Determinants of Economic Growth: Will Data Tell?

by

Antonio Ciccone and Marek Jarocinski*

September 2009

Abstract

Many factors inhibiting and facilitating economic growth have been suggested. Can agnostics rely on international income data to tell them which matter? We find that agnostic priors lead to conclusions that are sensitive to differences across available income estimates. For example, the PWT 6.2 revision of the 1960-96 income estimates in the PWT 6.1 leads to substantial changes regarding the role of government, international trade, demography, and geography. We conclude that margins of error in international income estimates appear too large for agnostic growth empirics.

Keywords: growth regressions, robust growth determinants, agnostic Bayesian econometrics
JEL Codes: E01, O47

---

* ICREA-Universitat Pompeu Fabra; and European Central Bank. Emails: antonio.ciccone@upf.edu and marek.jarocinski@ecb.int. We are grateful to Manuel Arellano, Federico Cingano, Tim Cogley, Steven Davis, Yuri Dikhanov, Eduardo Ley, and three referees for very useful comments. Ciccone gratefully acknowledges research support from the CREI and CREA research institutes. The opinions expressed herein are those of the authors and do not necessarily represent those of the European Central Bank.

1. Introduction

Why does income grow faster in some countries than others? Most empirical research addressing this question has in common that only a few explanatory variables are considered, but differs in the variables selected (e.g. Kormendi and Meguire, 1985; Grier and Tullock, 1989; Barro, 1991; for a review see Durlauf, Johnson, and Temple, 2005). Researchers select explanatory variables because there are almost as many candidate variables as countries, and classical regression analysis yields inconclusive or fragile results in this case.

The literature's focus on regression models with few explanatory variables has raised concerns that findings are non-robust to variable selection (e.g. Levine and Renelt, 1992). These concerns appear especially relevant in growth economics as researchers' choices point to a wide range of priors regarding relevant explanations, and the availability of multiple measures for each explanation leaves room for data mining. As a result, many economists appear to be discounting the cross-country evidence on growth determinants (e.g. Rodrik, 2006; Commission on Growth and Development, 2008).

Should cross-country growth evidence be discounted? Are there no growth determinants that are robust to variable selection? Fernandez, Ley, and Steel (2001b) and Sala-i-Martin, Doppelhofer, and Miller (2004) propose to answer these questions using Bayesian model averaging with agnostic priors. The goal is to see which growth determinants, if any, are robust when priors implicit in variable selection are relaxed as much as possible. Put differently, the objective is to see what the data tell a researcher who is completely agnostic a priori. Fernandez, Ley, and Steel and Sala-i-Martin, Doppelhofer, and Miller find that the data point strongly to a number of robust growth determinants. We show that agnostic Bayesian model averaging discriminates among variables based on small differences in the R-squared of relatively few specifications. This leads to results that are very sensitive to minor errors in measurement and turn out to differ substantially depending on the income estimates being used. We conclude that margins of error in international income estimates are too large for agnostic growth empirics.

Given the difficulties faced when estimating international income differences, see Heston (1994) for example, it is not surprising that estimates vary and are continuously revised. For example, the Penn World Table income data (the dataset used in most cross-country empirical work) have undergone periodic revisions to eliminate errors, incorporate improved national income data, or account for new price benchmarks.[1] These corrections turn out to have a substantial effect on the conclusions of Bayesian model averaging with agnostic priors. For example, using the Sala-i-Martin, Doppelhofer, and Miller procedure we find 10 variables with a posterior inclusion probability—the probability that a variable should be included in the empirical growth model—greater than 50% according to PWT 6.2 or PWT 6.1 data for the 1960-96 period. Hence, there are 10 variables more likely to be included than excluded in the empirical growth model according to one of the two versions of the PWT. But 8 of these variables are more likely to be included than excluded according to one version of the PWT and more likely to be excluded than included according to the other version. This disagreement is not driven by small changes around the 50% threshold, as each of the 8 variables sees a change in posterior inclusion probability greater than 40 percentage points. The criterion used by Sala-i-Martin, Doppelhofer, and Miller to classify variables as robust to model selection yields 23 growth determinants according to PWT 6.2 or 6.1. But 13 of these growth determinants are robust according to one of the datasets but not the other. The inclusion probabilities obtained with Fernandez, Ley, and Steel's approach are very similar and produce the same disagreements.

Disaccord concerning the 1960-1996 growth determinants across PWT income data revisions affects factors that have featured prominently in the literature. For instance, one of the influential findings of Sala-i-Martin, Doppelhofer, and Miller is a robust negative effect of malaria prevalence in the 1960s on economic growth over the 1960-1996 period (a finding used to estimate the economic costs of malaria by Sachs, 2005). But malaria prevalence is not a robust growth determinant according to the Sala-i-Martin, Doppelhofer, and Miller criterion when we use PWT 6.1 or PWT 6.2 data instead of PWT 6.0 data. Prominent potential growth determinants that are robust according to PWT 6.0 and PWT

[1] See Heston, Summers, and Aten (2001, 2002, 2006). PWT revisions are sometimes accompanied by a change in the base year for prices, which alone can change relative income estimates (e.g. Dowrick and Quiggin, 1997; Deaton and Heston, 2008). Johnson et al. (2009) explain why newer is not necessarily better when it comes to PWT income estimates.

6.1 data but not according to PWT 6.2 data are life expectancy, the abundance of mining resources, the relative price of investment goods, and location in the tropics (for earlier results on these growth determinants see Barro, 1991; DeLong and Summers, 1991; Jones, 1994; Sachs and Warner, 1995). For example, the posterior inclusion probabilities of the relative price of investment goods and of location in the tropics go from respectively 77% and 57% with PWT 6.0 data to 2% and 5% with PWT 6.2 data. On the other hand, the posterior inclusion probability of fertility is only 3% with PWT 6.0 data but 91% with PWT 6.2 data (on the link between fertility and growth see Barro, 1991, 1998; Barro and Lee, 1994). Fernandez, Ley, and Steel's approach yields very similar posterior inclusion probabilities.

As is well known, there is no best method for obtaining internationally comparable real income data (e.g. Neary, 2004). As different datasets use different methods, their income estimates would differ even if the underlying data was identical. For example, the PWT and the World Bank use different methods, which is why their international income estimates differ although they build on the same national income and price benchmark data (e.g. Kravis, Heston, and Summers, 1982; Neary, 2004; Dowrick, 2005). Differences between estimates in the Word Bank's World Development Indicators and the PWT are limited however. For example, the correlation between 1975-1996 growth rates in the PWT 6.1 and the WDI is 93.5%, and the correlation between 1975-1996 growth rates in the PWT 6.2 and the WDI is 96.2%. Still, agnostic Bayesian model averaging yields disagreement on the determinants of 1975-1996 growth between the two datasets. For example, there are 5 variables with posterior inclusion probabilities greater than 50% according to PWT 6.1 or PWT 6.2. For each of these 5 variables, switching to the WDI data leads to a change in the posterior inclusion probability greater than 40 percentage points for one of the PWT-WDI comparison pairs. Moreover, of the 26 variables with posterior inclusion probabilities greater than 10% in one of the two PWT datasets, 14 see a change in the posterior inclusion probability greater than 20 percentage points for one of the PWT-WDI comparison pairs (the 10% threshold corresponds to Sala-i-Martin, Doppelhofer, and Miller's robustness criterion).

The remainder of the paper is structured as follows. Section 2 introduces Bayesian model averaging with agnostic priors, and Section 3 explains why the conclusions of agnostic Bayesian model averaging can be very sensitive to measurement. Section 4 uses alternative income estimates for the same period and shows that they yield rather different results when using agnostic Bayesian model averaging. The section also presents a small-scale Monte Carlo study of the sensitivity of agnostic Bayesian model averaging to small changes in the data. Section 5 concludes.

2. Bayesian Model Averaging and Agnostic Priors

Bayesian model averaging with agnostic priors is a special case of Bayesian model averaging. We therefore first explain Bayesian model averaging in the context of growth regressions and then introduce agnostic priors.

Bayesian model averaging in growth regressions. Consider the problem of identifying the determinants of economic growth across countries. If the number of countries (*N*) were large relative to the number of explanatory variables (*K*), we could find the statistically significant explanatory variables by regressing the growth rate of countries on all candidate variables. With *N* close to *K*, this approach tends to yield estimates that are too imprecise to be of interest (the approach is infeasible when *N*<*K*). Bayesian methods therefore frame the problem of identifying the determinants of economic growth in terms of uncertainty about the true set of explanatory variables (model uncertainty).[2] The Bayesian approach to model uncertainty is to first attach prior probabilities to alternative sets of explanatory variables and then update these probabilities using data.

To develop the Bayesian approach to growth determinants more formally it is useful to collect all K candidate explanatory variables in a vector x. The 2^K subsets of x are denoted by x_j, $j=1,...,2^K$, and called models. The cross-country growth regressions considered are of the form

(1) $$y_n = \alpha + x_{jn}\beta_j + \varepsilon_{jn}$$

where y_n is the growth rate of per capita GDP in country *n*; α is the constant term; β_j is the effect of the explanatory variables in model *j* on growth; and ε_{jn} is a Gaussian error term. The ingredients of Bayesian Model Averaging (BMA) are: priors for models (p_j);

---

[2] Brock and Durlauf (2001) argue that in growth economics there is model uncertainty because of uncertainty about which growth determinants to include in a model and uncertainty about which observations in a dataset constitute draws from the same statistical model.

priors for all parameters (α, β_j and the variance of the error term); and the likelihood function for each model *j*. A key intermediate statistic is the likelihood of model *j* integrated with respect to the parameters using their prior distributions (the marginal likelihood of model *j*, $l_y(M_j)$). Bayesian approaches use Bayes' theorem to translate the density of the data conditional on the model (the marginal likelihood) into a posterior probability of the model conditional on the observed data,

(2) $$p(M_j \mid y) \propto l_y(M_j)p_j .$$

One can go from posterior probabilities of models to *posterior inclusion probabilities* for each of the *K* candidate explanatory variables.[3] The posterior inclusion probability of a variable is calculated by summing posterior probabilities of all models including the variable. The actual relationship of a variable with growth is summarized in the unconditional posterior mean of its coefficient (to distinguish it from the posterior mean conditional on the variable being included).[4]

Bayesian model averaging can also accommodate a focus on groups of variables rather than individual variables (e.g. Brock, Durlauf, and West, 2003; Durlauf, Kourtellos, and Tan, 2006 and 2008). A focus on groups reflects priors that some variables have to be considered jointly because they represent theories or that some variables capture the same underlying growth determinant.

BMA with agnostic priors. The idea of the agnostic Bayesian approaches to growth determinants of Fernandez, Ley, and Steel (2001b) and Sala-i-Martin, Doppelhofer, and Miller (2004) is to limit the subjectivity of Bayesian analysis. This is done by including a large number of candidate variables treated symmetrically a priori and by using coefficient priors that have a negligible effect on the posterior distribution of model coefficients (so-called loose priors). FLS assume equal prior probabilities for all models, irrespective of model size and composition.[5] SDM assume equal priors for models of the same size but

[3] BMA actually provides the full posterior distribution of all parameters. We focus on key summary statistics used in the growth regressions literature.
[4] Detailed discussions of BMA can be found in Leamer (1978) and Hoeting et al. (1999) for example.
[5] The FLS model prior implies that the expected model size is K/2, where K is the number of candidate variables. Ley and Steel (2009) find that results can be sensitive to the prior expected model size. Therefore, they advocate the use of hierarchical priors, which decrease the dependence on the prior expected model size specified by the researcher. They find that in the cross-country

favor models of a predetermined size (7 in their preferred specification). SDM specify non-informative priors for model coefficients that make posterior distributions equal to classical sampling distributions of ordinary least-squares coefficients. This is why they refer to their approach as Bayesian averaging of classical estimates. FLS use priors proposed in Fernandez, Ley and Steel (2001a) (so-called benchmark priors) that are designed to have a negligible effect on the posterior distribution of model coefficients. [6]

SDM chose priors for model coefficients that yield the following (approximate) marginal likelihood of the data

$$l_y(M_j) \propto N^{-\frac{k_j}{2}} SSE_j^{-\frac{N}{2}}, \tag{3}$$

where k_j is the number of candidate explanatory variables included in model j and SSE_j is the sum of squared ordinary least-squares residuals associated with the model. Hence, posterior probabilities of models are increasing in model fit and decreasing in the number of candidate variables included in the model. The marginal likelihood of the data in FLS (in their equation (8)) is

$$l_y(M_j) \propto \left(\frac{g}{g+1}\right)^{\frac{k_j}{2}} \left(\frac{1}{g+1} SSE_j + \frac{g}{g+1}(y-\bar{y})'(y-\bar{y})\right)^{-\frac{N-1}{2}}, \tag{4}$$

where $g = 1/\max\left\{N, K^2\right\}$, y is a vector collecting growth rates for all countries, and $\bar{y}$ is the average growth rate in the sample multiplied by a vector of ones.

3. Agnostic Priors and Imperfect Data

Agnostic Bayesian approaches to growth determinants put much weight on the sum of squared errors when assigning posterior inclusion probabilities to models. This can be seen immediately from the SDM marginal likelihood in (3) where the sum of squared errors (*SSE*) is raised to the power $-N/2$, which in SDM's case equals −44 as they have data on 88 countries. FLS's approach in (4) also implies posterior inclusion probabilities that are very sensitive to the sum of squared errors because their loose priors amount to a very small value for *g*.

---

growth context their preferred priors lead to posteriors which are concentrated on rather small models (2 to 7 variables). In the Web Appendix we report all calculations of this paper repeated using Ley and Steel (2009) priors and show that this does not affect our conclusions.

[6] Eicher, Papageorgiou, and Raftery (2009) and Ley and Steel (2009) examine a variety of priors.

To get a sense of the magnitude of this effect, suppose that we want to determine the posterior inclusion probabilities of the 67 candidate explanatory variables considered by SDM. To simplify, we limit attention to models of a predetermined size. In this case, substituting (3) into (2) and summing across all models containing a given variable, yields that the posterior inclusion probability of a candidate explanatory variable *v* relative to *w* is

$$\text{(6)} \qquad \frac{\text{Posterior probability variable } v}{\text{Posterior probability variable } w} = \frac{\sum_{j \in S_v} SSE_j^{-\frac{N}{2}}}{\sum_{j \in S_w} SSE_j^{-\frac{N}{2}}}.$$

where S_v and S_w denote the set of models containing variable *v* and *w* respectively. Now suppose that a data revision leads to a fall in the sum of squared errors generated by candidate variable *v* of 1.5% in all models. With data on 88 countries, this implies that the posterior inclusion probability of this variable almost doubles relative to other variables.

How strongly do actual data revisions affect posterior inclusion probabilities? To illustrate the effect we assume a predetermined model size of 1 and determine the posterior inclusion probability of the 67 variables in the SDM dataset with both PWT 6.1 and PWT 6.2 income data for the 1960-1996 period. In the top-left panel of Figure 1 we plot the R-squared (R^2) of all 67 models including just the constant term and each of the variables (sorted by decreasing R^2) using PWT 6.1 data. In the top-right panel we display the corresponding posterior probabilities (computed as in SDM) for the first 16 variables. The comparison of these two panels illustrates how small differences in R^2 translate into large differences in inclusion probabilities. The best variable (which turns out to be the number of years countries have been open to international trade) has an R^2 of 33% and gets a posterior inclusion probability of 84%. The sixth variable has an R^2 of 25% and an inclusion probability of around 0.6% (beyond the sixth variable inclusion probabilities are negligible). The bottom-left and bottom-right panels display the R^2 and inclusion probability for variables in the same order as in the top-left panel but using PWT 6.2 data. It can be seen that changing the dataset perturbs the inclusion probabilities drastically when compared to changes in R^2. For example, the number of years open goes from a posterior inclusion probability of 84% with PWT 6.1 data to a posterior inclusion probability of 3% with PWT 6.2 data. On the other hand, the posterior inclusion probability of the East Asia dummy goes from a posterior inclusion probability of 6% with PWT 6.1 data to a posterior inclusion probability of 97% with PWT 6.2 data.

When the predetermined model size is greater than 1, the posterior inclusion probability of a variable is the sum of posterior inclusion probabilities across models containing the variable. What if data revisions were to lead to changes in the sum of squared errors that are unsystematic across models containing this variable? Would such data imperfections average out and therefore have small effects on posterior inclusion probabilities? It turns out that they may not average out in theory and practice. To see this, note that when N is large, then $\sum_{j \in S_v} SSE_j^{-\frac{N}{2}}$ is dominated by the sum of squared errors of the best fitting model (the model with the lowest SSE). In this case, we can therefore approximate the relative posterior inclusion probabilities in (6) by an expression that only involves the best fitting models for each variable

$$\frac{\text{Posterior probability variable } v}{\text{Posterior probability variable } w} \cong \frac{\max\left\{ SSE_j^{-\frac{N}{2}} : j \in S_v \right\}}{\max\left\{ SSE_j^{-\frac{N}{2}} : j \in S_w \right\}}.$$

Small unsystematic changes in the sum of squared errors across models can therefore have large effects on posterior inclusion probabilities of variables.

To illustrate the effect of the best fitting models on posterior inclusion probabilities for actual data revisions, we return to the example where we try to determine the posterior inclusion probabilities of the 67 candidate explanatory variables for economic growth considered by SDM with PWT 6.0, PWT 6.1 and PWT 6.2 data. But now we take the predetermined model size to be 3. In this case, each variable is part of 66*65/2=2145 models, which means that the posterior inclusion probability of a variable is the sum of posterior inclusion probabilities across 2145 models. A useful perspective on the sensitivity of posterior inclusion probabilities to the sum of squared errors of the best-fitting model can be obtained in two steps. First, we compute for each variable the sum of squared errors of all models that contain the variable, sort the sums of squared errors from smallest to largest, and store the minimum as well as the sum of squared errors at the 1st, 5th, 25th, and 50th percentile. Then we regress the log of the posterior inclusion probabilities of all variables on the log sum of squared errors at these percentiles and the log sum of squared errors of the best-fitting model.

Table 1 shows the results of this regression for the posterior inclusion probabilities obtained using PWT 6.0 data, PWT 6.1 data, and PWT 6.2 data. According to the R^2, the smallest sum of squared errors and the sums of squared errors at the 1^{st}, 5^{th}, 25^{th}, and 50^{th} percentile explain 99% of the variation in posterior inclusion probabilities in each of the three datasets. It is also interesting to note that only the sum of squared errors of the best fitting model and at the 1^{st} percentile are statistically significant. Hence, the variation in posterior inclusion probabilities across variables is explained by relatively few specifications (1% of the 2145 specifications). Moreover, posterior inclusion probabilities turn out to be sensitive to the sum of squared errors of the best fitting model as a 1% fall in the minimum sum of squared error is associated with an increase in the posterior inclusion probability of at least 28%.

4. Determinants of Economic Growth: Does Data Tell?

So far we have argued that the conclusions of agnostic BMA might be sensitive to the margins of error in the available income data. We now examine whether this is the case when we do a full-fledged agnostic BMA analysis of the determinants of economic growth over the 1960-1996 period and over the 1960-1975 period.

4.1 Determinants of Economic Growth 1960-1996: The Effect of PWT Revisions

To assess the sensitivity of the results of agnostic BMA to PWT income data revisions, we compare PWT 6.2 results with those of earlier PWT income data covering the 1960-1996 period (PWT 6.0 and 6.1). Our starting point is the sample of Sala-i-Martin, Doppelhofer, and Miller (2004), who use PWT 6.0 income data and data on 67 potential growth determinants for 88 countries.[7] The PWT 6.1 income data are available for 84 of the countries in the SDM sample and the PWT 6.2 data for 79 countries. As we want to use the history of PWT revisions to examine how much posterior inclusion probabilities might change with future revisions, we always use the largest possible sample.

Growth determinants. Table 2 contains our results using SDM's approach. All variables with a posterior inclusion probability greater than 10% in one of the three PWT datasets are shown in boldface (PWT 6.0; PWT 6.1; and PWT 6.2). The 10% posterior inclusion

[7] Variables and samples are described in Web Appendix A.

probability threshold comes from SDM who use it to define robust growth determinants (they use the threshold 7/67≈10% because in their setup, variables with a posterior inclusion probability greater than this threshold have a posterior inclusion probability greater than the prior inclusion probability). The table shows that SDM's results are sensitive to PWT revisions. The SDM criterion yields 23 robust growth determinants according to PWT 6.2 or PWT 6.1. But the two versions of the PWT disagree on more than half of these variables (13).

The disagreement in Table 2 is not driven by small changes in posterior inclusion probabilities around the particular SDM robustness threshold. Among the 10 variables with a posterior inclusion probability greater than 50% according to PWT 6.2 or PWT 6.1, there are 8 variables where the PWT revision changes the posterior inclusion probability by more than 40 percentage points (the absolute difference in posterior inclusion probabilities across PWT revisions are shown in the last two columns of the table).

Many of the variables affected by PWT revisions have been prominent in the growth literature. For example, the investment price variable (which has played an important role in the growth literature, see for example DeLong and Summers, 1991, and Jones, 1994) is the variable with the third highest posterior inclusion probability (98%) according to PWT 6.1 income data, but practically irrelevant in the PWT 6.2 (the posterior inclusion probability is 2%). The posterior inclusion probability of the variable capturing location in the tropics (fraction of tropical area) drops from 70% to 5%. A similar drop is experienced by population density in 1960 and the population density of coastal areas in the 1960s. Air distance to big cities is another geographic country characteristic whose relevance for growth diminishes with the PWT 6.2 dataset. Life expectancy in 1960, the fraction of GDP produced in the mining sector, and political rights experience smaller, but still important decreases in their posterior inclusion probabilities (from around 25% to below 3%; for earlier results on the role of life expectancy and political rights for economic growth see Limongi and Przeworski, 1993; Barro, 1991, 1996). The share of government expenditures in GDP, on the other hand, obtains a posterior inclusion probability of 27% according to PWT 6.2 but is irrelevant according to PWT 6.1. Other variables with high posterior inclusion probabilities (above 83%) with PWT 6.2 data but low posterior inclusion probabilities (below 18%) according to PWT 6.1 are location in Africa, the fraction of the population that adheres to Confucianism, and fertility.

There is even greater disagreement regarding the determinants of 1960-1996 growth when we compare the results using PWT 6.2 data to those using PWT 6.0. Examples of variables that are irrelevant using PWT 6.0 but robust growth determinants according to the SDM criterion when using PWT 6.2 are fertility and primary export dependence (for earlier results see Sachs and Warner, 1995). Examples going in the opposite direction are the degree of ethnolinguistic fractionalization of the population, which was borderline with PWT 6.0 (for more on this variable, see Easterly and Levine, 1997; Alesina et al., 2003; Alesina and La Ferrara, 2005), and malaria prevalence. Disagreement is also substantial among the growth determinants with the highest posterior inclusion probabilities. For example, among the 8 variables with a posterior inclusion probability greater than 50% according to PWT 6.2 or PWT 6.0, there are 6 variables where the PWT revision changes the posterior inclusion probability by more than 40 percentage points. When we look across all three revisions of the PWT income data, we find that the SDM criterion yields 20 variables that are robust according to one version but non-robust according to another. And among the 10 variables with a posterior inclusion probability greater than 50% according to one of the datasets, there are 8 variables where the probability changes by more than 40 percentage points from one version of the PWT to another.

Applying BMA with benchmark priors of FLS instead of SDM's approach yields very similar posterior inclusion probabilities. The absolute difference in posterior inclusion probabilities between the two approaches averaged across all variables is only 1% for each of the three versions of the PWT.[8] As a result, BMA with benchmark priors of FLS is as sensitive to PWT revisions as SDM's approach.

Theory and proxy groups. There is no unique way to partition variables into relevant groups. We work with two conceptually distinct partitions. One of them contains groups of variables that can be argued to proxy for the same underlying growth determinant. We refer to these groups as proxy groups. Table 3 reports the proxy groups we employ; this table should be read as our priors on closely related variables. When we were doubtful on whether to include a variable in a group or not, we generally included the variable as we already know from our previous results that posterior inclusion probabilities are highly sensitive to PWT data revisions when groups are sufficiently small (singletons). Consider

[8] See Web Appendix Table C.2.1-FLS for the full results.

for example the proxy group called openness to trade. It seemed quite reasonable to include variables that appeared to reflect exports, imports, or tariff and non-tariff barriers to trade. But although we ultimately also included the real exchange rate distortion index in this group, this seemed less obvious (e.g. Rodriguez and Rodrik, 2001).

Table 3 also reports the second partition of variables we work with, theory groups. Here we follow Durlauf, Kourtellos, and Tan's (2008) definitions of broad economic theories as closely as possible. For example, just like Durlauf, Kourtellos, and Tan, we define the neoclassical theory group to contain initial GDP, population growth, and variables reflecting capital accumulation. But there are also differences. The Durlauf, Kourtellos, and Tan macroeconomic policy group only contains 3 variables, trade openness, government consumption, and inflation. The list of 67 potential growth determinants we start out with contains several variables reflecting similar concepts, for example various measures of public consumption as well as a measure of public investment. Our macroeconomic policy group is therefore larger than Durlauf, Kourtellos, and Tan's. Our list of potential growth determinants also contains several variables that capture economic effects of geography. We therefore deviate from Durlauf, Kourtellos, and Tan and define an absolute geography group, which contains variables related to countries' climate zone, and a geography and trade group, which captures aspects of geography that appear relevant for internal and international trade.

Once groups have been defined we can determine the posterior inclusion probabilities of groups, defined as the probability that at least one of the variables in a group is included in the model. For example, if PWT revisions only led to a reassignment of posterior inclusion probabilities across variables in the same group, the posterior inclusion probabilities of groups would be unaffected.

Table 4 reports posterior inclusion probabilities of proxy groups and theory groups based on the posterior probabilities of individual variables in Table 2. The table shows substantial disagreement about the posterior inclusion probability of proxy groups. For example, the posterior probability of inclusion of the population growth group varies from 92% with PWT 6.2 to 15% with PWT 6.1. Among the 4 groups of variables with a posterior inclusion probability greater than 50% according to PWT 6.2 or PWT 6.1, there are 3 groups where the PWT revision changes posterior inclusion probabilities by more than 40 percentage points. Comparing results across the three versions of the PWT, we find that among the 9 groups with a posterior inclusion probability greater than 10% according to one dataset, there are 7 groups where posterior inclusion probabilities change by at least 20 percentage points from one revision to another.

There continues to be substantial disagreement across PWT revisions when we examine the posterior inclusion probabilities of theory groups. Among the 7 groups of variables with a posterior inclusion probability greater than 50% according to PWT 6.2 or PWT 6.1, there are 5 groups where the PWT revision changes the posterior inclusion probability by more than 40 percentage points. It is interesting to examine the 2 groups with relatively consistent results, neoclassical theory and regional heterogeneity, in more detail. The neoclassical theory group turns out to produce consistent results across PWT revisions because the variables included in this group produce relatively consistent results individually, see Table 2. For the regional heterogeneity group, on the other hand, the consistency of the group is the result of offsetting effects of two component variables. As can be seen in Table 2, individually, the dummy variable for Africa has a substantially larger posterior inclusion probability using PWT 6.2 than PWT 6.1, while it is the other way round for the dummy variable for East Asia. When we consider the three versions of the PWT, we find that among the 10 groups with a posterior inclusion probability greater than 10% according to one dataset, there are 7 groups where posterior inclusion probabilities change by at least 20 percentage points from one revision to another.

Posterior inclusion probabilities of proxy groups and theory groups change by very little when we calculate them using BMA with benchmark priors of FLS instead of SDM's approach.[9] This is not surprising given our previous finding that the two approaches yielded nearly identical posterior inclusion probabilities for individual variables.

The presence of groups in BMA may have implications for model (group) priors. For example, the posterior probabilities of groups in Table 4 were obtained, just like the posterior probabilities of individual variables in Table 2, under the assumption that each variable has the same prior inclusion probability independent of the inclusion of other variables. This independence assumption implies that larger prior probabilities are assigned to larger groups. An alternative approach would be to assume that each group has the same prior inclusion probability. In this case it would also be necessary to specify the prior probabilities for all subsets of each group conditional on the group being represented. One

[9] See Web Appendix Table C.2.2-FLS for full results.

possibility would be to assign the same prior probability to all subsets (Brock, Durlauf, and West, 2003). Another possibility is to assign lower prior probabilities to subsets containing strongly correlated variables than subsets containing weakly correlated variables. This is the so-called dilution prior as implemented by Durlauf, Kourtellos, and Tan (2006, 2008).[10]

Table 5 presents posterior inclusion probabilities of groups of variables obtained by combining dilution priors with SDM's coefficient priors. The table shows that dilution priors also continue to yield substantial disagreement on posterior inclusion probabilities across the three versions of the PWT. There are 5 groups of variables with a posterior inclusion probability greater than 50% according to PWT 6.2 or PWT 6.1, and the two versions of the PWT disagree by more than 40 percentage points on 2 of them. There is a similar degree of disaccord for theory groups, and the coefficient priors of FLS also yield substantial disaccord for proxy groups and theory groups.[11]

4.2 Determinants of Economic Growth 1975-1996: PWT or WDI?

We also want to examine the sensitivity of agnostic Bayesian model averaging to the different methodological choices underlying the PWT and the World Bank international income data published in the World Development Indicators. This analysis is for the 1975-1996 period, as the World Bank's purchasing power parity income estimates are available for few countries before 1975. As potential determinants we continue to use the 67 variables compiled by SDM, with values updated as necessary.[12]

Growth determinants. Table 6 reports our results for individual growth determinants. We now use the BMA approach with the benchmark priors of FLS. Results using SDM's benchmark priors are almost identical however; for example, the absolute difference in posterior inclusion probabilities between the two approaches averaged across all variables never exceeds 1%.[13]

Table 6 shows substantial disagreement regarding posterior inclusion probabilities when using WDI instead of PWT income data. For example, there are 5 variables with a

[10] The prior is proportional to the determinants of the correlation matrix (see Durlauf, Kourtellos, and Tan, 2008, for details).
[11] See Web Appendix Table C.3.2-FLS and C.4.2-FLS for full results.
[12] Details on the updated variables are given in Web Appendix A, Table A1c.
[13] See Web Appendix Table D.1.1-SDM for full results.

posterior inclusion probability greater than 50% according to one of the two PWT datasets. For each of these 5 variables, switching to the WDI data produces a change in the posterior inclusion probability greater than 40 percentage points for one of the PWT-WDI comparison pairs. These differences in posterior inclusion probabilities are quite surprising as the correlation between WDI and PWT growth rates is very high. The correlation between 1975-1996 growth rates in the PWT 6.1 and the WDI is 93.5%, and the correlation between 1975-1996 growth rates in the PWT 6.2 and the WDI is 96.2%. Table 6 also shows that most of this disagreement comes from the comparison between the PWT 6.1 data and WDI data.[14]

Theory and proxy groups. Table 7 reports inclusion probabilities of proxy groups and theory groups based on the posterior probabilities of individual variables in Table 6. Now there is less disagreement. But there are still key groups with substantial disaccord. For example, the trade openness group goes from 27% using the PWT 6.2 to 66% using the WDI. For theory groups there is considerable agreement between WDI and PWT 6.2 income data but less agreement between WDI and PWT 6.1 data. Of the 7 groups with posterior inclusion probabilities above 50% according to the WDI or the PWT 6.1, 2 groups see a change in posterior inclusion probabilities of more than 40 percentage points. The priors of SDM yield similar results.[15]

Table 8 shows that combining dilution priors with FLS coefficient priors yields substantial disagreement for proxy groups. Both groups with posterior inclusion probabilities above 50% according to the WDI or the PWT 6.1 see a change in posterior inclusion probabilities of more than 40 percentage points when switching to WDI data. There is also disaccord for theory groups. Of the 4 groups with a posterior inclusion probability greater than 50% using either the PWT 6.2 or the WDI, 2 groups see a change of more than 40 percentage points when switching to WDI data (and a third group sees a change in the posterior inclusion probability of 39 percentage points). The coefficient priors of SDM yield less disagreement, especially for theory groups.[16]

---

[14] We cannot tell whether PWT 6.2 income estimates are closer to WDI estimates than PWT 6.1 estimates by coincidence or because there is some convergence in how the PWT and the WDI resolve contentious measurement issues. If it is the latter, PWT-WDI differences may become progressively smaller in the future.

[15] See Web Appendix Table D.1.2-SDM for full results.

[16] See Web Appendix Table D.3.2-SDM (proxy groups) and Table D.4.2-SDM (theory groups).

4.3 A Monte Carlo Study

As another check on the sensitivity of agnostic Bayesian approaches, we perform a Monte Carlo study. We first generate 30 artificial datasets by randomly perturbating the 1960-1996 annualized growth rates in the PWT 6.1. To make sure this perturbation is minor compared to the margins of error in the available income data, we calibrate it to the smallest difference between available datasets (which happens to be the difference between the PWT 6.1 and the PWT 6.0).[17] We then draw from the calibrated distribution until we have generated 30 growth perturbations whose correlation with PWT 6.1 growth is between 97.5% and 98%. For comparison, the correlation between 1960-1996 growth rates in the PWT 6.1 and the PWT 6.2 is 93.3%, the correlation between 1975-1996 growth rates in the PWT 6.1 and the WDI is 93.5%, and the correlation between 1975-1996 growth rates in the PWT 6.2 and the WDI is 96.2%. The construction of the perturbed growth rates is explained in more detail in the Appendix.

Applying SDM's approach to each of the 30 growth perturbations yields substantial variation in posterior inclusion probabilities. For example, of the 7 growth determinants with posterior inclusion probabilities above 50% according to PWT 6.1, more than 2 see a change in their posterior inclusion probability greater than 40 percentage points in an average perturbation.[18] Moreover, of the 67 candidate explanatory variables we consider, close to half emerge as growth determinants according to the SDM criterion for some perturbation but not for another. Repeating the exercise applying the BMA approach with benchmark priors of FLS instead of SDM's approach yields very similar results.[19]

[17] This calibration is second best and could be much improved upon if we had a better understanding of the main sources of uncertainty and measurement error in the data underlying the PWT or if we could isolate the effects of changes in the base year on PWT revisions.

[18] Formally, consider perturbation j and denote with $z(j)$ the number of variables that see a change in their posterior inclusion probability greater than 40 percentage points when comparing PWT 6.1 with perturbation j. The average of $z(j)$ across perturbations is 2.1.

[19] Ley and Steel (2009) perform a Monte Carlo experiment where they generate artificial samples by randomly dropping 15% of observations, and find posterior inclusion probabilities of some variables fluctuating between zero and almost certainty.

5. Conclusions

The empirical growth literature has focused on regression models with few explanatory variables, which has raised the question whether findings are robust to variable selection. One way to answer this question is by using statistical approaches that incorporate prior uncertainty about model specification, as in Fernandez, Ley, and Steel (2001b) and Sala-i-Martin, Doppelhofer, and Miller (2004). This allows treating all explanatory variables symmetrically a priori—to be agnostic on what matters for growth a priori—and see whether some explanatory variables end up receiving strong support from the data.

We show that such approaches yield conclusions that are sensitive to minor errors in measurement and turn out to differ substantially depending on the income estimates being used. For example, the PWT 6.2 revision of the PWT 6.1 1960-96 data lead to substantial changes regarding the role of government, international trade, demography, and geography. Overall, our findings suggest that margins of error in the available income data are too large for empirical analysis that is agnostic about model specification. It seems doubtful that the available international income data will tell an agnostic about the determinants of economic growth.

This finding puts growth empirics in a difficult situation. Levine and Renelt (1992) showed that when empirical work starts from a limited number of explanatory variables, results are likely to be non-robust to model specification. We show that when the net is cast widely, results are likely to be non-robust to minor errors in measurement. A practical way out of this dilemma is to use cross-country data only to shed additional light on hypotheses with previous empirical support from regional, industry, or micro data.

References

Alesina, Alberto and Eliana La Ferrara, 2005, "Ethnic Diversity and Economic Performance," Journal of Economic Literature, 43:721–61.

Alesina, Alberto, Arnaud Devleeschauwer, William Easterly, Sergio Kurlat, and Romain Wacziarg, 2003, "Fractionalization," Journal of Economic Growth, 8(2):155–94.

Barro, Robert J., 1991, "Economic Growth in a Cross Section of Countries," Quarterly Journal of Economics, 106(2):407–43.

Barro, Robert J., 1996, "Democracy and Growth," Journal of Economic Growth, 1(1):1–27.

Barro, Robert J., 1998, Determinants of Economic Growth: A Cross-Country Empirical Study, Lionel Robbins Lectures, MIT Press.

Barro, Robert J. and Jong-Wha Lee, 1994, "Sources of Economic Growth," Carnegie-Rochester Conference Series on Public Policy, 40:1–46.

Brock, William A. and Stephen N. Durlauf, 2001, "Growth Empirics and Reality," The World Bank Economic Review, 15(2):229-272.

Brock, William A., Steven N. Durlauf, and Kenneth D. West, 2003, "Policy Evaluation in Uncertain Economic Environments," Brookings Papers on Economic Activity, 34(2003-1):235-322.

Commission on Growth and Development, 2008, "The Growth Report Strategies for Sustained Growth and Inclusive Development," Washington: The International Bank for Reconstruction and Development / The World Bank on behalf of the Commission on Growth and Development.

DeLong, J. Bradford and Lawrence H. Summers, 1991, "Equipment Investment and Economic Growth," Quarterly Journal of Economics, 106(2):445–502.

Deaton, Angus and Alan Heston, 2008, "Understanding PPPs and PPP-Based National Accounts," NBER Working Paper 14499.

Dowrick, Steve, 2005, "The Penn World Table: A Review," Australian Economic Review, 38(2):223–228.

Dowrick, Steve and John Quiggin, 1997, "True Measures of GDP and Convergence," American Economic Review, 87(1):41–64.

Durlauf, Steven N., Paul A. Johnson, and Jonathan R. W. Temple, 2005, "Growth Econometrics," in Philippe Aghion and Steven N. Durlauf, eds., Handbook of Economic Growth, North-Holland.

Durlauf, Steven N., Andros Kourtellos, and Chih Ming Tan, 2006, "Is God in the Details? A Reexamination of the Role of Religion in Economic Growth," Discussion Papers Series, Department of Economics, Tufts University 0613, Department of Economics, Tufts University.

Durlauf, Steven N., Andros Kourtellos, and Chih Ming Tan, 2008, "Are Any Growth Theories Robust?" Economic Journal, 118(527): 329-346.

Easterly, William and Ross E. Levine, 1997, "Africa's Growth Tragedy: Policies and Ethnic Divisions," Quarterly Journal of Economics, 112(4):1203–50.

Eicher, Theo, Chris Papageorgiou, and Adrian E. Raftery, 2009, "Default Priors and Predictive Performance in Bayesian Model Averaging, with Application to Growth Determinants," Journal of Applied Econometrics, forthcoming.

Fernandez, Carmen, Eduardo Ley, and Mark F.J. Steel, 2001a, "Benchmark Priors for Bayesian Model Averaging," Journal of Econometrics, 100:381–427.

Fernandez, Carmen, Eduardo Ley, and Mark F.J. Steel, 2001b, "Model Uncertainty in Cross-Country Growth Regressions," Journal of Applied Econometrics, 16(5):563–76.

Grier, Kevin B. and Gordon Tullock, 1989, "An Empirical Analysis of Cross-National Economic Growth," Journal of Monetary Economics, 24(2):259–76.

Heston, Alan, 1994, "National Accounts: A Brief Review of Some Problems in Using National Accounts Data in Level of Output Comparisons and Growth Studies," Journal of Development Economics, 44:29–52.

Heston, Alan, Robert Summers, and Bettina Aten, 2001, 2002, 2006, "Penn World Table 6.0, 6.1, 6.2," Center for International Comparisons at the University of Pennsylvania (CICUP). Data Web Site: http://pwt.econ.upenn.edu/.

Hoeting, Jennifer A., David Madigan, Adrian E. Raftery, and Chris T. Volinsky, 1999, "Bayesian Model Averaging: A Tutorial," Statistical Science, 14(4):382–417.

Johnson, Simon, William Larson, Chris Papageorgiou, and Arvind Subramanian, 2009, "Is Newer Better? The Penn World Table Revisions in the Cross-Country Growth Literature", unpublished manuscript.

Jones, Charles I., 1994, "Economic Growth and the Relative Price of Capital," Journal of Monetary Economics, 34(3):359–382.

Kormendi, Roger C. and Philip Meguire, 1985, "Macroeconomic Determinants of Growth: Cross-Country Evidence," Journal of Monetary Economics, 16(2):141–63.

Kravis, Irving B., Alan Heston, and Robert Summers, 1982, World Product and Income: International Comparisons of Real Gross Products, Baltimore: The Johns Hopkins University Press.

Leamer, Edward E., 1978, Specification Searches, New York: John Wiley and Sons.

Levine, Ross E. and David Renelt, 1992, "A Sensitivity Analysis of Cross-Country Growth Regressions," American Economic Review, 82(4):942–63.

Ley, Eduardo and Mark F.J. Steel, 2009, "On the Effect of Prior Assumptions in Bayesian Model Averaging with Applications to Growth Regressions," Journal of Applied Econometrics, 24(4):651-674.

Limongi, Fernando and Adam Przeworski, 1993, "Political Regimes and Economic Growth," Journal of Economic Perspectives, 7(3):51-69.

Neary, J. Peter, 2004, “Rationalizing the Penn World Table: True Multilateral Indices for International Comparisons of Real Income,” American Economic Review, 94(5):1411–1428.

Rodriguez, Francisco and Dani Rodrik, 2001, “Trade Policy and Economic Growth: A Skeptic’s Guide to the Cross-National Evidence,” in Ben S. Bernanke and Kenneth Rogoff, eds., NBER Macroeconomics Annual 2000, Cambridge, MA: MIT Press.

Rodrik, Dani, 2006, “Goodbye Washington Consensus, Hello Washington Confusion? A Review of the World Bank's Economic Growth in the 1990s: Learning from a Decade of Reform,” Journal of Economic Literature, December, 44(4):973-987.

Sachs, Jeffrey D., 2005, “Can Extreme Poverty Be Eliminated?” Scientific American. 56-65.

Sachs, Jeffrey D. and Andrew M. Warner, 1995, “Economic Reform and the Process of Economic Integration,” Brookings Papers on Economic Activity, 1995(1):1–95.

Sala-i-Martin, Xavier, Gernot Doppelhofer, and Ronald I. Miller, 2004, “Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach,” The American Economic Review, 94(4):813–835.

World Bank World Development Indicators, 2004, World Bank. *World Development Indicators 2004* [CD-ROM], Washington, DC: World Bank [Producer and Distributor].

Appendix: Design of the Monte Carlo Study

We generate 30 perturbated 1960-96 growth series starting from PWT 6.1 GDP per capita growth. The perturbations are drawn from distributions that are calibrated to the difference between the PWT 6.0 and PWT 6.1 income data. The variance of these perturbations is taken to be decreasing in income per capita of a country. This reflects the observed heteroskedasticity of the measurement error; the income of richer countries is more exactly measured than that of poorer countries. In particular, we take the variance of the perturbations to be the fitted value from a regression of the squared differences between PWT 6.1 and 6.0 growth rates on a constant and PWT 6.1 log income per capita in 1960 (see Table 1 below for the results). Fitted values of the 17 richest (in 1960) countries are negative, so we replace them by 0, i.e. we do not perturb their growth rates. We draw from this distribution until we have generated 30 growth perturbations whose correlation with PWT 6.1 growth is between 0.975 and 0.979 (the interval is centered on 0.977, the correlation between PWT 6.1 and 6.0 growth rates). Summary statistics about perturbed data are reported in Table 2 below.

Appendix Table 1. Ordinary least-squares regression of squares of revisions of income data (growth and levels) on the level of income in 1960

Constant	0.000160
	(0.000048)
$\log y_{1960}^{PWT\,6.1}$	-0.000019
	(0.000006)
R^2	0.10
Number of observations	84

Notes: Standard errors are in parenthesis.

Appendix Table 2. Perturbed growth rate series compared to PWT 6.1 1960-1996 growth rates

	Correlation with PWT 6.1 1960-1996 growth rates	R^2 of regression on constant and PWT 6.1 1960-1996 growth rates
Min	0.975	0.950
Average	0.977	0.954
Max	0.979	0.959

Tables and Figures

Table 1. Determinants of Posterior Inclusion Probabilities

	PWT 6.0 coefficient (std.)	PWT 6.1 coefficient (std.)	PWT 6.2 coefficient (std.)
Intercept	-197.9 (4.0)	-163.7 (2.6)	-188.5 (3.0)
Log SSE at the 50th percentile	0.1 (1.1)	-1.1 (1.5)	1.8 (1.2)
Log SSE at the 25th percentile	1.4 (1.7)	2.0 (2.3)	0.2 (1.3)
Log SSE at the 5th percentile	-2.0 (1.7)	-0.7 (2.2)	-2.4 (1.8)
Log SSE at the 1st percentile	-7.3 (1.2)	-9.2 (1.7)	-6.9 (1.2)
Log of the smallest SSE	-37.0 (1.3)	-28.2 (1.2)	-30.6 (1.0)
R^2	0.99	0.99	0.99
Number of observations	67	67	67

Notes: Regression results. Dependent variable is the log of inclusion probabilities of variables in the SDM dataset.

Table 2. Determinants of 1960-1996 income growth with the SDM approach: Posterior inclusion probabilities using income data from Penn World Table versions 6.2, 6.1, and 6.0

	PWT 6.2	PWT 6.1	PWT 6.0	PWT 6.2/6.1	PWT 6.2/6.0
	posterior inclusion probabilities			abs.diff.	abs.diff.
GDP in 1960 (log)	**1.00**	**1.00**	**0.69**	0.00	0.31
Primary Schooling in 1960	**1.00**	**0.99**	**0.79**	0.01	0.21
Fertility in 1960s	**0.91**	**0.12**	0.03	0.78	0.88
African Dummy	**0.86**	**0.18**	**0.15**	0.68	0.71
Fraction Confucius	**0.83**	**0.12**	**0.20**	0.71	0.64
Fraction Muslim	**0.40**	**0.19**	**0.11**	0.21	0.29
Latin American Dummy	**0.35**	0.07	**0.14**	0.29	0.21
East Asian Dummy	**0.33**	**0.78**	**0.83**	0.45	0.50
Fraction Buddhist	**0.28**	**0.11**	**0.11**	0.18	0.17
Primary Exports 1970	**0.27**	**0.21**	0.05	0.05	0.22
Nominal Government GDP Share 1960s	**0.27**	0.02	0.04	0.25	0.23
Openness Measure 1965-74	**0.15**	0.05	0.07	0.09	0.07
Timing of Independence	**0.12**	0.08	0.02	0.04	0.10
Population Density Coastal in 1960s	0.10	**0.79**	**0.43**	0.69	0.33
Hydrocarbon Deposits in 1993	0.10	**0.12**	0.03	0.02	0.07
Years Open 1950-94	0.09	0.06	**0.11**	0.03	0.02
Fraction Protestants	0.07	0.02	0.05	0.05	0.02
Spanish Colony	0.06	0.02	**0.13**	0.04	0.06
Fraction Speaking Foreign Language	0.06	0.04	0.08	0.02	0.01
Fraction Catholic	0.06	0.02	0.03	0.04	0.03
European Dummy	0.06	0.03	0.03	0.03	0.03
Average Inflation 1960-90	0.05	0.02	0.02	0.04	0.03
Fraction of Tropical Area	0.05	**0.70**	**0.57**	0.65	0.52
Government Share of GDP in 1960s	0.05	0.04	0.06	0.01	0.01
Fraction Population Over 65	0.05	0.05	0.02	0.00	0.02
Air Distance to Big Cities	0.04	**0.45**	0.04	0.41	0.01

Square of Inflation 1960-90	0.04	0.02	0.02	0.02	0.02
Ethnolinguistic Fractionalization	0.04	0.02	0.10	0.01	0.07
Fraction Population in Tropics	0.03	**0.16**	0.06	0.12	0.03
Tropical Climate Zone	0.03	0.03	0.02	0.01	0.02
Defense Spending Share	0.03	0.02	0.02	0.01	0.01
Fraction Population Less than 15	0.03	0.02	0.04	0.01	0.01
Size of Economy	0.03	0.02	0.02	0.01	0.01
Life Expectancy in 1960	0.03	**0.25**	**0.22**	0.22	0.19
Revolutions and Coups	0.03	0.03	0.03	0.00	0.00
Landlocked Country Dummy	0.03	0.08	0.02	0.05	0.01
Higher Education 1960	0.03	0.02	0.06	0.01	0.03
Population Growth Rate 1960-90	0.03	0.03	0.02	0.00	0.01
Fraction Hindus	0.03	0.02	0.04	0.01	0.02
Absolute Latitude	0.03	0.03	0.03	0.00	0.00
Fraction Orthodox	0.03	0.02	0.01	0.01	0.01
Gov. Consumption Share 1960s	0.03	0.05	0.10	0.02	0.08
Interior Density	0.03	0.02	0.01	0.01	0.01
War Participation 1960-90	0.02	0.02	0.02	0.01	0.01
Socialist Dummy	0.02	0.03	0.02	0.01	0.01
Malaria Prevalence in 1960s	0.02	0.02	**0.26**	0.00	0.23
Investment Price	0.02	**0.98**	**0.77**	0.96	0.75
Political Rights	0.02	**0.25**	0.07	0.23	0.05
Colony Dummy	0.02	0.09	0.03	0.07	0.01
Public Investment Share	0.02	0.04	0.05	0.02	0.03
Oil Producing Country Dummy	0.02	0.02	0.02	0.00	0.00
Land Area	0.02	0.02	0.02	0.00	0.00
Capitalism	0.02	0.02	0.02	0.00	0.00
Real Exchange Rate Distortions	0.02	0.04	0.09	0.02	0.07
Population Density 1960	0.02	**0.74**	0.09	0.72	0.07
British Colony Dummy	0.02	0.02	0.03	0.00	0.01
Public Education Spending Share in GDP in 1960s	0.02	0.03	0.02	0.01	0.00
Population in 1960	0.02	0.02	0.02	0.00	0.01
Fraction of Land Area Near Navigable Water	0.02	0.05	0.02	0.03	0.00
Fraction GDP in Mining	0.02	**0.24**	**0.12**	0.22	0.10
Religion Measure	0.02	0.03	0.02	0.01	0.00
Fraction Spent in War 1960-90	0.02	0.01	0.01	0.00	0.00
Terms of Trade Growth in 1960s	0.02	0.02	0.02	0.01	0.01
Civil Liberties	0.02	0.02	0.03	0.00	0.01
English Speaking Population	0.02	0.02	0.02	0.00	0.00
Terms of Trade Ranking	0.02	0.02	0.02	0.00	0.00
Outward Orientation	0.01	0.03	0.03	0.02	0.02

Notes: Variables come from the Sala-i-Martin, Doppelhofer, and Miller (2004) dataset. Posterior inclusion probabilities higher than the prior inclusion probabilities (here: 7/67) are in boldface.

Table 3. Definitions of groups of variables

Group name	Variable names
A. Proxy groups	
Market Access	Population Density Coastal in 1960s Interior Density Landlocked Country Dummy Fraction of Land Area Near Navigable Water
Population Growth	Fertility in 1960s Population Growth Rate 1960-90
Climate Zones	Tropical Climate Zone Fraction of Tropical Area Fraction Population in Tropics Absolute Latitude
Health	Malaria Prevalence in 1960s Life Expectancy in 1960
Natural Resources	Fraction GDP in Mining Hydrocarbon Deposits in 1993 Oil Producing Country Dummy Primary Exports 1970
Size of Government	Nominal Government GDP Share 1960s Government Share of GDP in 1960s Gov. Consumption Share 1960s Public Investment Share
Inflation	Average Inflation 1960-90 Square of Inflation 1960-90
War and Conflict	Revolutions and Coups Fraction Spent in War 1960-90 War Participation 1960-90
Openness to Trade	Openness Measure 1965-74 Years Open 1950-94 Outward Orientation Real Exchange Rate Distortions
Size of the Economy	Size of Economy Population in 1960
Rights	Political Rights Civil Liberties
Age Structure	Fraction Population Less than 15 Fraction Population Over 65
Education	Public Education Spending Share in GDP in 1960s Higher Education 1960 Primary Schooling in 1960
B. Theory Groups	
Neoclassical	GDP in 1960 (log) Population Growth Rate 1960-90 Public Education Spending Share in GDP in 1960s Higher Education 1960 Primary Schooling in 1960
Demography	Life Expectancy in 1960 Fertility in 1960s Fraction Population Less than 15 Fraction Population Over 65
Macroeconomic Policy	Nominal Government GDP Share 1960s

	Government Share of GDP in 1960s Gov. Consumption Share 1960s Public Investment Share Average Inflation 1960-90 Square of Inflation 1960-90 Openness Measure 1965-74 Years Open 1950-94 Outward Orientation Real Exchange Rate Distortions Investment Price
Absolute Geography	Tropical Climate Zone Fraction of Tropical Area Fraction Population in Tropics Malaria Prevalence in 1960s Absolute Latitude
Regional Heterogeneity	African Dummy European Dummy Latin American Dummy East Asian Dummy
Religion	Fraction Confucius Fraction Muslim Fraction Buddhist Fraction Protestants Fraction Catholic Fraction Orthodox Religion Measure Fraction Hindus
Geography and Trade (Within Countries and International)	Air Distance to Big Cities Population Density 1960 Size of Economy Population in 1960 Land Area Population Density Coastal in 1960s Landlocked Country Dummy Interior Density Fraction of Land Area Near Navigable Water
Institutions	Political Rights Civil Liberties Socialist Dummy Capitalism
War and Conflict	Revolutions and Coups Fraction Spent in War 1960-90 War Participation 1960-90
Colonial History	British Colony Dummy Spanish Colony Colony Dummy Timing of Independence
Natural Resources	Fraction GDP in Mining Hydrocarbon Deposits in 1993 Oil Producing Country Dummy Primary Exports 1970
Terms of Trade	Terms of Trade Growth in 1960s Terms of Trade Ranking

Table 4. Posterior inclusion probabilities of groups of variables in the SDM approach, using income data from Penn World Table versions 6.2, 6.1, 6.0

	PWT 6.2	PWT 6.1	PWT 6.0
A. Proxy groups			
Education	1.00	0.99	0.80
Population Growth	0.92	0.15	0.05
Natural Resources	0.35	0.44	0.20
Size of Government	0.34	0.14	0.23
Openness to Trade	0.25	0.17	0.26
Market Access	0.17	0.81	0.46
Climate Zones	0.14	0.84	0.64
Inflation	0.09	0.03	0.04
Age Structure	0.08	0.07	0.06
War and Conflict	0.07	0.05	0.06
Health	0.05	0.26	0.40
Size of the Economy	0.05	0.04	0.04
Rights	0.04	0.27	0.09
B. Theory groups			
Neoclassical	1.00	1.00	0.92
Demography	0.94	0.39	0.29
Regional Heterogeneity	0.93	0.89	0.94
Religion	0.90	0.38	0.39
Macroeconomic Policy	0.54	0.99	0.90
Natural Resources	0.35	0.44	0.20
Geography and Trade (Within Countries and International)	0.27	0.89	0.54
Colonial History	0.20	0.19	0.19
Absolute Geography	0.16	0.84	0.84
Institutions	0.08	0.30	0.12
War and Conflict	0.07	0.05	0.06
Terms of Trade	0.03	0.04	0.04

Table 5. Posterior inclusion probabilities of groups of variables obtained with 'dilution' model priors and SDM coefficient priors, using growth data from Penn World Table versions 6.2, 6.1, 6.0

	PWT 6.2	PWT 6.1	PWT 6.0
A. Proxy groups			
Education	1.00	1.00	0.93
Population Growth	0.94	0.50	0.24
Natural Resources	0.42	0.91	0.48
Size of Government	0.50	0.38	0.75
Openness to Trade	0.24	0.22	0.21
Market Access	0.09	0.29	0.13
Climate Zones	0.16	0.29	0.18
Inflation	0.27	0.13	0.11
Age Structure	0.24	0.36	0.19
War and Conflict	0.13	0.17	0.16
Health	0.17	0.53	0.53
Size of the Economy	0.13	0.12	0.12
Rights	0.17	0.15	0.14
B. Theory groups			
Neoclassical	1.00	1.00	0.96
Demography	0.89	0.58	0.43
Regional Heterogeneity	0.94	0.91	0.94
Religion	0.75	0.58	0.43
Macroeconomic Policy	0.11	0.96	0.86
Natural Resources	0.48	0.98	0.56
Geography and Trade (Within Countries and International)	0.02	0.14	0.06
Colonial History	0.26	0.26	0.14
Absolute Geography	0.10	0.27	0.38
Institutions	0.08	0.08	0.10
War and Conflict	0.10	0.17	0.13
Terms of Trade	0.09	0.16	0.09

Table 6. Determinants of 1975-1996 income growth with the FLS approach. Posterior inclusion probabilities using income data from PWT versions 6.1 and 6.2, and WDI

	PWT 6.2	WDI	PWT 6.1	WDI	PWT 6.2/WDI	PWT 6.1/WDI
	(common sample N=87)		(common sample N=86)		abs.diff.	abs.diff
East Asian Dummy	0.98	0.99	0.50	0.99	0.01	0.49
Investment Price	0.97	0.24	0.34	0.06	0.73	0.28
GDP in 1975 (log)	0.91	1.00	0.60	1.00	0.09	0.40
Life Expectancy in 1975	0.88	0.95	0.47	0.99	0.07	0.51
Fraction of Tropical Area	0.72	0.68	0.20	0.72	0.05	0.52
Fraction GDP in Mining	0.32	0.18	0.59	0.25	0.14	0.34
Absolute Latitude	0.21	0.32	0.22	0.27	0.10	0.05
Fraction Confucius	0.14	0.07	0.45	0.06	0.07	0.39
Openness Measure 1965-74	0.11	0.19	0.12	0.28	0.08	0.16
Political Rights	0.11	0.26	0.03	0.21	0.16	0.18
Primary Schooling in 1975	0.10	0.03	0.03	0.04	0.07	0.01
Real Exchange Rate Distortions	0.09	0.34	0.35	0.38	0.25	0.03
British Colony Dummy	0.09	0.12	0.10	0.08	0.03	0.02
Public Investment Share	0.09	0.03	0.06	0.03	0.06	0.03
Population Density Coastal in 1960s	0.08	0.09	0.06	0.07	0.01	0.01
Years Open 1950-94	0.08	0.32	0.09	0.26	0.25	0.18
Population Density 1975	0.07	0.08	0.07	0.07	0.01	0.00
African Dummy	0.07	0.03	0.57	0.04	0.04	0.53
Fraction Population in Tropics	0.06	0.04	0.19	0.04	0.03	0.15
Fraction Buddhist	0.05	0.02	0.30	0.02	0.03	0.28
Terms of Trade Ranking	0.05	0.06	0.11	0.06	0.01	0.06
Fraction Speaking Foreign Language	0.05	0.13	0.03	0.10	0.08	0.08
Malaria Prevalence in 1960s	0.05	0.09	0.02	0.10	0.04	0.08
Revolutions and Coups	0.04	0.03	0.04	0.03	0.02	0.01
Ethnolinguistic Fractionalization	0.04	0.06	0.10	0.05	0.01	0.05
Higher Education 1975	0.04	0.04	0.04	0.03	0.00	0.00
Fraction Muslim	0.04	0.05	0.12	0.04	0.01	0.08
Population in 1975	0.04	0.04	0.05	0.06	0.00	0.01
Latin American Dummy	0.04	0.03	0.14	0.03	0.01	0.12
Government Share of GDP in 1970s	0.04	0.02	0.33	0.20	0.01	0.14
Fraction Orthodox	0.04	0.02	0.05	0.03	0.01	0.02
Fraction Hindus	0.04	0.03	0.05	0.03	0.00	0.02
Capitalism	0.03	0.03	0.02	0.02	0.00	0.00
Civil Liberties	0.03	0.03	0.02	0.03	0.00	0.01
Timing of Independence	0.03	0.03	0.03	0.04	0.00	0.00
Land Area	0.03	0.03	0.02	0.03	0.00	0.01
Gov. Consumption Share 1970s	0.03	0.18	0.12	0.21	0.15	0.09
Fraction Population Less than 15	0.03	0.02	0.13	0.02	0.01	0.11
Nominal Government GDP Share 1970s	0.03	0.02	0.30	0.06	0.01	0.24
Religion Measure	0.02	0.02	0.02	0.02	0.00	0.00
Average Inflation 1960-90	0.02	0.02	0.04	0.02	0.01	0.02
Fraction Spent in War 1960-90	0.02	0.02	0.02	0.02	0.01	0.00
Fraction Protestants	0.02	0.04	0.05	0.03	0.01	0.02
Size of Economy	0.02	0.02	0.03	0.02	0.00	0.01

Defense Spending Share	0.02	0.05	0.28	0.06	0.03	0.21
Fraction Population Over 65	0.02	0.02	0.06	0.02	0.00	0.04
Square of Inflation 1960-90	0.02	0.02	0.03	0.02	0.00	0.01
Interior Density	0.02	0.02	0.02	0.02	0.00	0.00
European Dummy	0.02	0.02	0.05	0.02	0.00	0.02
Primary Exports 1970	0.02	0.02	0.03	0.02	0.00	0.01
Spanish Colony	0.02	0.02	0.10	0.02	0.00	0.07
Fraction of Land Area Near Navigable Water	0.02	0.02	0.02	0.02	0.00	0.00
Fertility in 1960s	0.02	0.02	0.04	0.02	0.00	0.03
Hydrocarbon Deposits in 1993	0.02	0.02	0.03	0.02	0.00	0.01
Fraction Catholic	0.02	0.02	0.04	0.02	0.00	0.02
Population Growth Rate 1960-90	0.02	0.02	0.03	0.02	0.00	0.02
Colony Dummy	0.02	0.02	0.02	0.02	0.00	0.00
Outward Orientation	0.02	0.04	0.02	0.04	0.02	0.01
Oil Producing Country Dummy	0.02	0.02	0.02	0.02	0.00	0.00
Terms of Trade Growth in 1960s	0.02	0.02	0.02	0.02	0.00	0.00
Public Education Spending Share in GDP in 1970s	0.02	0.02	0.02	0.02	0.00	0.00
Air Distance to Big Cities	0.02	0.02	0.03	0.02	0.00	0.01
Tropical Climate Zone	0.02	0.04	0.02	0.05	0.02	0.03
Landlocked Country Dummy	0.02	0.02	0.02	0.02	0.00	0.00
English Speaking Population	0.02	0.02	0.02	0.02	0.00	0.01
War Participation 1960-90	0.02	0.02	0.02	0.02	0.00	0.00
Socialist Dummy	0.02	0.02	0.03	0.02	0.00	0.02

Notes: The variables are based on Sala-i-Martin, Doppelhofer, and Miller (2004), but wherever applicable, variables were updated from the 1960s to the 1970s, see Web Appendix A.

Table 7. Posterior inclusion probabilities of groups of variables in the FLS approach, using income data from PWT versions 6.1 and 6.2, and WDI

	PWT 6.2	WDI	PWT 6.1	WDI
	(common sample N=87)		(common sample N=86)	
A. Proxy groups				
Climate Zones	0.95	0.98	0.59	0.98
Health	0.89	0.96	0.49	0.99
Natural Resources	0.36	0.22	0.62	0.29
Openness to Trade	0.27	0.66	0.49	0.69
Size of Government	0.17	0.24	0.75	0.46
Education	0.15	0.09	0.08	0.09
Rights	0.13	0.29	0.05	0.24
Market Access	0.13	0.14	0.12	0.12
War and Conflict	0.08	0.06	0.08	0.06
Size of the Economy	0.06	0.06	0.07	0.08
Inflation	0.04	0.03	0.06	0.03
Age Structure	0.05	0.04	0.19	0.04
Population Growth	0.04	0.04	0.08	0.04
B. Theory groups				
Regional Heterogeneity	0.99	0.99	0.90	0.99
Macroeconomic Policy	0.99	0.81	0.91	0.83
Absolute Geography	0.96	0.99	0.60	0.99
Neoclassical	0.92	1.00	0.64	1.00
Demography	0.89	0.96	0.57	0.99
Natural Resources	0.36	0.22	0.62	0.29
Religion	0.30	0.24	0.64	0.22
Geography and Trade (Within Countries and International)	0.28	0.30	0.28	0.29
Institutions	0.17	0.33	0.10	0.27
Colonial History	0.14	0.18	0.24	0.15
War and Conflict	0.08	0.06	0.08	0.06
Terms of Trade	0.07	0.08	0.13	0.07

Table 8. Posterior inclusion probabilities of groups of variables obtained with 'dilution' model priors and FLS benchmark coefficient priors, using income data from PWT versions 6.1 and 6.2, and WDI

	PWT 6.2	WDI	PWT 6.1	WDI
	(common sample N=87)		(common sample N=86)	
A. Proxy groups				
Climate Zones	0.71	0.87	0.14	0.86
Health	0.70	0.98	0.07	0.99
Rights	0.06	0.17	0.02	0.13
Inflation	0.03	0.02	0.04	0.02
Openness to Trade	0.02	0.12	0.04	0.11
Natural Resources	0.02	0.01	0.03	0.02
Age Structure	0.02	0.02	0.02	0.02
Population Growth	0.02	0.02	0.02	0.02
Size of the Economy	0.02	0.02	0.02	0.02
War and Conflict	0.02	0.01	0.02	0.01
Education	0.02	0.01	0.01	0.01
Size of Government	0.01	0.02	0.11	0.06
Market Access	0.01	0.01	0.01	0.01
B. Theory groups				
Regional Heterogeneity	1.00	1.00	0.97	1.00
Absolute Geography	0.58	0.97	0.22	0.97
Demography	0.10	0.96	0.04	0.97
Neoclassical	0.07	0.97	0.01	0.97
Colonial History	0.04	0.02	0.09	0.02
Macroeconomic Policy	0.04	0.00	0.01	0.01
War and Conflict	0.02	0.01	0.02	0.01
Terms of Trade	0.02	0.04	0.04	0.03
Natural Resources	0.01	0.01	0.01	0.01
Religion	0.01	0.00	0.05	0.00
Institutions	0.01	0.04	0.01	0.03
Geography and Trade (Within Countries and International)	0.00	0.00	0.00	0.00

Figure 1. R^2s and posterior probabilities in one-variable models, with PWT 6.1 and PWT 6.2 data