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DETERMINANTS OF ECONOMIC GROWTH: DIFFERENT TIME DIFFERENT ANSWER?

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Abstract

Almost all studies that use Bayesian Model Averaging to identify robust growth determinants focus on the growth period between 1960 and the 1990s. We apply Bayesian Model Averaging to a rolling time window of 20 and 35 years using a newly compiled dataset with 37 growth determinants for the years 1960 to 2010. Our findings indicate instabilities in the inferences on growth determinants across growth periods. In line with prior research, we find support for robust ambiguity in early growth periods, that is, cross-country growth regressions provide little support for some growth determinants being more important than others. However, determinants related to demography, education, trade, investment and to some extent religion seem to matter in the subsequent growth periods with education and demography being most important in recent growth periods.

Keywords: Bayesian Model Averaging, growth regressions, model uncertainty, heterogeneity.

JEL classification: C51, O40, O47.

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1 Introduction

A large empirical literature estimates the determinants of cross-country growth differences. Recent studies focus on Bayesian Model Averaging (BMA) to address the substantial model uncertainty inherent to growth regressions (e.g. Fernandez et al., 2001b; Sala-i-Martin et al., 2004; Durlauf et al., 2008; Masanjala and Papageorgiou, 2008; Ciccone and Jarocinski, 2010; Eicher et al., 2011; Feldkircher and Zeugner, 2012; Rockey and Temple, 2016). These studies focus their analysis on identifying growth determinants either for the growth period 1960-1992 or the growth period 1960-1996. Using a new data set, we provide the first systematic assessment of the stability of inferences on growth determinants across growth periods. Our findings indicate that inferences are unstable across growth periods, but determinants related to demography and education tend to become important in recent growth periods.

Many variables have been suggested to determine economic growth. Durlauf et al. (2005) tabulate 145 growth determinants that have been discussed in the literature with the vast majority of them being statistically significant at least in one study. However, many of these variables may appear statistically significant due to specification searching. Hendry (1980) and Leamer (1983) have pointed to the flexibility of econometric research and the wide range of estimates that can be obtained for a given coefficient of interest. Estimates that appear to be non-significant in the research process may remain unreported, while estimates that are statistically significant may be selected for presentation in an article. This specification searching and selective reporting is the response of researchers to the incentive system of academic publishing as discussed by Ioannidis (2005) and Glaeser (2011) and it may be particularly prevalent if model uncertainty is large with little consensus about what control variables should be included in the regression model.

Recent empirical evidence indicates the prevalence of specification searching in economics. For the top economics journals, Brodeur et al. (2016) find a lack of p-values just above the significance thresholds of 0.05 - 0.10 and conclude that researchers may have preferred (marginally) significant p-values resulting in an abundance of p-values just below the significance threshold of 0.05. This indicates that authors may have searched across a variety of specifications to turn their marginally insignificant estimates into statistically significant findings. Similarly, Bruns et al. (2019) and Vivalt (2019) find evidence for discontinuities in the distribution of published t-values, with marginally significant t-values being overrepresented compared to marginally insignificant t-values. Ioannidis et al. (2016) show for 159 research fields in economics with more than 60,000 estimates that power is low in many economics studies while the point estimates of these studies are frequently statistically significant. This finding indicates that authors with sample sizes that are actually too small to reliably detect the effect of interest may engage in specification searching to exaggerate the point estimates in order to achieve statistical significance.

These findings demonstrate the need for methods that reduce some of the flexibility of econometric research by basing inference on the coefficient of interest on a large set of models rather than on a single model or a small selective set of models. The growth literature put very early emphasis on model uncertainty to improve credibility and reliability of growth regressions. Prominently, Levine and Renelt (1992) and Sala-i-Martin (1997) assess the robustness of growth determinants with respect to different sets of control variables based on Extreme Bounds Analysis (Leamer, 1983; Leamer and Leonard, 1983). Fernandez et al. (2001b) and Sala-i-Martin et al. (2004) pioneer the use of BMA to identify robust growth determinants. Many studies followed in this vein including studies that analyze the jointness of growth determinants (Doppelhofer and Weeks, 2009; Ley and Steel, 2007), the relative importance of alternative growth theories (Durlauf et al., 2008), the specific growth determinants for African countries (Masanjala and Papageorgiou, 2008), and studies with a more methodological focus (e.g. Ley and Steel, 2009; Eicher et al., 2011).

However, the priors on model coefficients used in these studies have been shown to result in fragile inferences due to minor changes in international income data leading to minor changes in the dependent variable. Ciccone and Jarocinski (2010) show that posterior inclusion probabilities (PIPs) are sensitive to different vintages of the Penn World Table (PWT). The PIP is a measure of whether models including the variable under consideration account for a high proportion of the posterior mass (over the model space). This finding has stimulated a discussion how BMA can be made more robust. Feldkircher and Zeugner (2009) propose the use of priors on model coefficients that allow for data-adaptive shrinkage and Feldkircher and Zeugner (2012) show that the use of these priors makes the inference more robust to changes in international income data. Rockey and Temple (2016) demonstrate that the use of particular fixed regressors also improves the stability of inferences across different vintages of the PWT. However, both the use of priors on model coefficients that allow for data-adaptive shrinkage and the use of fixed regressors come to the conclusion that PIPs are evenly distributed across the potential growth determinants for the growth period 1960-1996. This means that it is difficult to identify some growth determinants to be more important than others. Feldkircher and Zeugner (2012) and Rockey and Temple (2016) conclude that BMA leads to robust ambiguity.

The contribution of this study is threefold. First, we provide a systematic assessment of the stability of inferences on growth determinants across growth periods. Prior studies are either based on the data by Sala-i-Martin et al. (2004) which analyses the growth period 1960-1996 or the data by Fernandez et al. (2001b) which is a subset of the data by Sala-i-Martin (1997) which analyses the growth period 1960-1992. We apply BMA to growth regressions using a rolling time window of 20 and 35 years to a dataset with 37 growth determinants between 1960 and 2010. We use the priors on model coefficients suggested by Feldkircher and Zeugner (2009; 2012) in combination with the fixed regressors suggested by Rockey and Temple (2016) to ensure that the inferences obtained by BMA are robust regarding noise in the dependent variable. We show that inferences on growth determinants with respect to PIPs are substantially unstable across growth periods.

Further analyses provide suggestive evidence that these instabilities may represent substantive changes in what explains growth across the rolling time window rather than being merely caused by noise in the data or improvements in data quality in some specific variables over time. Second, we find support for robust ambiguity as suggested by Feldkircher and Zeugner (2012) and Rockey and Temple (2016) in the early growth periods but PIPs become less evenly distributed over time. Our analysis shows that growth determinants can be identified in more recent growth periods. Particularly, determinants related to demography and education seem to matter most in recent growth periods. Education was also found to be an important growth determinant in Rockey and Temple (2016). Third, determinants of 20 year growth periods differ from determinants of 35 year growth periods. While determinants related to demography, trade, investment, and education matter for at least some of the growth periods of both 20 and 35 years, religion seems to matter only for growth periods of 20 years.

Section 2 provides an introduction to BMA, Section 3 introduces the estimation strategy, and Section 4 presents the data. Section 5 provides an overview of the results, Section 6 discusses the results, and Section 7 concludes.

2 Bayesian Model Averaging

Consider the linear regression model with N observations and K regressors with $k = 1, ..., K$:

$$\boldsymbol{y} = \alpha + \boldsymbol{X}_j \boldsymbol{\beta}_j^{'} + \boldsymbol{\epsilon}, \tag{1}$$

where $\boldsymbol{y}$ is a $N \times 1$ vector, $\boldsymbol{\epsilon} \sim N(\boldsymbol{0}, \sigma^2 \boldsymbol{I})$, $\boldsymbol{X}$ is a $N \times K$ matrix of regressors and $\boldsymbol{X}_j$ are the regressors included in model M_j. There are 2^K different models M_j with $j = 1, ..., 2^K$. The constant is given by α and $\boldsymbol{\beta}_j^{'}$ is a $K \times 1$ vector of coefficients corresponding to $\boldsymbol{X}_j$. Our aim is to learn which regressors help us to explain $\boldsymbol{y}$. For a comprehensive introduction to BMA see Hoeting et al. (1999).

Our main interest is in the *posterior inclusion probability* (PIP), which is a measure of whether models including the regressor $\boldsymbol{x}_k$ account for a high proportion of the posterior mass (over the model space):

$$P(I_k = 1|\boldsymbol{y}) = \sum_{A} P(M_j|\boldsymbol{y}) \tag{2}$$

where $I_k = 1$ is an indicator function that is 1 if regressor $\boldsymbol{x}_k$ is included in model j and 0 otherwise and $A = \{M_j : j = 1, \ldots, 2^K; I_k = 1\}$ which is the set of models that include $\boldsymbol{x}_k$. Put differently, the PIP of $\boldsymbol{x}_k$ is the sum of posterior model probabilities over those models where $\boldsymbol{x}_k$ is included. The posterior model probabilities are obtained by Bayes' theorem:

$$P(M_j|\boldsymbol{y}) = \frac{P(\boldsymbol{y}|M_j)P(M_j)}{\sum_{l=1}^{2^K} P(\boldsymbol{y}|M_l)P(M_l)} \tag{3}$$

where $P(M_j)$ is the model prior that is discussed below and $P(\boldsymbol{y}|M_j)$ is the marginal likelihood of model M_j. The denominator follows from the law of total probability and is the same for all models. The marginal likelihood of model M_j is given by

$$P(\boldsymbol{y}|M_j) = \int P(\boldsymbol{y}|\alpha, \boldsymbol{\beta}_j, \sigma, M_j)P(\alpha, \boldsymbol{\beta}_j, \sigma|M_j)d\alpha d\boldsymbol{\beta}_j d\sigma \tag{4}$$

where $P(\boldsymbol{y}|\alpha, \boldsymbol{\beta}_j, \sigma, M_j)$ is the likelihood of model M_j and $P(\alpha, \boldsymbol{\beta}_j, \sigma|M_j)$ is the prior density of the coefficients of model M_j. Typically BMA tries to choose priors that are non-informative, i.e. the priors have little impact on posterior inferences. We follow the suggestions of Fernandez et al. (2001a) and assign a g-prior (Zellner, 1986) on $\boldsymbol{\beta}_j$ and improper priors on α and σ:

$$\begin{aligned} P(\alpha) &\propto 1, \\ P(\sigma) &\propto \sigma^{-1}, \\ \boldsymbol{\beta}_j|\sigma, M_j &\sim N(\boldsymbol{0}, \sigma^2 g(\boldsymbol{X}_j'\boldsymbol{X}_j)^{-1}). \end{aligned} \tag{5}$$

The choice of the hyperprior g can be critical for the analysis. A small g mirrors prior beliefs closely centered around zero. A larger g implies a larger shrinkage factor $(g/(1+g))$ that tends to concentrate posterior model probabilities on a few best-fitting models, which was termed the 'supermodel effect' (Feldkircher and Zeugner, 2009). The majority of the growth literature uses fixed choices for g that imply a very large shrinkage factor (Feldkircher and Zeugner, 2012). Ciccone and Jarocinski (2010) illustrate that these fixed choices for g result in a concentration on a few best-fitting models that render the inference of BMA on growth determinants to be highly fragile. They show that updates in international income data and the corresponding small changes in the R^2 of the growth regressions lead to substantially changing PIPs.

As a remedy to this fragility, Feldkircher and Zeugner (2009) propose a hyperprior distribution on g that allows for data-dependent shrinkage based on Liang et al. (2008). This hyper-g prior ensures that the posterior model probabilities are distributed more evenly when the data are noisy. The hyper-g prior can be expressed as a Beta prior distribution on the shrinkage factor:

$$\frac{g}{1+g} \sim Beta(1, \frac{a}{2} - 1). \tag{6}$$

Feldkircher and Zeugner (2012) demonstrate that the use of this data-adaptive shrinkage factor substantially reduces the variation of PIPs across different vintages of national income data. They use $a = 2 + 2/K^2$ which ensures that the expected shrinkage factor equals the benchmark prior proposed by Fernandez et al. (2001a) which is predominantly used in the literature. We follow their recommendation and use the hyper-g prior with an expected shrinkage factor equal to the benchmark prior to ensure the robustness of our PIPs. Further discussion of hyperprior distributions on g is provided by Ley and Steel (2012).

Rockey and Temple (2016) demonstrate that an alternative approach to improve the robustness of BMA is to reduce the degree of agnosticism by including specific fixed regressors. They show that always including initial GDP as well as dummies for regions greatly reduces the variation of PIPs over vintages of the PWT. They also combine the use of these fixed regressors with the hyper-g prior suggested by Feldkircher and Zeugner (2009) and show that PIPs are evenly distributed for the growth period 1960-1996. We also use the combination of hyper-g prior and fixed regressors to ensure that the inferences of BMA are more robust to noise in the dependent variable.

Finally, we need to specify a model prior for each model in (3):

$$p(M_j) = \theta^{k_j}(1-\theta)^{K-k_j} \tag{7}$$

where θ is the inclusion probability of each regressor and k_j is the number of regressors included in M_j. The prior probability of model M_j depends then on the size of this model and is obtained by the product of inclusion and exclusion probabilities. We are interested in choosing a non-informative model prior to ensure that posterior inferences do not depend on prior specifications. A common choice is $\theta = 0.5$ which is known as the uniform model prior (e.g. Raftery et al., 1997; Fernandez et al., 2001a). The uniform model prior was considered to be non-informative as it assigns the same probability to each model, i.e. $P(M_j) = 2^{-K}$. However, Ley and Steel (2009) demonstrate that a fixed choice for θ concentrates prior model size around the expected model size which is $K/2$ and, thus, a fixed choice for θ turns out to be quite informative. We follow their suggestion of using a beta distribution for θ. They show that making θ random rather than fixed ensures that the prior is less sensitive to the choice of the expected model size and that the prior structure will adapt to the observed data.

3 Stability of inferences across growth periods

We analyze the stability of inferences on growth determinants across growth periods by applying BMA to growth regressions using a rolling time window:

$$\Delta \boldsymbol{y}_t = \alpha_t + \boldsymbol{Z}_t \boldsymbol{\gamma}_{jt}^{'} + \boldsymbol{X}_{jt} \boldsymbol{\beta}_{jt}^{'} + \boldsymbol{\epsilon}_t \tag{8}$$

where $\Delta \boldsymbol{y}_t$ denotes the annualized average growth rate of per capita GDP between $t-s$ and t. We consider a medium run growth period of 20 years ($s = 20$) and a long run growth period of 35 years ($s = 35$). A growth period of 35 years mirrors the growth periods 1960-1996 and 1960-1992 that have been analyzed in previous studies in this literature while a growth period of 20 years allows us to test whether stability in the inferences on growth determinants depends on the length of the growth period. $\boldsymbol{X}_{jt}$ is the matrix of regressors included in model M_{jt} and $\boldsymbol{\beta}'_{jt}$ is the corresponding vector of coefficients. As introduced in Section 4, some regressors in $\boldsymbol{X}_{jt}$ are measured in t or are averaged over the first four years of the growth period while other regressors may be time invariant. We also include a $N \times 5$ matrix of fixed regressors, $\boldsymbol{Z}_t$, that are common to all models. These fixed explanatory variables include dummies for regions (Europe, East Asia, Sub-Saharan Africa, and Latin America) and log GDP per capita in t. Including these fixed regressors reduces the degree of agnosticism and is recommended by Rockey and Temple (2016) to improve the robustness of BMA. For $s = 35$, we separately apply BMA to four overlapping growth periods ($t = 1960, 1965, 1970, 1975$). For $s = 20$, we separately apply BMA to seven overlapping growth periods ($t = 1960, \ldots, 1990$).The previous literature concluded that a model size of seven is typical for the growth literature (Sala-i-Martin, 1997; Sala-i-Martin et al., 2004). Therefore, we consider an expected model size of twelve as five regressors are fixed in our analysis.[1]

The dataset that will be introduced in the next section contains 37 variables of which five variables are fixed so that the model space consists of 2^{32} models. Estimating all of these models is intractable. We use a Markov Chain Monte Carlo (MCMC) sampler that is used in many studies to approximate the most important part of the posterior model distribution (e.g. Fernandez et al., 2001a; Ley and Steel, 2009). Eicher et al. (2011) compare the MCMC sampler with the leaps-and-bounds method (Raftery, 1995) and find that both perform very well. We use 20 million iterations after a burn in phase of 10 million iterations.[2]

While we combine the hyper-g prior with fixed regressors to improve the robustness of inferences with respect to noise in the dependent variable, we also perform two additional analyses

[1] We also used an expected model size of seven. The results are largely identical. Section 6 discusses the differences and the results are reported in the Online Appendix.

[2] All estimations are conducted by using the *bms* package in *R* (Zeugner and Feldkircher, 2015).

to explore (and largely refute) the possibility that our findings are merely caused by noise in the data or improvements in data quality over time.[3] First, we analyze the rank correlations of growth determinants between growth periods. For growth periods that largely overlap, the probability to observe similar growth rates per country and similar values for the explanatory variables is increased. If the rank correlations are large and positive for growth periods with substantial overlap and if these rank correlations decrease as the overlap becomes less prominent, then we interpret this as an indication that the variation in PIPs may represent substantive changes. We would expect the variation in PIPs to be more erratic if it is mostly due to noise in the data. Second, we analyze how PIPs increase between the first and last growth period. As will be shown in Section 5, we find evidence for robust ambiguity in the early growth periods, but PIPs tend to increase for some growth determinants over time. This finding would be consistent with improvements in data quality over time that reduce attenuation biases and, consequently, increase PIPs. However, improvements in data quality affect growth determinants differently. We explore whether the set of growth determinants with large increases in PIPs is dominated by determinants that were likely to be measured with higher measurement error in the first growth period. If instead determinants that were likely to be measured with little or no measurement error even in the first growth period show large increases in PIPs as well, we interpret this as an indication that improvements in data quality and reduction of measurement error alone cannot explain the observed variation in PIPs.

4 Data

The dataset contains the annualized average growth rate of GDP per capita for growth periods of 20 and 35 years between 1960-2010 and 37 explanatory variables that are measured at the beginning of each growth period.

The 37 explanatory variables consist of some variables that do not change over time such as

[3] We are grateful to an anonymous reviewer for suggesting these two analyses.

being a landlocked country or having a colonial history. We included these time-invariant variables directly from the widely-used data set of Sala-i-Martin et al. (2004). For those explanatory variables with temporal variation, we used the variables considered by Sala-i-Martin et al. (2004) as orientation. This ensures comparability with previous results. The aim to consider as many of these variables as possible needs to be balanced with sample size considerations as data for these variables need to be available for all growth periods. This trade-off results in 37 explanatory variables for 63 countries. Table 1 provides details on the variables included in our dataset and their data sources. Table A1 in the appendix provides the list of countries.

We measure all explanatory variables strictly at the beginning of each growth period to reduce the problem of simultaneity. Endogenous variables may result in an unfair competition between models as some models may have a seemingly large explanatory power due to endogenous regressors (Temple, 2000; Rockey and Temple, 2016). This excludes some of the variables included in the data set of Sala-i-Martin et al. (2004) such as a socialist dummy (that measures whether a country was under Socialist rule for a considerable time during the growth period) or the average inflation rate over the growth period. The number of explanatory variables that we consider is comparable to the data set of Fernandez et al. (2001b) which includes 41 variables.

[Table 1 about here]

5 Results

We assess the performance of the MCMC sampler by comparing analytical posterior model probabilities with the outcome of the MCMC sampler for the 100,000 top models. These 100,000 top models account for 0.62 to 0.96 of the posterior mass for the growth periods of 35 years and 0.63 to 0.86 of the posterior mass for the growth periods of 20 years. For both the growth periods of 35 years and 20 years, the correlation between analytical posterior model probabilities and the outcome of the MCMC sampler is either 0.99 or 1. These findings indicate that the MCMC sampler approximated the important part of the posterior model distribution very well. Note that inference is based on the approximation of the complete posterior model distribution and not only on the 100,000 top models.

Sala-i-Martin et al. (2004) suggest the prior inclusion probability as a threshold of 'significance' (relevance). If the PIP is larger than this threshold, seeing the data increases our belief that the regressor belongs to the model. We consider 37 regressors but five of these regressors are always included. Thus, the corresponding threshold is 7/32 = 0.218 for an expected model size of twelve.

PIPs for the growth periods of 35 years are presented in Table 2. For the growth period 1960-1995 the PIPs are evenly distributed and only Landlocked has a PIP that is larger than 0.218. For 1965-2000 none of the regressors exceeds this threshold. However, for 1970-2005, the PIPs become less evenly distributed. Population (in millions) and Tertiary Education (share of population that completed tertiary schooling) have a PIP that is about twice as large as the threshold. For 1975-2010, population reaches a PIP of 0.82 and Tertiary Education, Investment Share, Population Density, Human Capital, and Fertility have a PIP that is about twice as large as the threshold of 0.218. Generally, growth determinants that exceed the threshold are related to demography, education, investment, and trade.

[Table 2 about here]

The distributions of PIPs for each growth period of 35 years are summarized in Table 3. The interquartile range of the PIPs increases from 0.0107 to 0.1791 while the range increases from 0.3012 to 0.7302 from the growth period 1960-1995 to the growth period 1975-2010. At the same time, the number of growth determinants that exceeds the threshold of 0.218 increases from one to nine. The distributions of PIPs become less evenly distributed over time and several growth determinants seem to find more support in recent growth periods compared to early growth periods.

[Table 3 about here]

The typical patterns of the PIPs and posterior means are illustrated in Figure 1. While the PIPs of Population, Human Capital, and Investment Share increase across growth periods, the posterior mean of Population and Human Capital increases but the posterior mean of Investment Share decreases and becomes negative as also found in Sala-i-Martin et al. (2004). The PIPs of Landlocked remain close to the threshold of 0.218 and the posterior mean remains largely unchanged across growth periods. Figures for all growth determinants for the growth periods of 35 years are given in Figure OA1 in the Online Appendix.

Moreover, we find evidence for regional heterogeneity as suggested by Rockey and Temple (2016). The dummies for regions are always included and, thus, the PIP is by definition one. However, the posterior mean can change and as shown in Figure OA1 in the Online Appendix, Sub-Saharan Africa has a negative posterior mean and both the 0.025 and 0.975 quantiles of the posterior distribution are negative as well. The posterior mean for East Asia is positive but declining over time and the 0.025 and 0.975 quantiles of the posterior distribution include zero for the growth period 1975-2010. Europe has a positive posterior mean that becomes slightly negative for the growth period 1975-2010 and Latin America has a negative and declining posterior mean. For both the dummy variables for Europe and Latin America the 0.025 and 0.975 quantiles of the posterior distribution include zero for all growth periods. The posterior mean of log GDP per capita is negative and ranges between -0.00265 and -0.00557 which is consistent with conditional convergence.

[Figure 1 about here]

The rank correlations for growth determinants between growth periods of 35 years are reported in Table A2 in the Appendix. For growth periods with the largest overlap, the rank correlations range between 0.51 and 0.66 while rank correlations for more distant growth periods tend to be smaller. These findings indicate that the observed changes in PIPs and posterior means may indeed represent (slow) changes in what explains economic growth across the rolling time window. The BMA set-up used in this study has been shown to be largely robust to noise at least in the dependent variable (Feldkircher and Zeugner, 2012; Rockey and Temple, 2016) and we would expect more erratic changes in the ranks if noise is the main source of variation in PIPs (Ciccone and Jarocinski, 2010).

Growth determinants ranked by the differences in PIPs between the growth periods 1960-1995 and 1975-2010 are presented in Table A3 in the Appendix. The growth determinants with PIPs above the threshold in the growth period 1975-2010 are also the determinants with the largest increases in PIPs except for Landlock. These determinants are related to demography, education, investment and trade. We suspect determinants related to demography such as Population and Fertility to have been measured with small measurement errors in the early growth period, while larger measurement error in early periods is possible for determinants related to investment and education, such as Investment Share and Human Capital. The set of growth determinants with large increases in PIPs also includes Landarea which is likely to be measured without error across growth periods. Therefore, improvements in data quality alone do not seem to be a potential explanation for all increases in PIPs.

PIPs for the growth periods of 20 years are presented in Table 4. Comparing these PIPs with the PIPs for the growth periods of 35 years, it appears that growth determinants differ with respect to the length of the growth period. For the growth periods 1960-1980 and 1960-1995, only Landlocked exceeds the threshold in both growth periods while Life Expectancy and Buddhism also seem to be relevant for the growth periods of 20 years. For 1965-1985 and 1965-2000, the results are consistent and none of the determinants exceed the threshold. For 1970-1990 and

1970-2005, it is only Tertiary Education that exceeds the threshold in both growth periods while Population and Land Area seem to matter for growth periods of 35 years and Life Expectancy and Investment Price for growth periods of 20 years. For 1975-1995 and 1975-2010, Tertiary Education, Investment Share, Fertility, and Life Expectancy matter for both growth periods while five additional growth variables matter for growth periods of 35 years. However, if one considers the growth determinants that matter at least in one growth period, then the overlap between growth determinants that matter for growth periods of 20 and 35 years is very strong. In fact, determinants related to demography, education, investment, and trade matter for growth periods of both 20 and 35 years while determinants related to religion seem to also matter for growth periods of 20 years.

[Table 4 about here]

The distributions of PIPs for each growth period of 20 years are summarized in Table 5. The range increases again from the first growth period (1960-1980) to the last growth period (1990-2010), but the interquartile range has its maximum for the growth period 1980-2000. The number of determinants that exceed the threshold still increases from three to five but its maximum (seven) occurs in the growth period 1980-2000.

[Table 5 about here]

Typical patterns of PIPs and posterior means are shown in Figure 2 and they reveal why the interquartile range is not increasing across all growth periods. Some growth determinants show a drop in the PIP for the last growth period (1990-2010) as illustrated by Investment Share and Landlocked. As shown in Figure OA2 in the Online Appendix, evidence for regional heterogeneity is less strong than for the growth periods of 35 years. The posterior mean for East Asia is still positive and declining but the 0.025 and 0.975 quantiles of the posterior distribution are both only positive for the growth periods 1970-1990 and 1975-1995. The posterior mean of Sub-Saharan Africa is again negative but the 0.025 and 0.975 quantiles of the posterior distribution are both only negative for the growth periods 1970-1990, 1975-1995, and 1980-2000. The posterior mean of Europe fluctuates around zero and the posterior mean of Latin America is negative. For both dummy variables, the posterior distribution includes zero for all growth periods. The posterior mean for log GDP per capita is again consistent with conditional convergence and ranges between -0.00233 and -0.00859.

[Figure 2 about here]

The rank correlations for growth determinants between growth periods of 20 years are reported in Table A4 in the Appendix. These results largely support the findings for growth periods of 35 years. Specifically, the rank correlations for growth periods with the largest overlap are mostly larger than 0.5 and rank correlations between growth periods with smaller overlap tend to become smaller and insignificant. Growth determinants ranked by the differences in PIPs between the growth period 1960-1980 and 1990-2010 are presented in Table A5 in the Appendix and these results are similar to those obtained for growth periods of 35 years.

6 Discussion

We show that inferences on growth determinants are unstable across growth periods. While early growth periods show little support for the growth determinants considered in this study, more recent growth periods allow us to identify some determinants that are more important than others in explaining cross-country growth differences.

Our findings are consistent with the recent studies by Feldkircher and Zeugner (2012) and Rockey and Temple (2016). Both studies also apply a hyperprior distribution on g that allows for data-dependent shrinkage and ensures that inferences are more robust. These studies analyze the growth period 1960-1996 and find evenly distributed PIPs, i.e. inferences by means of BMA do not allow the identification of growth determinants that are more important than others. They summarize that the use of BMA to identify growth determinants results in robust ambiguity. Our findings support these results by using different data, different model priors, and different lengths of the growth period. Both Feldkircher and Zeugner (2012) and Rockey and Temple (2016) use the data of Sala-i-Martin et al. (2004) with a growth period of 36 years and they both use uniform model priors rather than the random model prior used in the present study. Moreover, Feldkircher and Zeugner (2012) do not include fixed regressors. The finding of evenly distributed PIPs is robust to these differences in methods and data and, thus, robust ambiguity appears to be a strong finding for early growth periods.

The finding of robust ambiguity is an important step forward with respect to the multitude of variables that have been found before to be significant growth determinants for the growth period of 1960-1996 by means of BMA. Our results show, however, that later growth periods tend to provide more support for some of the growth determinants considered in this study. This indicates that robust ambiguity may only hold for the early growth periods and that incorporating recent growth periods in the analysis may help to learn more about determinants of cross-country growth differences while taking model uncertainty explicitly into account.

An important concern regarding the interpretability of growth regressions is the reliability of the underlying data (e.g. Jerven, 2013). We find some suggestive evidence that the changes in PIPs may indeed represent substantive changes in what explains growth across the rolling time window. Specifically, we find that rank correlations of growth determinants are particularly high for growth periods with a large overlap and tend to become smaller for growth periods with less overlap. We would expect more erratic changes in PIPs across growth periods if noise in the data is the main source of unstable PIPs. Moreover, we do not find evidence that improvements in data quality appear to be the main driver of changes in PIPs. Data quality tends to improve over time and decreasing attenuation biases would be a potential explanation for increasing PIPs. However, the set of growth determinants with large increases in PIPs includes mostly growth determinants that are likely to have been measured with little measurement errors across all growth periods. We cannot exclude the possibility that reduction of measurement error may be involved in some education and investment variables that might have had substantial measurement errors in early periods, but real changes in explanatory ability of these variables over time is also possible.

For the growth periods of 35 years, determinants related to demography, education, trade, and investment tend to matter. Moreover, the dummy for Sub-Saharan countries has a negative effect on growth while the dummy for East Asian countries has a positive but declining effect on growth. The overlap of growth determinants for the growth periods of 20 and 35 years is limited for each direct comparison of growth periods. However, if one compares the determinants that matter in at least one growth period, similar growth determinants appear to be relevant for the growth periods of 20 and 35 years. The main difference is that determinants related to religion matter for growth periods of 20 years while they do not seem to matter for growth periods of 35 years. Moreover, the distributions of PIPs for the growth periods of 20 years become again more evenly distributed for recent growth periods. In the most recent growth period between 1990 and 2010, determinants related to demography and education tend to matter most. The relevance of education in determining economic growth was also found by Rockey and Temple (2016) and appears to be particularly important with regards to policy implications.

The differences between determinants of growth periods of 20 years and 35 years may stem from the influence of the business cycle on determinants of growth periods of 20 years while the business cycle is likely to have a smaller influence on determinants of growth periods of 35 years. Moreover, data revision of GDP may also play a role in explaining these differences. Johnson et al. (2013) show that data revisions of GDP can affect inferences on growth determinants and inferences based on longer growth periods are less affected by data revisions.

The instability of inferences across growth periods indicates that temporal heterogeneity may be present for many growth determinants. Our analysis does not allow us to identify the sources of this temporal heterogeneity. Potential causes are omitted nonlinearities in the functional form (e.g. Minier, 2007) and cross-sectional heterogeneity across countries that depends on initial conditions such as GDP or human capital. This introduces non-linearity in the regressors as the initial conditions of each country can change over time (e.g. Durlauf and Johnson, 1995; Durlauf et al., 2001; Masanjala and Papageorgiou, 2004; Durlauf et al., 2008; Salimans, 2012). Our findings are also consistent with an evolving process of economic growth (e.g. Nelson and Winter, 1982; Beaudry et al., 2005) or with the 1960s being particularly chaotic due to the process of decolonization and the Cold War.

As a robustness check, we also considered an expected model size of seven (results reported in the Online Appendix). The results for a model size of seven are remarkably similar to the results with a model size of twelve. For the growth period 1960-1995, the rank correlation between PIPs for a model size of seven and PIPs for a model size of twelve is 0.95. For the growth periods 1965-2000, 1970-2005, and 1975-2010 the rank correlations are 0.97, 0.98, and 0.93 respectively. This shows that the expected model size has little influence on the ranking of growth determinants by PIPs. PIPs are systematically larger for an expected model size of twelve as the prior inclusion probability is larger compared to an expected model size of seven, but variables that exceed the threshold of 'significance' are similar to those with an expected model size of seven. Some of the variables that exceed the threshold of 'significance' for an expected model size of seven do not exceed the threshold for an expected model size of twelve but not vice versa. One possible explanation might be that some of the growth determinants that are found to be relevant for a model size of seven may only appear to be relevant due to omitted variable biases that are resolved for larger model sizes. As a further robustness check, we rerun our analysis without fixed regressors (results reported in the Online Appendix). The rank correlations range between 0.81 and 0.95.

7 Conclusions

Prior studies focussed on the analysis of growth determinants for the growth period between 1960 and the 1990s. We systematically assess the stability of inferences on growth determinants across growth periods between 1960 and 2010. We ensure inferences by means of Bayesian Model Averaging to be robust regarding noise in the dependent variable by combining a hyperprior distribution on g that allows for data-dependent shrinkage and fixed regressors that reflect regional heterogeneity and initial GDP per capita, to allow for conditional convergence.

Our findings support robust ambiguity for early growth periods, that is, the posterior inclusion probabilities are evenly distributed and do not allow the identification of growth determinants that are more important than others (Feldkircher and Zeugner, 2012; Rockey and Temple, 2016). However, the inferences on growth determinants are not stable across growth periods and more recent growth periods result in less evenly distributed posterior inclusion probabilities. We find that determinants related to demography, education, investment, and trade tend to matter for economic growth for both growth periods of 20 and 35 years while religion seems to matter only for growth periods of 20 years. Our findings suggest that determinants related to demography and education matter most in recent growth periods.

We find suggestive evidence that the variation in PIPs may represent substantive changes in what explains cross-country growth rates across the rolling time window rather than being only caused by noise in the data or improvements in data quality.

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Appendix

[Table A1 about here]

[Table A2 about here]

[Table A3 about here]

[Table A4 about here]

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Supplementary materials

The Online Appendix as well as data and code are available at the online versionof this article.

Tables and Figures

Table 1: Data Description and Sources

Variable names	Description and source
Dependent Variable	
Average growth rate of GDP per capita	Average annual growth rate of real GDP per capita at constant 2005 national prices (in mil. 2005US$) from PWT 8.1 (Feenstra et al., 2015)
Regional heterogeneity	
East Asian dummy	Dummy for East Asian countries from Sala-i-Martin et al. (2004)
Europe dummy	Dummy for European countries from Sala-i-Martin et al. (2004)
Latin American dummy	Dummy for Latin American countries from Sala-i-Martin et al. (2004)
African dummy	Dummy for Sub-Saharan African countries from Sala-i-Martin et al. (2004)
Climate zones	
Absolute latitude	Absolute latitude from Sala-i-Martin et al. (2004)
Fraction of tropical area	Proportion of country's land area within geographical tropics from Sala-i-Martin et al. (2004)
Tropical climate zone	Fraction tropical climate zone from Sala-i-Martin et al. (2004)
Colonial history	
British colony dummy	Dummy for former British colony after 1776 from Sala-i-Martin et al. (2004)
Spanish colony dummy	Dummy for former Spanish colonies from Sala-i-Martin et al. (2004)
Colony dummy	Dummy for former colony from Sala-i-Martin et al. (2004)
Trade	
Landlocked country dummy	Dummy for landlocked countries from Sala-i-Martin et al. (2004)
Fraction of land area near navigable water	Proportion of country's land area within 100 km of ocean or ocean-navigable river from Sala-i-Martin et al. (2004)
Average terms of trade of t=0,1,2,3	Ratio of price level of exports and price level of imports with price level of USA GDPo in 2005=1 from PWT 8.1 (Feenstra et al., 2015)
Average growth rate of terms of trade of t=0,1,2,3	Average annual growth rate of the ratio of price level of exports and price level of imports with price level of USA GDPo in 2005=1 from PWT 8.1 (Feenstra et al., 2015)
Average openness measure of t=0,1,2,3	Share of merchandise exports at current PPPs + Share of merchandise imports at current PPPs from Feenstra et al. (2015)
Air distance to big cities	Logarithm of minimal distance (in km) from New York, Rotterdam, or Tokyo from Sala-i-Martin et al. (2004)
Land area	Area in km2 from Sala-i-Martin et al. (2004)

Table 1 (continued)

Variable names	Description and source
Religion	
Share of Christianity in t=0	Percentage of adherents of Christianity from Association of Religion Data Archives (Maoz and Henderson, 2013)
Share of Judaism in t=0	Percentage of adherents of Judaism from Association of Religion Data Archives (Maoz and Henderson, 2013)
Share of Islam in t=0	Percentage of adherents of Islam from Association of Religion Data Archives (Maoz and Henderson, 2013)
Share of Buddhism in t=0	Percentage of adherents of Buddhism from Association of Religion Data Archives (Maoz and Henderson, 2013)
Share of Hindu in t=0	Percentage of adherents of Hindu from Association of Religion Data Archives (Maoz and Henderson, 2013)
Macroeconomy	
Average governement consumption share of t=0,1,2,3	Share of government consumption at current PPPs from PWT 8.1 (Feenstra et al., 2015)
Average investment price level of t=0,1,2,3	Price level of capital formation with price level of USA GDPo in 2005=1 from PWT 8.1 (Feenstra et al., 2015)
Average investment share of t=0,1,2,3	Share of gross capital formation at current PPPs from PWT 8.1 (Feenstra et al., 2015)
Total GDP in t=0 (log)	Logarithm of expenditure-side real GDP at current PPPs (in mil. 2005US$) from PWT 8.1 (Feenstra et al., 2015)
GDP per capita in t=0 (log)	Logarithm of expenditure-side real GDP per capita at current PPPs (in mil. 2005US$) from PWT 8.1 (Feenstra et al., 2015)
Education	
Human capital index in t=0	Index of human capital per person based on years of schooling and returns to education from PWT 8.1 (Feenstra et al., 2015)
Primary schooling in t=0	Share of population (over 15) that is enrolled in or finished primary schooling in t=0 from Barro and Lee (2013)
Tertiary education in t=0	Share of population (over 15) that completed tertiary schooling in t=0 from Barro and Lee (2013)
Demography	
Fertility in t=0	Total fertility rate (total births per woman) from World Bank (2015)
Population in t=0	Population (in millions) in t=0 from PWT 8.1 (Feenstra et al., 2015)
Population density in t=0	Population density (people per sq. km of land area) in t=0 from WorldBank (2015)
Life Expectancy in t=0	Life expectancy at birth in years in t=0 from WorldBank (2015)
Institutions	
Polity score in t=0	Polity2 score from Polity IV (2014)
Duration since regime change in t=0	Number of years since the most recent regime change from Polity IV (2014)
Natural Resources	
Average share of exports of fuel and lubricants of t=0,1,2,3	Share of exports of fuel and lubricants at current PPPs from PWT 8.1 (Feenstra et al., 2015)

Table 2: Posterior inclusion probabilities for growth periods of 35 years

	1960-1995	1965-2000	1970-2005	1975-2010
Population	0.0417	0.0714	**0.4246**	**0.8230**
Tertiary Education	0.0616	0.0924	**0.4986**	**0.6329**
Investment Share	0.0346	0.0444	0.1620	**0.4632**
Population Density	0.0371	0.0273	0.1495	**0.4544**
Human Capital	0.0475	0.0285	0.1849	**0.4432**
Fertility	0.1279	0.0841	0.0860	**0.4233**
Landlock	**0.3328**	0.1621	0.2025	**0.2948**
Land Area	0.0392	0.0491	**0.3354**	**0.2942**
Life Expectancy	0.0856	0.0569	0.0874	**0.2824**
Terms of Trade Growth	0.0851	0.0240	0.1248	0.1881
Primary Exports	0.0410	0.0241	0.0523	0.1858
Christianity	0.0321	0.0261	0.0556	0.1793
Hindu	0.0376	0.0265	0.0805	0.1578
Buddhism	0.2021	0.0838	0.0694	0.1548
Openness	0.0382	0.0248	0.0655	0.1524
Primary Schooling	0.0349	0.0354	0.0924	0.1459
Terms of Trade	0.0371	0.0451	0.1355	0.1384
Judaism	0.0325	0.0245	0.0834	0.1359
Distance to City	0.0328	0.0264	0.0541	0.1273
Spanish Colony	0.0379	0.0304	0.0551	0.1265
Islam	0.0329	0.0326	0.0514	0.1191
British Colony	0.0316	0.0251	0.0607	0.1170
Polity	0.0323	0.0248	0.0559	0.1168
Land Near Navigable Water	0.0348	0.0331	0.0888	0.1065
Duration Regime Change	0.0357	0.0273	0.0766	0.1053
Total GDP	0.0329	0.0306	0.0630	0.1027
Investment Price	0.0498	0.0611	0.1553	0.1004
Latitude	0.0356	0.0248	0.0545	0.0990
Colony	0.0374	0.0264	0.0694	0.0981
Fraction Tropics	0.0402	0.0292	0.0585	0.0964
Tropical Climate Zone	0.0440	0.0269	0.0523	0.0960
Government Consumption Share	0.0317	0.0250	0.0536	0.0928

Notes: Variables are ordered by posterior inclusion probabilities (PIPs) of the growth period 1975-2010. PIPs that exceed the threshold of 0.218 are in bold.

Table 3: Distribution of posterior inclusion probabilities for growth periods of 35 years

	1960-1995	1965-2000	1970-2005	1975-2010
0	0.0316	0.0240	0.0514	0.0928
0.25	0.0342	0.0258	0.0558	0.1062
0.5	0.0375	0.0288	0.0785	0.1421
0.75	0.0449	0.0461	0.1390	0.2853
1	0.3328	0.1621	0.4986	0.8230
IQR	0.0107	0.0203	0.0831	0.1791
Range	0.3012	0.1382	0.4473	0.7302
#PIP $\geq$ 7/32	1	0	3	9

Notes: Quartiles of the posterior inclusion probabilities are reported. Range denotes the difference between the maximum and minimum and IQR denotes the interquartile range.

Table 4: Posterior inclusion probabilities for growth periods of 20 years

	1960-1980	1965-1985	1970-1990	1975-1995	1980-2000	1985-2005	1990-2010
Population	0.1477	0.0662	0.0706	0.1351	**0.4533**	**0.7720**	**0.9871**
Tertiary Education	0.1292	0.0928	**0.3214**	**0.4142**	**0.2937**	0.1280	0.0756
Investment Share	0.1916	0.0644	0.0633	**0.2573**	**0.3122**	**0.4049**	0.0835
Population Density	0.1430	0.0774	0.0777	0.1901	**0.2244**	**0.2579**	**0.3782**
Human Capital	0.1591	0.0797	0.0665	0.0877	0.0887	0.0892	**0.2464**
Fertility	0.2038	0.1316	0.1277	**0.7228**	**0.9762**	**0.9120**	**0.4620**
Landlock	**0.3895**	0.1614	0.0659	0.1337	**0.2322**	0.1469	0.0995
Land Area	0.1245	0.0731	0.1517	0.1898	0.0995	0.0929	0.0746
Life Expectancy	**0.2730**	0.1614	0.1084	**0.2896**	0.0673	0.0871	**0.3916**
Terms of Trade Growth	0.1675	0.0653	**0.2538**	0.0650	0.0740	0.1238	0.1626
Primary Exports	0.1835	0.0741	0.0463	0.0828	0.0735	0.0871	0.0748
Christianity	0.1475	0.0799	0.0477	0.1993	**0.2416**	**0.4410**	0.1432
Hindu	0.1661	0.0832	0.0587	0.0881	0.0724	0.1019	0.1104
Buddhism	**0.2259**	0.1238	0.0593	0.1138	0.0690	0.1035	0.0760
Openess	0.1390	0.0636	0.0454	0.0634	0.1821	0.1799	0.1166
Primary Schooling	0.1295	0.0698	0.0562	0.0668	0.0756	0.0803	0.1276
Terms of Trade	0.1340	0.0664	0.0653	0.0672	0.0738	0.1205	0.0697
Judaism	0.1173	0.0632	0.0937	0.1855	0.1750	0.1105	0.0709
Distance to City	0.1388	0.0699	0.0489	0.0694	0.0915	0.0807	0.0782
Spanish Colony	0.1250	0.0721	0.0535	0.0707	0.0615	0.0758	0.0717
Islam	0.1269	0.0800	0.0492	0.0768	0.0785	**0.2369**	0.1787
British Colony	0.1726	0.0796	0.0470	0.1589	0.1994	0.2009	0.0751
Polity	0.1203	0.0672	0.0457	0.0641	0.0639	0.1111	0.0900
Land Near Navigable Water	0.1259	0.0642	0.0489	0.0767	0.0719	0.1252	0.1232
Duration Regime Change	0.1355	0.0709	0.0692	0.0892	0.0782	0.0809	0.0751
Total GDP	0.1243	0.0638	0.0542	0.0773	0.0836	0.1034	0.0973
Investment Price	0.1235	0.0958	**0.2420**	0.0827	0.0850	0.1777	0.1304
Latitude	0.1613	0.0826	0.0534	0.0622	0.0645	0.0972	0.1033
Colony	0.1336	0.0659	0.0593	0.0907	0.0742	0.0965	0.0736
Fraction Tropics	0.1316	0.0668	0.0529	0.0754	0.0758	0.0804	0.0758
Tropical Climate Zone	0.1553	0.0876	0.0522	0.0621	0.0627	0.0823	0.0690
Government Consumption Share	0.1185	0.0714	0.0483	0.0697	0.0663	0.0806	0.0684

Notes: Variables are ordered by posterior inclusion probabilities (PIPs) of the growth period 1975-2010 of Table 2. PIPs that exceed the threshold of 0.218 are in bold.

Table 5: Distribution of posterior inclusion probabilities for growth periods of 20 years

	1960-1980	1965-1985	1970-1990	1975-1995	1980-2000	1985-2005	1990-2010
0	0.1173	0.0632	0.0454	0.0621	0.0615	0.0758	0.0684
0.25	0.1267	0.0664	0.0491	0.0696	0.0723	0.0871	0.0750
0.5	0.1389	0.0726	0.0590	0.0853	0.0784	0.1070	0.0936
0.75	0.1665	0.0827	0.0724	0.1656	0.1864	0.1782	0.1336
1	0.3895	0.1614	0.3214	0.7228	0.9762	0.9120	0.9871
IQR	0.0398	0.0163	0.0233	0.0959	0.1141	0.0911	0.0586
Range	0.2722	0.0983	0.2760	0.6607	0.9147	0.8362	0.9187
#PIP $\geq$ 7/32	3	0	3	4	7	6	5

Notes: Quartiles of the posterior inclusion probabilities are reported. Range denotes the difference between the maximum and minimum and IQR denotes the interquartile range.

Table A1: List of Countries

Argentina	Ecuador	Jordan	Portugal
Australia	Egypt	Malaysia	Senegal
Austria	El Salvador	Mali	South Africa
Benin	Finland	Mauritania	Spain
Bolivia	France	Mexico	Sri Lanka
Brazil	Gabon	Morocco	Sweden
Cameroon	Ghana	Nepal	Switzerland
Canada	Greece	Netherlands	Thailand
Cent'l Afr. Rep.	Guatemala	New Zealand	Togo
Chile	Honduras	Niger	Tunisia
China	India	Norway	Turkey
Colombia	Iran, I.R. of	Pakistan	United Kingdom
Congo	Ireland	Panama	United States
Costa Rica	Italy	Paraguay	Uruguay
Denmark	Jamaica	Peru	Venezuela
Dominican Rep.	Japan	Philippines	

Table A2: Rank correlations for growth determinants between growth periods of 35 years

	1960-1995	1965-2000	1970-2005	1975-2010
1960-1995	1			
1965-2000	0.51	1		
	[0.20, 0.73]			
1970-2005	0.44	0.58	1	
	[0.11, 0.69]	[0.29, 0.77]		
1975-2010	0.42	0.39	0.66	1
	[0.08, 0.67]	[0.04, 0.65]	[0.40, 0.82]	

Notes: Spearman rank correlations for growth determinants between growth periods are reported based on posterior inclusion probabilities. 0.95 confidence intervals in brackets.

Table A3: Differences and growths of PIPs between the growth periods 1960-1995 and 1975-2010 (35 years)

	PIP (1960-1995)	PIP (1975-2010)	Difference	Rank (Difference)	Growth	Rank (Growth)
Population	0.0417	0.8230	0.7813	1	18.7189	1
Tertiary Education	0.0616	0.6329	0.5712	2	9.2701	4
Investment Share	0.0346	0.4632	0.4286	3	12.3782	2
Population Density	0.0371	0.4544	0.4173	4	11.2504	3
Human Capital	0.0475	0.4432	0.3958	5	8.3356	5
Fertility	0.1279	0.4233	0.2954	6	2.3093	19
Land Area	0.0392	0.2942	0.2550	7	6.5028	6
Life Expectancy	0.0856	0.2824	0.1967	8	2.2968	20
Christianity	0.0321	0.1793	0.1472	9	4.5893	7
Primary Exports	0.0410	0.1858	0.1448	10	3.5340	8
Hindu	0.0376	0.1578	0.1202	11	3.1980	9
Openess	0.0382	0.1524	0.1142	12	2.9911	12
Primary Schooling	0.0349	0.1459	0.1110	13	3.1841	10
Judaism	0.0325	0.1359	0.1034	14	3.1835	11
d Terms of Trade	0.0851	0.1881	0.1030	15	1.2102	28
Terms of Trade	0.0371	0.1384	0.1012	16	2.7259	14
Distance to City	0.0328	0.1273	0.0945	17	2.8850	13
Spanish Colony	0.0379	0.1265	0.0886	18	2.3392	18
Islam	0.0329	0.1191	0.0862	19	2.6213	16
British Colony	0.0316	0.1170	0.0855	20	2.7077	15
Polity	0.0323	0.1168	0.0845	21	2.6152	17
Land Near Navigable Water	0.0348	0.1065	0.0716	22	2.0575	22
Total GDP	0.0329	0.1027	0.0698	23	2.1211	21
Duration Regime Change	0.0357	0.1053	0.0696	24	1.9468	23
Latitude	0.0356	0.0990	0.0634	25	1.7794	25
Government Consumption Share	0.0317	0.0928	0.0612	26	1.9327	24
Colony	0.0374	0.0981	0.0607	27	1.6233	26
Fraction Tropics	0.0402	0.0964	0.0563	28	1.3995	27
Tropical Climate Zone	0.0440	0.0960	0.0520	29	1.1811	29
Investment Price	0.0498	0.1004	0.0506	30	1.0151	30
Landlock	0.3328	0.2948	-0.0380	31	-0.1141	31
Buddhism	0.2021	0.1548	-0.0473	32	-0.2342	32

Notes: The PIPs for the growth periods 1960-1995 and 1975-2010, the difference and growth of each PIP between these two growth periods and the corresponding ranks are presented.

Table A4: Rank correlations for growth determinants between growth periods of 20 years

	1960-1980	1965-1985	1970-1990	1975-1995	1980-2000	1985-2005	1990-2010
1960-1980	1						
1965-1985	0.45	1					
	[0.12, 0.69]						
1970-1990	0.1	0.22	1				
	[-0.26, 0.43]	[-0.14, 0.53]					
1975-1995	0.29	0.31	0.5	1			
	[-0.07, 0.58]	[-0.05, 0.59]	[0.19, 0.73]				
1980-2000	0.16	-0.03	0.34	0.63	1		
	[-0.20, 0.48]	[-0.37, 0.32]	[-0.01, 0.61]	[0.37, 0.81]			
1985-2005	0.23	0.06	0.17	0.44	0.66	1	
	[-0.12, 0.54]	[-0.30, 0.40]	[-0.19, 0.49]	[0.11, 0.69]	[0.40, 0.82]		
1990-2010	0.33	0.21	0.24	0.22	0.35	0.5	1
	[-0.02, 0.61]	[-0.15, 0.52]	[-0.12, 0.54]	[-0.14, 0.52]	[0.00, 0.62]	[0.19, 0.72]	

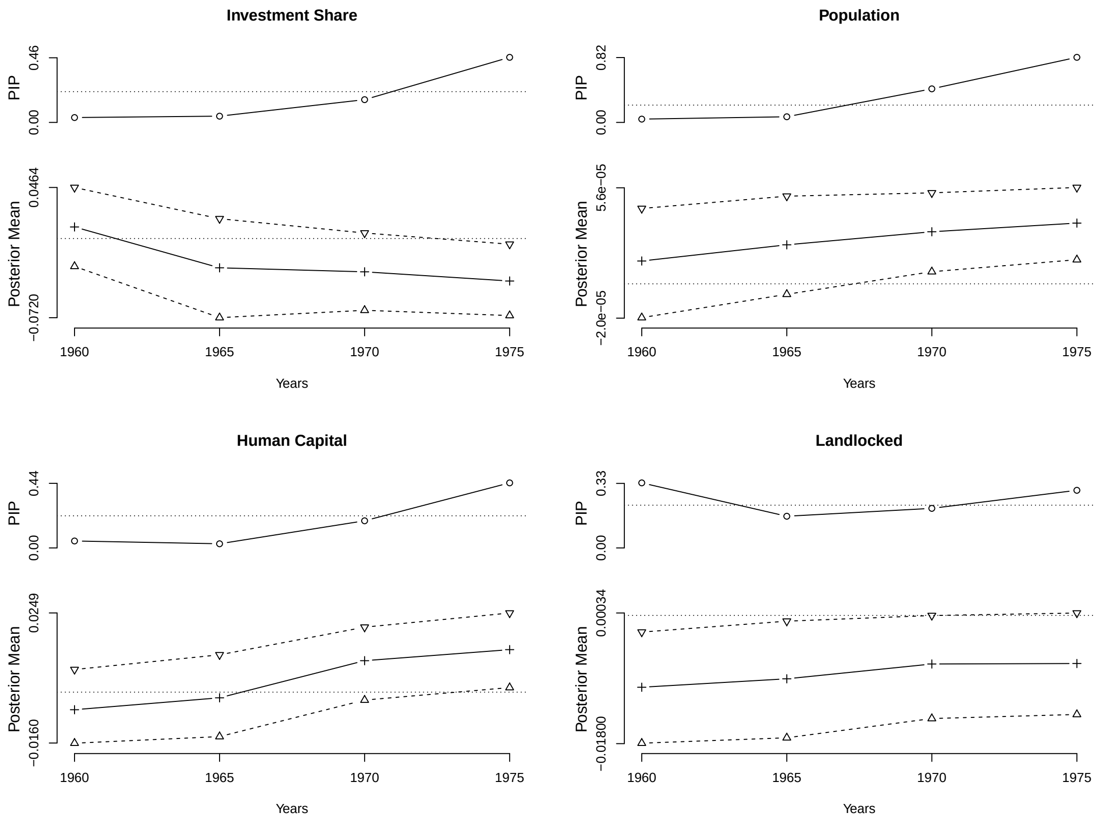
Notes: Spearman rank correlations for growth determinants between growth periods are reported based on posterior inclusion probabilities. 0.95 confidence intervals in brackets.

Table A5: Differences and growths of PIPs between the growth periods 1960-1980 and 1990-2010 (20 years)

	PIP (1960-1980)	PIP (1990-2010)	Difference	Rank (Difference)	Growth	Rank (Growth)
Population	0.1477	0.9871	0.8394	1	5.6850	1
Fertility	0.2038	0.4620	0.2581	2	1.2665	3
Population Density	0.1430	0.3782	0.2352	3	1.6445	2
Life Expectancy	0.2730	0.3916	0.1186	4	0.4345	5
Human Capital	0.1591	0.2464	0.0873	5	0.5487	4
Islam	0.1269	0.1787	0.0517	6	0.4077	6
Investment Price	0.1235	0.1304	0.0069	7	0.0557	7
Primary Schooling	0.1295	0.1276	-0.0019	8	-0.0150	8
Land Near Navigable Water	0.1259	0.1232	-0.0026	9	-0.0209	9
Christianity	0.1475	0.1432	-0.0043	10	-0.0293	11
d Terms of Trade	0.1675	0.1626	-0.0049	11	-0.0292	10
Openess	0.1390	0.1166	-0.0224	12	-0.1612	12
Total GDP	0.1243	0.0973	-0.0270	13	-0.2171	13
Polity	0.1203	0.0900	-0.0303	14	-0.2516	14
Judaism	0.1173	0.0709	-0.0465	15	-0.3961	17
Land Area	0.1245	0.0746	-0.0499	16	-0.4006	18
Government Consumption Share	0.1185	0.0684	-0.0501	17	-0.4229	20
Spanish Colony	0.1250	0.0717	-0.0533	18	-0.4264	22
Tertiary Education	0.1292	0.0756	-0.0535	19	-0.4144	19
Hindu	0.1661	0.1104	-0.0557	20	-0.3354	15
Fraction Tropics	0.1316	0.0758	-0.0557	21	-0.4237	21
Latitude	0.1613	0.1033	-0.0581	22	-0.3598	16
Colony	0.1336	0.0736	-0.0600	23	-0.4491	25
Duration Regime Change	0.1355	0.0751	-0.0604	24	-0.4457	24
Distance to City	0.1388	0.0782	-0.0606	25	-0.4364	23
Terms of Trade	0.1340	0.0697	-0.0643	26	-0.4796	26
Tropical Climate Zone	0.1553	0.0690	-0.0862	27	-0.5554	27
British Colony	0.1726	0.0751	-0.0976	28	-0.5652	29
Investment Share	0.1916	0.0835	-0.1081	29	-0.5643	28
Primary Exports	0.1835	0.0748	-0.1087	30	-0.5924	30
Buddhism	0.2259	0.0760	-0.1499	31	-0.6636	31
Landlock	0.3895	0.0995	-0.2900	32	-0.7445	32

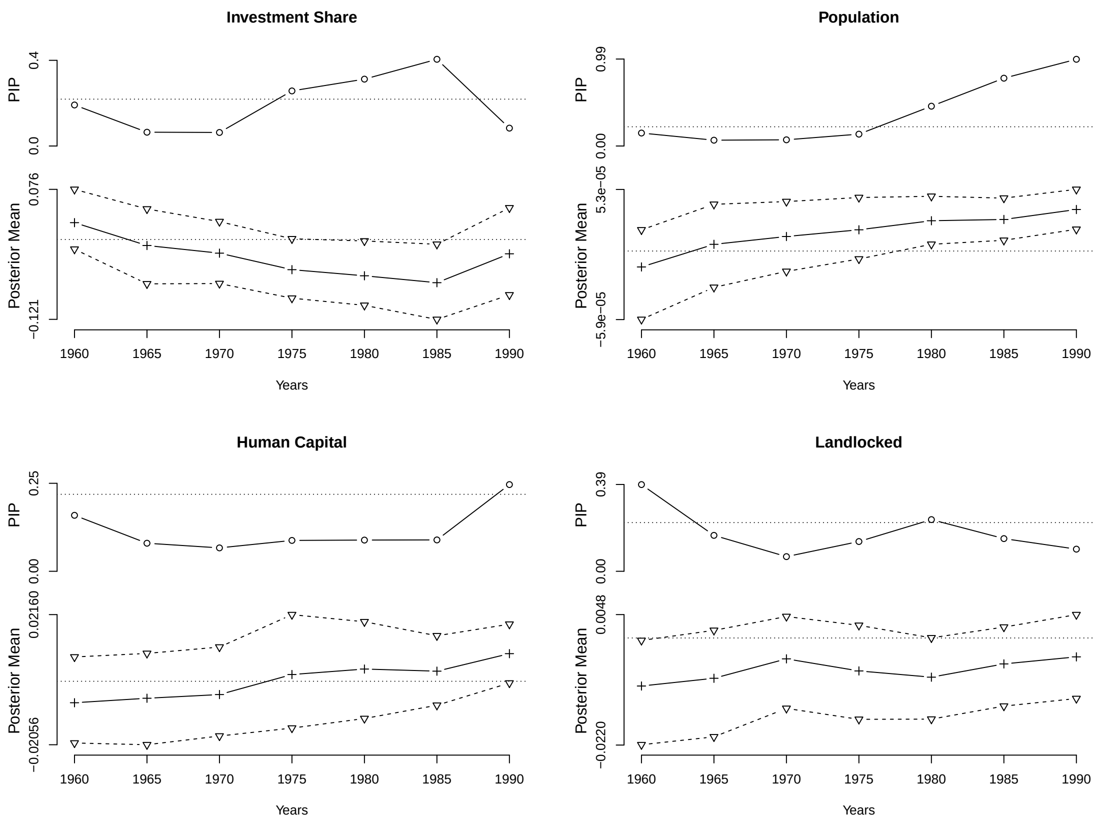
Notes: The PIPs for the growth periods 1960-1980 and 1990-2010, the difference and growth of each PIP between these two growth periods and the corresponding ranks are presented.

Figure 1: Selected posterior inclusion probabilities and posterior means for growth periods of 35 years



Notes: Posterior inclusion probabilities (PIPs) and means, 0.025 quantiles, and 0.975 quantiles of the posterior distribution conditional on inclusion are shown for four growth determinants. For the PIP, the dotted line represents the threshold of 'significance' of 0.218 and for the posterior mean, the dotted line represents 0. The years represent the starting years of the growth periods 1960-1995 to 1975-2010.

Figure 2: Selected posterior inclusion probabilities and posterior means for growth periods of 20 years



Notes: Posterior inclusion probabilities (PIPs) and means, 0.025 quantiles, and 0.975 quantiles of the posterior distributions conditional on inclusion are shown for four growth determinants. For the PIP, the dotted line represents the threshold of ‘significance’ of 0.218 and for the posterior mean, the dotted line represents 0. The years represent the starting years of the growth periods 1960-1980 to 1990-2010.