 0.292221.

Table 4. The ranking of model probability.

Model *j*:	M_1	M_2	M_3	M_4	M_5
P(M$_j$)	**0.163989**	**0.062339**	**0.031046**	**0.024026**	**0.010821**
Variable	$\hat{\beta}^{(M_1)}$	$\hat{\beta}^{(M_2)}$	$\hat{\beta}^{(M_3)}$	$\hat{\beta}^{(M_4)}$	$\hat{\beta}^{(M_5)}$
X_2	0.0728331	0.0696883	0.0723425	0.0790534	0.0771949
X_9	−0.784934	−0.917864	−0.747125	−0.999765	−0.936388
X_{12}	0.0663038	0.0670735	0.0697037	0.0698610	0.0735666
X_{17}		0.0292134		0.0429118	0.0397535
X_{24}			−0.147470		−0.179877
D_5	1.26420	1.00520	1.13430		

It is easy to see that the best model had a posterior probability equal to 0.16, and the posterior probabilities of the others were lower than 0.07. This means that there was no one dominant specification, and inferences based on just one model were very misleading because much information included in the whole model space would be omitted. Therefore, these results justify the necessity of using the BMA approach instead of classical inference. The top five models consist of a small set of variables. The variables X_2 (gross national savings (% of GDP), average 2002–2013), X_9 (natural logarithm of GDP per capita in 2002), and X_{12} (gross fixed capital formation (% of GDP), average 2005–2012) appear in each model. Variable X_{17} (stock of immigrants (% of population) in 2013) is in three specifications (M_2, M_4, and M_5); variable D_5 (country located in Asia and Oceania) appears in three specifications (M_1, M_2, and M_3); and variable X_{24} (expenditure on education (% of GDP), average 2005–2013) is in two specifications (M_3 and M_5).

As an extension of the standard Bayesian model averaging framework, the jointness analysis by Ley and Steel [21] was also conducted. The results reveal the following pairs of strong complementary variables: X_2 (gross national savings (% of GDP), average 2002–2013) and X_9 (natural logarithm of GDP per capita in 2002), X_9 (natural logarithm of GDP per capita in 2002) and X_{12} (gross fixed capital formation (% of GDP), average 2005–2012), as well as X_2 (gross national savings (% of GDP), average 2002–2013) and X_9 (natural logarithm of GDP per capita in 2002). These results follow the growth and convergence theory. The high levels of gross fixed capital formation and gross national savings together with the low level of Initial GDP per Capital were the set of variables that led to dynamic economic growth, although one should note the possible trade offs between them. The strongest substitutability occurred between X_2 (gross national savings (% of GDP), average 2002–2013) and X_9 (natural logarithm of GDP per capita in 2002) and between X_9 (natural logarithm of GDP per capita in 2002) and X_{12} (gross fixed capital formation (% of GDP), average 2005–2012), which is consistent with the "Asian development model". The identified substitutability among variables also confirms the "Asian development model", especially the most related pair, X_8 (population per square mile in 2002), X_{13} (general government final consumption expenditure (% of GDP), average 2005–2012), which is typical for Asian countries with a high population density. The conclusions for the two other pairs were similar. Table 5 includes the results of the jointness analysis.

Table 5. Results of the jointness analysis.

Strong Substitutes		**Strong Complements**	
Variables	***J* Value**	**Variables**	***J* Value**
X_8, X_{13}	−4.129432	X_2, X_9	3.231319
X_8, X_{10}	−4.096544	X_9, X_{12}	2.610985
X_{10}, X_{22}	−4.088457	X_2, X_{12}	2.263495

In order to perform the confirmation analysis (i.e., with the use of another similar approach), we decided to conduct the entire Monte Carlo experiment in the BACE framework. We used the BACE 1.0 package (the BACE 1.0 package is available at http://ricardo.ecn.wfu.edu/gretl/cgi-bin/gretldata.cgi?opt=SHOW_FUNCS) written by Błażejowski and Kwiatkowski [72] for the gretl program, and we obtained almost the same results as with the BMA package.

4. Conclusions

In the presented paper, we analyzed 30 determinants of economic growth for 168 economies. These determinants cover three groups of variables responsible for the dynamics of economic growth in 2002–2013 at the global level: variables associated with the initial conditions that determine the subsequent growth rate; average values of the potential of sources of economic growth; and dummy variables for different geographic regions and religions.

The most probable factors of economic growth were identified on the basis of 10,000,000 regressions, and these were gross national savings (% of GDP), the natural logarithm of GDP per capita in 2002, the gross fixed capital formation (% of GDP), and the location of the country in Asia and Oceania. Our results suggest that the most important determinants of economic growth in the analyzed period were variables associated with the so-called "Asian development model". This model features a low initial level of development and is fostered by a high level of savings and investment. It is quite likely that if this recommendation is applied by economic policy-makers in underdeveloped economies, it could generate positive outcomes in the future.

Further research could focus on taking into account more potential explanatory variables. Furthermore, an interesting direction of future research would be the analysis of Asian and non-Asian economies separately. Another extension could be to use the panel-data methods and different prior assumptions to examine their impact on the outcome of BMA analyses.

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Abbreviations

The following abbreviations are used in this manuscript:

BMA	Bayesian Model Averaging
BACE	Bayesian Averaging of Classical Estimates
PIP	Posterior Inclusion Probability
GDP	Gross Domestic Product
MC^3	Markov Chain Monte Carlo Model Composition

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