Growth Determinants Revisited*

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Abstract

We revisit the cross-country growth empirics debate using a novel Limited Information Bayesian Model Averaging framework to address model uncertainty in the context of a dynamic growth model in panel data with endogenous regressors. Our empirical findings suggest that once endogeneity, dynamics, and model uncertainty are accounted for, various economic factors such as initial conditions and macroeconomic environment are robustly correlated with economic growth. In particular, we find the strongest evidence that initial income, investment, life expectancy, inflation, and aid are robust growth determinants. In addition, we find significant differences between our set of robust determinants and those identified when we apply model averaging methodologies in the literature that address model uncertainty but fail to account for dynamics and/or endogeneity. These differences underscore the importance of addressing dynamics and endogeneity in addition to model uncertainty in growth empirics.

JEL Classifications: O40, C11, C15, C23, C52.

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1 Introduction

The topics of economic growth and human development have been examined since the beginning of recorded history.[1] Over the last two decades, the philosophical rhetoric has emphasized the primacy of human development as the ultimate objective of economic pursuits, while empirical work has tried to explain why some countries have experienced rapid long-term growth rates in income while others have not. Economic growth has been described as "the part of macroeconomics that really matters," not least because relatively small differences in growth rates, when cumulated over time, can have major consequences for standards of living.

Despite the vast literature of cross-country studies of economic growth, there is little consensus on the mechanics of economic growth. A fundamental problem confronting researchers is the lack of an explicit theory identifying the determinants of growth. Various extensions to the neoclassical and endogenous growth models are what Brock and Durlauf (2001) call "open-ended," as they admit a broad number of possible specifications and a vast range of logical and testable additions. In fact, a survey of the empirical growth literature by Durlauf, Johnson, and Temple (2005) identifies over 140 proxies of growth determinants put forward by various empirical studies—essentially more variables partially correlated with growth rates than the number of countries for which data are available. This "open-endedness" of growth theories highlights the degree of uncertainty surrounding the relevance of competing theories as unsystematic searches and "ad hoc" specifications often result in overconfident and fragile inferences or even contradictory conclusions.

As a result, a growing number of growth researchers are turning to the Bayesian Model Averaging (BMA) methods in order to investigate the robustness of growth determinants. The various BMA techniques—advanced through the work of Raftery (1995)—provide a conceptually attractive solution to the problem of model uncertainty by assuming that the researcher does not know which model is "true" and thus needs to attach probabilities to different possible models. Inferences are then based on a weighted average of the full model space instead of on one model, thus incorporating uncertainty in both predictions and parameter estimates. The work of Fernández, Ley and Steel (2001a), Brock and Durlauf (2001), and Sala-i-Martin, Doppelhofer and Miller (2004) formally introduced model averaging to the growth empirics literature. More recent applications of BMA to investigate growth empirics suggest several modifications of the early BMA framework, such as testing the strength of various growth theories instead of concentrating on the individual explanatory variables.[2]

Despite the increasing interest in using BMA to investigate growth empirics, most of the work has been in the form of static models, with variables of interest averaged over the period of analysis, essentially ignoring both dynamic relationships among variables, and the evolution of the growth process. In addition, a common issue in growth empirics is that many explanatory variables are endogenously determined. In turn, this implies a strong chance

[1] Anand and Sen (2000), for example, quote Aristotle as favoring human development: "Wealth is evidently not the good we are seeking, for it is merely useful and for the sake of something else."

[2] Brock, Durlauf, and West (2003), and Durlauf, Kourtelos and Tan (2008) discuss testing for growth theories instead of particular variables, while Ley and Steel (2007), and Doppelhofer and Weeks (2009) attempt to quantify the degree to which development determinants act "jointly" to affect growth.

that they are endogenous in the statistical sense, that is, correlated with the disturbance term, and failure to account for this may lead to inconsistent estimates. While both of these issues—modeling dynamics and incorporating endogeneity—are issues of particular relevance to growth analyses, they have not received much attention in the literature. Only recent work began to model dynamics in the context of BMA by exploring the use of panel data in the context of model uncertainty and started to investigate how to account for heterogeneity, including omitted country-specific effects, and address endogeneity.[3]

This paper revisits the cross-country growth empirics debate using a novel Limited Information Bayesian Model Averaging methodology to address model uncertainty in the context of a dynamic panel data growth model with endogenous regressors. The proposed methodology is a small sample counterpart of the LIBMA developed by Chen, Mirestean, and Tsangarides (2009) based on Generalized Method of Moments (GMM) estimation where the posteriors are obtained through a simple Bayesian procedure using the linear structure of the model. To the best of our knowledge, this is the first attempt to address simultaneously the modeling of dynamics and incorporating endogeneity in the growth empirics using a method for constructing the model likelihoods and posteriors based only on information elicited from moment conditions, with no specific distributional assumptions. Our approach differs from Tsangarides (2004) who approximates the model marginal likelihood by quasi likelihood functions whose specifications were justified only through large sample properties; Durlauf, Kourtellos, and Tan (2008) who construct instruments for the endogenous variables and introduce a model-averaged version of two-stage least squares; and Eicher, Lenkoski, and Raftery (2009) who develop an instrumental variable BMA methodology.[4]

Our empirical findings suggest that once endogeneity and model uncertainty are accounted for, various economic factors such as initial conditions and macroeconomic environment are robustly correlated with economic growth. In particular, we find the strongest evidence that initial income, investment, life expectancy, inflation and aid are robust growth determinants. Importantly, the set of growth determinants identified as robust using our LIBMA methodology is different from the sets found when we apply methodologies used by other studies that incorporate model uncertainty but don't account for dynamics or endogeneity. Overall, our results underline the importance of investigating growth empirics in a setting that not only incorporates model uncertainty but also explicitly accounts for *both* dynamics and endogeneity.

The rest of the paper is organized as follows. Section 2 presents the model specification, discusses estimation issues, and describes the estimator used for the robustness analysis. Section 3 presents the data and identifies the growth determinants. Section 4 summarizes the results. Section 5 concludes.

[3] See, for example, Tsangarides (2004), Moral-Benito (2009), and Chen, Mirestean and Tsangarides (2009).

[4] While not directly comparable to our approach, Moral–Benito (2009) considers a panel data model where the lagged dependent variable is correlated with the individual effects but not correlated with the error term.

2 Theoretical considerations

2.1 A dynamic growth model with endogenous regressors

A generic representation of the canonical cross-country growth regression is

$$g = \breve{Z}\theta + u \tag{1}$$

where g is the real growth rate of output per worker, $\mathcal{Y}$, between the period t and $t-1$; $\breve{Z}$ is an $n \times k$ matrix of growth regressors which includes those suggested by the Solow (1956) growth model (namely, population growth, technological change, physical and human capital, and savings rates) and those suggested by new growth theories; $\theta = \begin{pmatrix} \theta_1 & \theta_2 & ... & \theta_k \end{pmatrix}$ is a vector of unknown parameters to be estimated; and u is the error term.

Much of the work on growth empirics attempts to identify the variables k that comprise $\breve{Z}$. Suppose there is a universe of k possible explanatory variables indexed by $U = \{1, 2, ..., j, j+1, ..., k\}$. Let Z be the matrix of all possible explanatory variables. For a given model M_j that considers only a subset of the possible explanatory variables, $M_j \subset U$, let $C_{M_j} = \left\{c_{mn,M_j}\right\}_{m,n=1}^{k}$ be a $k \times k$ diagonal choice matrix such that its diagonal will have 1's if the corresponding variable is included in the model and 0's otherwise. Hence, $c_{ii,M_j} = 1\{i \in M_j\}$, and for a given model M_j, $\breve{Z} = ZC_{M_j}$.

Assume further that the universe of potential explanatory variables, indexed by the set U, consists of the lagged output per worker, indexed by 1, a set of m exogenous variables, indexed by X, a set of p predetermined variables, indexed by P, as well as a set of q endogenous variables, indexed by W, such that $\{\{1\}, X, P, W\}$ is a partition of U.

Define y_{it} as the log of the output per worker, $\mathcal{Y}_{it}$, that is, $y_{it} = \log(\mathcal{Y}_{it})$. Then, $g = y_{it} - y_{i,t-1}$, and the dynamic growth model for panel data for a given set of explanatory variables, that is, a particular model $M_j \subset U$, can be written as

$$\begin{array}{l} y_{it} = \begin{pmatrix} y_{i,t-1} & x_{it} & w_{it} & p_{it} \end{pmatrix} C_{M_j} \begin{pmatrix} \alpha & \theta_x & \theta_w & \theta_p \end{pmatrix}' + u_{it} \\ u_{it} = \eta_i + v_{it} \\ |\alpha| < 1;\ i = 1, 2, ..., N;\ t = 1, 2, ..., T \end{array} \tag{2}$$

where y_{it}, x_{it} , p_{it},and w_{it} are observed variables, η_i is the unobserved individual effect while v_{it} is the idiosyncratic random error. The exact distributions for v_{it} and η_i are not specified here, but assumptions about some of their moments and correlation with the regressors are made explicit below. It is assumed that $E(v_{it}) = 0$ and that v_{it}'s are not serially correlated. Also, x_{it} is a $1 \times m$ vector of exogenous variables, p_{it} is a $1 \times p$ vector of predetermined variables, while w_{it} is a $1 \times q$ vector of endogenous variables. Therefore, the total number of possible explanatory variables is $k = m + q + p + 1$.

The observed variables span N countries and T periods, where T is small relative to N. The unknown parameters α, θ_x,θ_p, and θ_w are to be estimated. In this model, α is a scalar, θ_x is a $1 \times m$ vector, θ_p is a $1 \times p$ vector, while θ_w is a $1 \times q$ vector.

Given the assumptions made so far, for any model M_j, and any set of exogenous variables, x_{it}, we have $E(x_{it}^l v_{is}) = 0$, $\forall i, t, s$; $x_{it}^l \in x_{it}$. Similarly, for any endogenous variable we have

$$E(w_{it}^{l}v_{is})\begin{cases}\neq 0,\ s\leq t\\ =0,\ \text{otherwise}\end{cases},\ w_{it}^{l}\in w_{it},$$

while for predetermined variables the conditions are

$$E(p_{it}^{l}v_{is})\begin{cases}\neq 0,\ s< t\\ =0,\ \text{otherwise}\end{cases},\ p_{it}^{l}\in p_{it}.$$

2.2 Estimation and moment conditions

A common approach for estimating the model in (2) is to use the system GMM framework (see Arellano and Bover (1995), and Blundell and Bond (1998)). This implies constructing the instruments set and moment conditions for the "levels equation" (2) and combining them with the moment conditions using the instruments corresponding to the "first-difference" equation written as

$$\begin{array}{l}\Delta y_{it}=\left(\begin{array}{cccc}\Delta y_{i,t-1} & \Delta x_{it} & \Delta w_{it} & \Delta p_{it}\end{array}\right)C_{M_j}\left(\begin{array}{cccc}\alpha & \theta_x & \theta_w & \theta_p\end{array}\right)^{'}+\Delta v_{it}\\ |\alpha|<1;\ i=1,2,...,N;\ \ t=2,3,...,T.\end{array}\tag{3}$$

One assumption required for the first difference equation is that the initial value of y, y_{i0}, is predetermined, that is, $E\left(y_{i0}v_{is}\right)=0$ for $s=2,3,...,T$. Since $y_{i,t-2}$ is not correlated with Δv_{it} it can be used as an instrument, and we have $E\left(y_{i,t-2}\Delta v_{it}\right)\neq 0$ for $t=2,3,...,T$. Moreover, since $y_{i,t-3}$ is also not correlated with Δv_{it} (and as long as we have enough observations (that is $T\geq 3$)) $y_{i,t-3}$ can be used as an instrument. Assuming that we have more than two observations in the time dimension, the following moment conditions could be used for estimation

$$E(y_{i,t-s}\Delta v_{it})=0,\ t=2,3,...,T;\ s=2,3,...,t;\ \text{for } T\geq 2,\ i=1,2,...,N.$$

Similarly, the exogenous variable x_{it}^{l}, $x_{it}^{l}\in x_{it}$ is not correlated with Δv_{it} and therefore can be used as an instrument, giving additional moment conditions

$$E(x_{it}^{l}\Delta v_{it})=0,\ t=2,3,...,T;\ l=1,...,m;\ i=1,2,...,N.$$

The predetermined variable $p_{i,t-1}^{l}$, $p_{i,t-1}^{l}\in p_{it}$, is not correlated with Δv_{it} and therefore it can be used as an instrument. We have the following possible moment conditions

$$\begin{array}{r}E(p_{i,t-s}^{l}\Delta v_{it})=0,\ t=2,3,...,T;\ s=1,...t-1;\\ \text{for } T\geq 2,\ l\!=1,2,...,p;\ i=1,...,N.\end{array}$$

The endogenous variable $w_{i,t-2}^{l}$, $w_{i,t-2}^{l}\in w_{it}$, is not correlated with Δv_{it} and therefore it can be used as an instrument. We have the following possible moment conditions

$$\begin{array}{r}E(w_{i,t-s}^{l}\Delta v_{it})=0,\ t=3,4,...,T;\ s=2,...t-1;\\ \text{for } T\geq 3,\ l\!=1,2,...,q;\ i=1,...,N.\end{array}$$

Table A summarizes the moment conditions that could be used for the first difference equation. Basically, the first difference equation provides $T\left(T-1\right)/2$ moment conditions for the lagged dependent variable, $m\,(T-1)$ moment conditions for the exogenous variables, and $q\,(T-2)\,(T-1)\,/2$ moment conditions for the endogenous variables.

Table A. Moment Conditions for the First Difference Equation

Variable	Instruments	Moment conditions
$\Delta y_{i,t-1}$	$y_{i,t-2},...,y_{i,0}$	$E(y_{i,t-s}\Delta v_{it})=0,\ t=2,3,...,T;\ s=2,3,...,t$
Δx^l_{it}	$x^l_{it},...,x^l_{i1}$	$E(x^l_{it}\Delta v_{it})=0,\ t=2,3,...,T;\ l=1,2,...,m$
Δp_{it}	$p^l_{i,t-1},...,p^l_{i,1}$	$E(p^l_{i,t-s}\Delta v_{it})=0,\ t=2,3,...,T;\ s=1,2,...,t-1;$ $l=1,2,...,p$
Δw^l_{it}	$w^l_{i,t-2},...,w^l_{i,1}$	$E(w^l_{i,t-s}\Delta v_{it})=0,\ t=3,4,...,T;\ s=2,3,...,t-1;$ $l=1,2,...,q$

For the levels equation (2), it is easy to see that first differences for the lagged dependent variable are not correlated with either the individual effects or the idiosyncratic error term. Then we can use the following moment conditions

$$E(\Delta y_{i,t-1}u_{it})=0,\ t=2,3,...,T.$$

Similarly, for the endogenous variables, the first difference $\Delta w^l_{i,t-1}$ is not correlated with u_{it}. Therefore, assuming that $w^l_{i,1}$ is observable, and as long as $T\geq 3$ we have the following additional moment conditions

$$E(\Delta w^l_{i,t-1}u_{it})=0,\ t=3,4,...,T,\ l=1,2,...,q.$$

For the predetermined variables, the first difference $\Delta p^l_{i,t}$ is not correlated with u_{it}. Therefore, assuming that $p^l_{i,1}$ is observable, and as long as $T\geq 2$ we have the following additional moment conditions

$$E(\Delta p^l_{i,t}u_{it})=0,\ t=2,3,...,T,\ l=1,2,...,p.$$

Finally, based on the assumptions made so far, the first difference of the exogenous variables Δx^l_{it} , $x^l_{it}\in x_{it}$ are not correlated with current realizations of u_{it} and hence one can use another set of moment conditions

$$E(\Delta x^l_{it}u_{it})=0,\ t=2,3,...,T,\ l=1,2,...,m.$$

Table B summarizes the moment conditions for the levels equation.

Table B. Moment Conditions for the Levels Equation

Variable	Instruments	Moment conditions
$y_{i,t-1}$	$\Delta y_{i,t-1}$	$E(\Delta y_{i,t-1}u_{it})=0,\ t=2,3,...,T$
x^l_{it}	Δx^l_{it}	$E(\Delta x^l_{it}u_{it})=0,\ t=2,3,...,T;\ l=1,2,...,m$
p^l_{it}	$\Delta p^l_{i,t-1}$	$E(\Delta p^l_{i,t}u_{it})=0,\ t=2,3,...,T;\ l=1,2,...,p$
w^l_{it}	$\Delta w^l_{i,t-1}$	$E(\Delta w^l_{i,t-1}u_{it})=0,\ t=3,4,...,T;\ l=1,2,...,q$

The equation in levels provides $(T-1)$ moment conditions for the lagged dependent variable, $m\,(T-1)$ moment conditions for the exogenous variables, and $q\,(T-2)$ moment conditions for the endogenous variables, and $p\,(T-1)$ moment conditions for the predetermined variables.

Furthermore, as shown by Ahn and Schmidt (1995), $(T-1)$ additional linear moment conditions are available if the v_{it} disturbances are assumed to be homoskedastic through time and $E(\Delta y_{i1}u_{i2}) = 0$. Specifically,

$$E(y_{i,t}u_{i,t} - y_{i,t-1}u_{i,t-1}) = 0,\ t = 2, 3, ..., T;\ i = 1, ..., N.$$

Let u_i and Dv_i denote the $T \times 1$ and $(T-1) \times 1$ matrices of the error term and the first differenced idiosyncratic random error, respectively, as defined in model (2), $u_i = \begin{pmatrix} u_{i1} & u_{i2} & \cdots & u_{iT} \end{pmatrix}'$ and $Dv_i = \begin{pmatrix} \Delta v_{i2} & \Delta v_{i3} & \cdots & \Delta v_{iT} \end{pmatrix}'$. Define a $(2T-1)\times 1$ matrix $U_i = \begin{pmatrix} u_i' & Dv_i' \end{pmatrix}'$ that contains both the error term and the first differenced idiosyncratic random error. The full set of moment conditions can now be written in matrix form

$$E\left[G_i'U_i\right] = 0 \tag{4}$$

where G_i is a $(2T-1)\times(T + 2m - 2 + p(T+2)(T-1)/2 + (T+1)\left((T-2)\,q + T\right)/2)$ matrix defined as

$$G_i = \begin{pmatrix} DX_i & 0 & DY_i & 0 & DW_i & 0 & DP_i & 0 & Y_i^- \\ 0 & X_i & 0 & Y_i & 0 & W_i & 0 & P_i & 0 \end{pmatrix}. \tag{5}$$

2.3 Model uncertainty

Given a universe of k possible explanatory variables in the growth regression, we have a set of $K = 2^k$ models $\mathcal{M} = (M_1, ..., M_K)$ under consideration. In the spirit of Bayesian inference, priors $p(\theta|M_j)$ for the parameters of each model, and a prior $p(M_j)$ for each model in the model space $\mathcal{M}$ are specified. Let $D = \begin{pmatrix} Y & Z \end{pmatrix}$ denote the data set available to the researcher. Using Bayes' rule the probability that M_j is the correct model, given the data D, is

$$p(M_j|D) = \frac{p(D|M_j)p(M_j)}{\sum_{l=1}^{K} p(D|M_l)p(M_l)} \tag{6}$$

where

$$p(D|M_j) = \int p(D|\theta_j, M_j)p(\theta_j|M_j)d\theta_j \tag{7}$$

is the marginal probability of the data given model M_j.

Hypothesis testing for the comparison of model M_j against M_i is based on the posterior probabilities and expressed by the posterior odds ratio $\frac{p(M_j|D)}{p(M_i|D)} = \frac{p(D|M_j)}{p(D|M_i)} \cdot \frac{p(M_j)}{p(M_i)}$. Essentially the data updates the prior odds ratio $\frac{p(M_j)}{p(M_i)}$ through the Bayes factor $\frac{p(D|M_j)}{p(D|M_i)}$ to measure the extent to which the data support M_j over M_i.[5] Evaluating the Bayes factors needed

[5] Often the prior odds ratio is set to 1 representing the lack of preference for either model, in which case the posterior odds ratio is equal to the Bayes factor B_{ji}.

for hypothesis testing and Bayesian model selection or model averaging requires calculating the marginal likelihood $p(D|M_j) = \int p(D|\theta, M_j)\, p(\theta|M_j)\, d\theta$.

Chen, Mirestean, and Tsangarides (2009) propose a method for constructing the marginal likelihoods (and posteriors) based only on information elicited from moment conditions, with no specific distributional assumptions. They consider a likelihood dependent, unit information prior (see Kass and Wasserman (1995)) which enables the derivation of a posterior in a simple Bayesian Information Criterion (BIC)-like form. Following their approach the model likelihood for a given model M_j for which θ has k_j elements different from zero is given by

$$\int_{\Theta} p\left(N^{-1}\sum_{i=1}^{N} G_i'\widetilde{y}_i\,|\theta, M_j\right) p(\theta)\, d\theta \propto \exp\left(-\frac{1}{2}N\widehat{g}_N'\left(\widehat{\theta}_{0,j}\right)S^{-1}\left(\widehat{\theta}_{0,j}\right)\widehat{g}_N\left(\widehat{\theta}_{0,j}\right) - \frac{k_j}{2}\log N\right) \tag{8}$$

where $\widehat{\theta}_{0,j}$ denotes the estimate for θ.

Then the moment conditions associated with model M_j can be written as $E\left[G_i'\left(\widetilde{y}_i - \widetilde{z}_i C_{M_j}\theta_0\right)\right] = 0$ where G_i is the instrument matrix. Using (8), the posterior odds ratio of two models M_1 and M_2 is given by

$$\begin{aligned}
\frac{p\left(M_1|N^{-1}\sum_{i=1}^{N} G_i'\widetilde{y}_i\right)}{p\left(M_2|N^{-1}\sum_{i=1}^{N} G_i'\widetilde{y}_i\right)} &= \frac{p(M_1)}{p(M_2)}\frac{p\left(N^{-1}\sum_{i=1}^{N} G_i'\widetilde{y}_i|M_1\right)}{p\left(N^{-1}\sum_{i=1}^{N} G_i'\widetilde{y}_i|M_2\right)} \\
&= \frac{p(M_1)}{p(M_2)}\exp\begin{pmatrix} -\frac{1}{2}N\widehat{g}_N'\left(\widehat{\theta}_{0,1}\right)S^{-1}\left(\widehat{\theta}_{0,1}\right)\widehat{g}_N\left(\widehat{\theta}_{0,1}\right) \\ +\frac{1}{2}\widehat{g}_N'\left(\widehat{\theta}_{0,2}\right)S^{-1}\left(\widehat{\theta}_{0,2}\right)\widehat{g}_N\left(\widehat{\theta}_{0,2}\right) \\ -\left(\frac{k_1-k_2}{2}\log N\right)\end{pmatrix}
\end{aligned} \tag{9}$$

which has the same form of BIC as fully specified models. We further assume a Uniform distribution over the model space, which implies that there is no preference for a specific model so $p(M_1) = p(M_2) = ... = p(M_K) = \frac{1}{K}$.

Using Bayesian Model Averaging, inference for a quantity of interest Γ can be constructed based on the posterior distribution

$$p(\Gamma|D) = \sum_{j=1}^{K} p(\Gamma|D, M_j)p(M_j|D) \tag{10}$$

which follows by the law of total probability.[6] Therefore, the full posterior distribution of Γ is a weighted average of the posterior distributions under each model $(M_1, ..., M_K)$, where the weights are the posterior model probabilities $p(M_j|D)$. Going back to the linear regression model (2), BMA allows the computation of the inclusion probability for every possible explanatory variable

$$p(Z_i|D) = \sum_{j=1}^{K} I(Z_i|M_j)p(M_j|D) \tag{11}$$

[6] Model selection seeks to find the model M_j in $\mathcal{M} = (M_1, ..., M_K)$ that actually generated the data. So, a natural strategy for model selection is to chose the most probable model M_j, namely the one with the highest posterior probability, $p(M_j|D)$.

where

$$I(Z_i|M_j) = \begin{cases} 1 & if \quad Z_i \in M_j \\ 0 & if \quad Z_i \notin M_j \end{cases} .$$

Using (10) posterior means and variances for parameters θ_l can be constructed, respectively, as follows

$$E(\theta_l|D) = \sum_{j=1}^{K} E(\theta_l|D, M_j)p(M_j|D) \tag{12}$$

and

$$\begin{aligned} Var(\theta_l|D) &= E(\theta_l^2|D) - [E(\theta_l|D)]^2 \\ &= \sum_{j=1}^{K} p(M_j|D) \left\{ Var(\theta_l|D, M_j) + [E(\theta_l|D, M_j)]^2 \right\} - E(\theta_l|D)^2 \\ &= \sum_{j=1}^{K} p(M_j|D)Var(\theta_l|D, M_j) + \sum_{j=1}^{K} p(M_j|D) [E(\theta_l|D, M_j) - E(\theta_l|D)]^2 \end{aligned} \tag{13}$$

2.4 Reducing the number of moment conditions

As suggested by (5) the number of instruments grows quadratically with T. Adding more instruments increases asymptotic efficiency but can also cause bias and/or increased variance in small samples (Donald, Imbens, and Newey (2008)). The finite sample properties of GMM estimators are sensitive to the number of moment conditions used.(persistent and/or too many instruments). Bun and Kiviet (2006) show that the finite sample bias of GMM estimators increases with the number of moment conditions used.[7] Windmeijer (2005) finds that GMM becomes more efficient when less lags are used in the estimation, and Roodman (2009) shows that using too many instruments overfits endogenous variables and results in imprecise estimates of the GMM optimal weighting matrix.

Attempts in the literature to address the "instrument proliferation" issue include Roodman (2009), who proposes transformations of the instrument set the make the instrument count linear in T (such as limiting the lag length of the instruments and/or collapsing the instrument set), and Arellano (2002), and Donald, Imbens, and Newey (2008) who attempt to model or select the optimal instruments.

We follow the approach suggested by Roodman (2009) and construct Monte Carlo simulations to experiment with reducing the number of moment conditions. Below, we discuss several ways to reduce the number of instruments by collapsing the instruments matrix *and* reducing the number of lags used. Appendices A1 and A2 present the Monte Carlo simulations and results, respectively, used to assess the performance of our estimator with reduced instrument count.

We begin by grouping the moment conditions for the first-difference and levels equations into matrices as follows.

[7] In addition, the small-sample performance of some GMM estimators deteriorates as the ratio of variance of the individual effect and the overall error term icreases (see Bun and Windmeijer (2010)).

First difference equation

The first difference equation provides $T\,(T-1)\,/2$ moment conditions for the lagged dependent variable. We can reduce the count of moment conditions to $(T-1)$ by stacking the instruments as in matrix Y_i^a. In this case we are still using all the all possible lags of the dependent variable for a given period t.

$$Y_i^a = \begin{pmatrix} y_{i0} & 0 & 0 & 0 & \cdots 0 \\ y_{i1} & y_{i0} & 0 & 0 & \cdots 0 \\ y_{i2} & y_{i1} & y_{i0} & 0 & \cdots 0 \\ y_{i3} & y_{i2} & y_{i1} & y_{i0} & \cdots 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{i,T_i-2} & y_{i,T_i-3} & y_{i,T_i-4} & y_{i,T_i-5} & \cdots y_{i0} \end{pmatrix}.$$

We can further reduce the count of instruments by limiting the number of lags used. For example, Y_i^1, Y_i^2, Y_i^3 are the $(T-1)\times 1$, $(T-1)\times 2$, $(T-1)\times 3$ stacked matrices of instruments using at most 1, 2, or 3 of all the possible lags of the dependent variable:

$$Y_i^1 = \begin{pmatrix} y_{i0} \\ y_{i1} \\ y_{i2} \\ y_{i3} \\ \vdots \\ y_{i,T_i-2} \end{pmatrix}, Y_i^2 = \begin{pmatrix} y_{i0} & 0 \\ y_{i1} & y_{i0} \\ y_{i2} & y_{i1} \\ y_{i3} & y_{i2} \\ \vdots & \vdots \\ y_{i,T_i-2} & y_{i,T_i-3} \end{pmatrix}, \text{ and } Y_i^3 = \begin{pmatrix} y_{i0} & 0 & 0 \\ y_{i1} & y_{i0} & 0 \\ y_{i2} & y_{i1} & y_{i0} \\ y_{i3} & y_{i2} & y_{i1} \\ \vdots & \vdots & \vdots \\ y_{i,T_i-2} & y_{i,T_i-3} & y_{i,T_i-4} \end{pmatrix}.$$

The lagged dependent variable is in fact a predetermined variable. Therefore, the discussion on the instruments of the lagged dependent variable also applies to the instruments of the predetermined variables. The only difference may occur from the fact that at time $t=0$ the predetermined variables may not have been observed and hence y_{i0} would be replaced by 0 in the instruments matrix. Assuming that L represents the maximum number of lags used, the number of moment conditions for the predetermined variables will be Lp.

The first difference equation provides $q\,(T-2)\,(T-1)\,/2$ moment conditions for the endogenous variables. As discussed in the case of the lagged dependent variable, we can reduce the count of moment conditions for the endogenous variables by stacking the matrix of instruments and limiting the umber of lags. Hence the matrix of instruments using at most 1 and 2 of all the possible lags of the endogenous variables, W_i^1, W_i^2, are given by

$$W_i^1 = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ w_{i1}^1 & w_{i1}^2 & \cdots & w_{i1}^q \\ w_{i2}^1 & w_{i2}^2 & \cdots & w_{i2}^q \\ w_{i3}^1 & w_{i3}^2 & \cdots & w_{i3}^q \\ \vdots & \vdots & \vdots & \vdots \\ w_{i,T-2}^1 & w_{i,T-2}^1 & \cdots & w_{i,T-2}^q \end{pmatrix},$$

$$W_i^2 = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 & 0 \\ w_{i1}^1 & 0 & w_{i1}^2 & \cdots & w_{i1}^q & 0 \\ w_{i2}^1 & w_{i1}^1 & w_{i2}^2 & \cdots & w_{i2}^q & w_{i1}^q \\ w_{i3}^1 & w_{i2}^1 & w_{i3}^2 & \cdots & w_{i3}^q & w_{i2}^q \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{i,T-2}^1 & w_{i,T-3}^1 & w_{i,T-2}^1 & \cdots & w_{i,T-2}^q & w_{i,T-3}^q \end{pmatrix}.$$

Therefore, the number of moment conditions for the endogenous variables has been reduced to q, and $2q$, respectively. Further, in a similar manner, we can reduce the number of moment conditions for the exogenous variables from $m\,(T-1)$ to m. Let X_i denote the $(T-1)\times m$ matrix of instruments for the exogenous variables:

$$X_i = \begin{pmatrix} x_{i2}^1 & x_{i2}^2 & x_{i2}^3 & \cdots & x_{i2}^m \\ x_{i3}^1 & x_{i3}^2 & x_{i3}^3 & \cdots & x_{i3}^m \\ x_{i4}^1 & x_{i4}^2 & x_{i4}^3 & \cdots & x_{i4}^m \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ x_{iT}^1 & x_{iT}^2 & x_{iT}^3 & \cdots & x_{iT}^m \end{pmatrix}.$$

Levels equation

For the levels equation we can reduce the number of moment conditions by simply stacking the instruments. For example, we can reduce the number of moment conditions for the lagged dependent variable from $T-1$ to 1 by just stacking the $(T-1)$ instruments. matrix DY_i consisting of first differences of the dependent variable and the $T \times q$ instruments matrix DW_i consisting of first differences of the endogenous variables.

$$DY_i = \begin{pmatrix} 0 \\ \Delta y_{i1} \\ \Delta y_{i2} \\ \Delta y_{i3} \\ \vdots \\ \Delta y_{i,T-1} \end{pmatrix}, DW_i = \begin{pmatrix} 0 & 0 \cdots & 0 \\ 0 & 0 \cdots & 0 \\ \Delta w_{i2}^1 & \Delta w_{i2}^2 \cdots & \Delta w_{i2}^q \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ \Delta w_{i,T-1}^1 & \Delta w_{i,T-1}^2 \cdots & \Delta w_{i,T-1}^q \end{pmatrix}.$$

Further, let DX_i denote the $T \times m$ matrix of the first differenced exogenous variables

$$DX_i = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ \Delta x_{i2}^1 & \Delta x_{i2}^2 & \Delta x_{i2}^3 & \cdots & \Delta x_{i2}^m \\ \Delta x_{i3}^1 & \Delta x_{i3}^2 & \Delta x_{i3}^3 & \cdots & \Delta x_{i3}^m \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \Delta x_{iT}^1 & \Delta x_{iT}^2 & \Delta x_{iT}^3 & \cdots & \Delta x_{iT}^m \end{pmatrix}.$$

Finally, let Y_i^- be the $T \times (T-1)$ instrument matrix used for the moment conditions derived from the Ahn and Schmidt (1995) homoskedasticity restriction:

$$Y_i^- = \begin{pmatrix} -y_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots 0 \\ y_{i2} & -y_{i2} & 0 & 0 & 0 & 0 & \cdots 0 \\ 0 & y_{i3} & -y_{i3} & 0 & 0 & 0 & \cdots 0 \\ 0 & 0 & y_{i4} & 0 & 0 & 0 & \cdots 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots y_{i,T} \end{pmatrix}.$$

Finally, depending on the maximum number of lags used, we can define the moment conditions in matrix form as:

$$E\left[G_i^{a\prime}U_i\right] = 0,\ E\left[G_i^{1\prime}U_i\right] = 0, or\ E\left[G_i^{2\prime}U_i\right] = 0 \tag{14}$$

where the matrix G_i^a corresponds to all lags, G_i^1 to 1 lag and G_i^2 to a maximum of 2 lags. G_i^a is a $(2T-1) \times (m+1+(2+q)(T-1))$ matrix defined as

$$G_i^a = \begin{pmatrix} DX_i & DY_i & 0_{T\times(T-1)} & DW_i & 0_{T\times q(T-2)} & Y_i^- \\ X_i & 0_{(T-1)\times 1} & Y_i & 0_{(T-1)\times q} & W_i & 0_{(T-1)\times(T-1)} \end{pmatrix}.$$

Similarly, G_i^1 and G_i^2 are $(2T-1) \times (T+2q+m+1)\,, (2T-1) \times (T+3q+m+2)$ matrices.

As an illustration, Table C below presents the number of moment conditions for various options of T, m, and q for the full set of instruments as well as the collapsed and/or lag reduced options. All the cases presented assume that only one predetermined variable enters the model, the lagged dependent variable. As indicated from the table, collapsing and/or reducing the lags yields dramatic reductions in the number of moment conditions. For example, for a case of 19 regressors (with 6 exogenous, one predetermined and 12 endogenous regressors) and 6 time periods, simply collapsing reduces the number of instruments from 205 to 77, while collapsing and further reducing the lag length to, say, 2, reduces the lags further to 50. This is particularly relevant for the analysis in this paper where N is limited.

Table C. Instruments for various options of T, m, and q

	$T=6$			$T=10$		
Exogenous	$m=5$	$m=5$	$m=6$	$m=5$	$m=5$	$m=6$
Endogenous	$q=6$	$q=8$	$q=12$	$q=6$	$q=8$	$q=12$
Uncollapsed full	119	147	205	337	425	603
Uncollapsed 2 lags	95	117	163	183	229	323
Uncollapsed 1 lag	73	87	123	133	165	231
Collapsed full	46	56	77	78	96	133
Collapsed 3 lags	38	46	63	42	50	67
Collapsed 2 lags	31	37	50	35	41	54
Collapsed 1 lag	24	28	37	28	32	41

3 Data

3.1 Growth determinants

We consider growth determinants that capture (proxy) proposed growth theories, policies, institutional characteristics, and other exogenous factors that stimulate growth. In addition to the variables suggested by the "augmented" neoclassical Solow model, surveys of the empirical growth literature (e.g. Durlauf and Quah (1999), and Durlauf, Johnson and Temple (2005)) identify a large number of explanatory variables grouped into "categories" or distinct growth theories.[8] Following these approaches, we construct a our sample of growth determinants grouped in eight categories. We describe the variables and the broad categories below.

- **Solow determinants and human capital:** The three variables suggested by the "augmented" neoclassical Solow model are rates of human and physical capital, and population growth. We capture the effect of physical capital through ratios of real investment to GDP; human capital development through measures of health and educational status (namely, life expectancy and school enrollment rates); and population through population growth rates.

- **Macroeconomic stability:** Macroeconomic policies can affect economic growth directly through their effect on accumulation of capital, or indirectly through their impact on the efficiency with which the factors of production are used. Sound macroeconomic policies send important signals to the private sector about the commitment and credibility of a country's authorities to efficiently manage the economy and increase the opportunity for profitable investments. Macroeconomic stability is reflected in low government consumption to GDP ratios, low and stable rates of inflation, a limited departure of the real exchange rate regime from its equilibrium levels, and low levels of debt. In our analysis, the impact of macroeconomic stability is captured by the government consumption relative to GDP, inflation, an index of exchange rate overvaluation, and the debt to GDP ratio.

- **Trade:** The proposition that more outward-oriented economies tend to grow faster has been tested extensively in the literature. Most studies tend to support the idea that openness to international trade accelerates development and growth by increasing access to free markets and returns from specialization. The trade regime and the external terms of trade effects are captured by the degree of openness and exogenous terms-of-trade changes, respectively.

- **External environment:** We capture changes in external environment by improvements in the terms of trade which is associated with improved international competitiveness. We also capture other changes in the external environment by foreign aid as percent of GDP.

[8] The former survey identifies 36 different categories of 87 explanatory variables, while the latter identifies 43 categories and 143 explanatory variables. With cross-country datasets of 100 or, in the best of cases, 120 country observations, the empirical investigation of growth determinants essentially becomes an exercise in small sample econometrics.

- **Internal environment:** In examining the hypothesis that ethnic divisions influence economic growth, polarized societies may have more difficulties agreeing on the provision of such public goods as infrastructure, education, and growth-enhancing policies, simply because polarization impedes agreement between ethnic groups engaged in competitive rent-seeking. We use proxies for the characteristics of the population like measures of ethnic heterogeneity and ethno-linguistic diversity, and proxies for war prevalence.

- **Institutions and governance:** The distribution of growth benefits are likely to depend not only on the sectoral pattern of growth but also on the degree of popular representation at the policy making level and the effectiveness of the governing institutions. Also, through its likely positive impact on the rule of law and the rate of investment, democracy's main impact on growth is indirect through the role of secure property rights. In this paper we examine the hypothesis that political freedom is a significant determinant of economic growth using the democracy and autocracy variables as measures of the general openness of political institutions, as well as indices of civil liberties.

- **Geography and fixed factors:** The relationship between geography and growth is complex. While the majority of empirical evidence concludes that geographic attributes like tropical climate or being landlocked correlate negatively with growth, some research finds evidence that after controlling for institutions geography has limited or no impact on growth. To examine the extent to which geography does matter, we use the percentage of land area in tropics as a proxy.

- **Regional characteristics/unobserved heterogeneity:** To capture possible unexplained regional heterogeneity, we include a set of dummy variables that capture regional groups (for example, sub-Saharan African countries) and the advanced country income groups.

3.2 Variable definitions and sources

The database constructed for the analysis consists of annual data from the Summers and Heston data set (Penn World Tables, version 6.2) and data from other sources. Switching from the yearly time series to panel estimation is made possible by dividing the total period into shorter time spans. We focus on eight-year time intervals, so we obtain a total of six panels, namely, 1961-1968, 1969-1976, 1977-1984, 1985-1992, 1993-2000, and 2001-2008. Differences in data availability across countries and variables lead to different sample sizes for different combinations of explanatory variables. Given that for variables classified as endogenous we need at least three observations in order to have useful moment conditions, we filter out countries with less than three observations, but we do allow for sample variation across countries in order to use as much information as possible. In this fashion, we arrive at an unbalanced, regularly spaced panel set of observations. Table B1 in Appendix B contains details for each category, the component variables, and their sources.

From the categories described in the previous section, we identify 18 proxies and consider additional time variables to capture time effects corresponding to the span on which the data was averaged. As a result, we have 2^{23} possible models, namely, the 18 variables and 5 time variables (corresponding to 5 of the 6 time spans) and universe of $2^k = 2^{23}$ $(8,388,608)$ regressions. Importantly, we choose to depart from the standard demeaning procedures commonly used in the literature because the demeaning approach would be equivalent to having all the time variables present in all the models, effectively assigning them a probability of inclusion equal to 1. Said differently, we choose to let the time effects enter as any other variable in order to effectively avoid imposing the presence of time effects in all models. Therefore, we create time variables for the periods considered in the sample and include them in the set of possible explanatory variables, thus allowing inferences about the relevance of time effects for all the periods considered.

The baseline estimation covers 105 countries with 416 observations over the period 1960-2008 with and average of 4 (out of maximum 6) observations per country. Based on the discussion in Section 2, the Monte Carlo results (see Appendices I and II), and the structure of the data we focus on collapsed instruments with one lag.

4 Results

4.1 Impact of model uncertainty in "ad hoc" growth regressions

We begin by demonstrating how model uncertainty affects inferences, by examining how fragile the results of "ad hoc" cross-country growth specifications are. Following Tsangarides (2003), Table 1 estimates various"ad hoc" growth regressions using the 23 regressors that will be used in our robustness analysis.[9] Column (1) uses the full set of all the 23 variables and identifies initial income, investment, aid, polity, inflation, and debt, as statistically significant. The rest of the columns in the table present estimation of variations of the set of explanatory variables. Looking at the regression results, it is striking to see how inferences about the estimated parameters change with sometimes small variations in the set of explanatory variables. For example, restricting the set of explanatory variables to the "Solow specification" in columns (2) and (3), the statistical significance of initial income and investment disappears. Columns (4)-(10) remove from specification (1) various combinations of the Solow determinants, the panel dummies, and groups of variables. The statistical significance of the estimated parameters changes dramatically: variables not statistically significant in specification (1) (for example, population, tropics, war, terms of trade, the overvaluation index, and openness) appear as statistically significant in some specifications, while statistically significant variables in specification (1) lose their statistical significance in several specifications. In fact, removing only one variable from the baseline specification (namely, openness in column (6), or aid in column (7), or the sub-Saharan dummy in column (10)) is enough to change the statistical significance of some of the regressors. In addition, in some cases (for example, population in columns (5) and (8)) estimated statistically significant coefficients change sign, while their size tends to fluctuate a lot across the specifications.

The fragility of parameter estimates and the impact of model uncertainty is also documented in Appendix B of Durlauf, Johnson and Temple (2005) which summarizes the results of recent empirical work on growth correlates. The significance of parameter estimates tends

[9] All regressions are estimated using the Arellano-Bond 2-step systems (robust) GMM estimator.

to fluctuate a lot across studies that use different subsets of the control variables.[10] Overall, results in Table 1 and results from survey papers confirm that any lessons drawn from "ad hoc" specifications can be problematic. Also, this confirms the common tendency for some growth empirical investigations to yield fragile econometric estimates, and underscores the importance of incorporating model uncertainty in the estimation, which is the purpose of this paper.

[Insert Table 1 here]

4.2 Robustness analysis of growth determinants

4.2.1 Results using LIBMA

We now turn to the main focus of our paper and apply our LIBMA methodology to the investigation of growth determinants. Table 2 presents the results of the baseline estimation based on a universe of 2^k possible models. recall, that the set of k variables includes 18 variables from the categories described in Section 3, and 5 time variables corresponding to the spans on which the data was averaged. Our priors are based on the assumption that each variable considered has the same probability of being included in the model, namely equal to 0.50. The posterior inclusion probability shown in the second column of Table 2 reflects how much the data favors including a particular variable in the regression. The area above the horizontal line in Table 2 indicate variables identified as "robust", essentially the variables for which the posterior inclusion probability is above the prior (that is, $p(Z_i|D) \geq 0.50$).[11] The unconditional mean and standard deviation, shown in the third and fourth columns, respectively, are computed taking into account all the possible models according to equations (12) and (13). These statistics are useful in examining the marginal impact of a variable, without accounting for the inclusion probability.

The results from the robustness analysis on growth determinants can be summarized as follows. The baseline estimation in Table 2 identifies five variables as robust growth determinants: initial income, investment, life expectancy, aid, and inflation. The first three reflect the neoclassical theory variables "augmented" to include measures of human capital. The elasticity of per capita growth rate with respect to initial income is negative and strongly robust providing empirical evidence that conditional convergence holds. In addition, the two Solow determinants—investment, and life expectancy—enter with high inclusion probabilities, indicating that the data favors their inclusion. Evidence is weak about the inclusion of the second proxy for human capital, education. The finding that inflation is a robust growth determinant confirms the importance of macroeconomic stability in fostering growth, particularly as higher rates of inflation usually translate in reduced levels of business investment, and lower real balances reduce the efficiency of factors of

[10] Clearly, different authors also use different datasets, so presumably some (though not all) of the differences in results can be attributed to that. Sometimes the same authors even present different conclusions in studies from different years or when their control variables change.

[11] Some researchers (see, for example, Raftery (1995)) further identify inclusion probability thresholds to label variables as "strongly robust," "very strongly robust," etc. suggesting stronger evidence. However, these chosen cutoffs are not strictly grounded in statistical theory and remain, therefore, merely indicative of a set of variables that we consider well estimated or robust.

production. The finding that aid may have a negative effect on growth reflects findings in earlier literature on aid fostering growth conditional on "good policies" and more broadly on the lack of aid effectiveness. In addition, several time variables "panel 1976", "panel 1992", "panel 2000", and "panel 2008" are identified as robust, indicating that time effects may be present.[12]

Compared to the BMA literature, the finding that initial income and investment are robustly related with growth is in line with the results from the robustness analyses of Fernández, Ley, and Steel (2001a), Sala-i-Martin, Doppelhofer, and Miller (2004), Papageorgiou and Masanjala (2005), and Moral-Benito (2009). All these BMA studies find the strongest evidence of robustness for initial income, and strong evidence of robustness for the investment measure. In addition, although the magnitudes of the inclusion probabilities in those studies are significantly higher than the ones we report, Fernández, Ley and Steel (2001a), Sala-i-Martin, Doppelhofer, and Miller (2004), and Papageorgiou and Masanjala (2005) also find high inclusion probabilities for life expectancy, while Sala-i-Martin, Doppelhofer, and Miller (2004) also add school enrollment as a robust determinant, and Moral-Benito (2009) adds the price of investment goods, distance, and political rights.

Finally, a number of variables that have been shown in the empirical literature to affect economic growth—such as other proxies of macroeconomic stability, institutions, political environment and geographical factors—appear to have a less robust association with growth in our analysis, since they enter with lower inclusion probabilities than the 0.50 cutoff. While this does not suggest that these determinants are not important for growth, but rather that they may have a less important role than the ones identified as robust.

[Insert Table 2 here]

4.2.2 Results using methods not accounting for dynamics and endogeneity

How does the set identified in Table 2 compare to results using methodologies that fail to account for dynamics and/or endogeneity? To answer this question we compare our LIBMA results (i) with cross section BMA methodologies which do not account for both dynamics and endogeneity; and (ii) with constructed panel BMA methodologies which potentially fail to account for endogeneity.

We transform our data in order to be able to conduct the cross section analysis exactly as it has been done by Fernández, Ley, and Steel (FLS, 2001a) and the BACE approach of Sala-i-Martin, Doppelhofer, and Miller (BACE, 2004). The former is a fully Bayesian method that allows for the explicit specification of the parameter priors, while the latter assumes diffuse priors, in a sense reflecting the researcher's ignorance. For the FLS methodology we use improper non-informative priors for the parameters that are common to all models, and a g-prior structure for the slope parameters (with two values for the latter, identified as "prior 1" and "prior 9" in Fernández, Ley, and Steel (2001b)). For all the simulations we assume an equal prior probability for all the models ($= 2^{-k}$). Since the FLS and BACE

[12] While commenting on the sign and magnitude of estimated parameters is beyond the scope of this paper, some of our results (such as the one on aid) may shed some light to the on going policy debates about the importance of these variables.

are cross-section analyses, they do not explicitly model dynamics. As a result, differences between the LIBMA results and the FLS and BACE results are attributed to accounting for dynamics and endogeneity.

Table 3 presents the results of applying the cross section BMA methodologies used by Fernández, Ley, and Steel (2001a) and also Sala-i-Martin, Doppelhofer, and Miller (2004) to our data set. The area above the line indicates inclusion probabilities above 0.50. Starred variables in the first column are variables identified as robust by LIBMA in Table 2; therefore, a collection of all the starred variables above the line would indicate that the identified sets of robust variables between LIBMA and FLS/BACE and is similar. The results in Table 3 show that both the FLS and BACE methodologies identify a different set of robust determinants compared to LIBMA in Table 2. While initial income, investment, and life expectancy—which are identified as robust growth determinants using LIBMA in Table 2—are also identified as robust by the cross section BMA methodologies, FLS and BACE fail to identify aid and inflation as robust (both of which enter with inclusion probabilities less than 0.15). In addition, debt, openness, and the overvaluation index are "wrongly" identified as robust. These differences suggest that panel growth analyses that investigate dynamics—and perhaps give a richer picture of growth patterns that is missing from cross-sectional analyses—identify a different set of robust growth determinants as compared to those of cross section analyses.

[Insert Table 3 here]

Next, we modify the FLS and BACE approaches for implementation in a panel context.[13] While these approaches were built with the cross-section analysis in mind (and hence do not address dynamics or endogeneity issues), we construct their "panel analogues" in order to explicitly investigate differences with the LIBMA results. By construction, since the resulting "panel FLS" and "panel BACE"estimators are constructed in a panel context, a comparison with the LIBMA results in Table 2 would identify differences arising from accounting for endogeneity.

Table 4 shows the results from estimating robust growth determinants using the "panel FLS" and "panel BACE" methods. Eight variables and two time effects are identified as robust growth determinants in Table 4: initial income, overvaluation, life expectancy, investment, debt, inflation, population growth, the dummy variable for sub-Saharan Africa, as well as the 1984 and 2008 panel periods. Comparing, first, with the results in Table 3, the panel analogues of FLS and BACE seem to identify three more robust variables compared to their cross-section counterparts (inflation, population, and the dummy for sub-Saharan Africa). Differences in the identified robust determinants between Tables 4 and 3 suggest that accounting for dynamics does matter, which is also reinforced by the high inclusion probability of the two panel dummies.

Next, a comparison of Table 4 and Table 2 results identifies differences arising from accounting for endogeneity (as both the LIBMA and the constructed "panel FLS" and "panel

[13] For brevity, we don't report the details about the construction of the "panel FLS" and "panel BACE"estimators, but these are available from the authors. We thank the authors for making their original codes available.

BACE"estimators incorporate dynamics). About half of the robust determinants identified by LIBMA in Table 2 are also identified by the "panel FLS" and "panel BACE" in Table 4—initial income, life expectancy, investment, inflation, and the panel 2008 dummy. However, aid and the three panel dummies are not identified as robust by "panel FLS" and "panel BACE" (but identified as robust by LIBMA), while several variables—overvaluation, debt, population, and the sub-Saharan Africa dummy—not identified robust by LIBMA are identified as robust by "panel FLS" and "panel BACE" (with inclusion probabilities above 0.70 for two, and about 1.00 for two others). In summary, there are eight "wrongly" identified variables in Table 4 compared to Table 2. These differences suggest that accounting for endogeneity using LIBMA results in a different set of robust determinants than using "panel FLS" or "panel BACE" where endogeneity is not accounted for.

[Insert Table 4 here]

5 Conclusions

This paper provides some insights into the mechanics of economic growth by investigating the robustness of growth determinants. We employ LIBMA, a novel methodology that incorporates a dynamic panel estimation and Bayesian Model Averaging to simultaneously address endogeneity, omitted variable bias, and model uncertainty—problems that have previously plagued empirical work on growth. Based on a broad number of growth determinants, and once model uncertainty and other potential inconsistencies are accounted for, our ivestigation identifies several factors that robustly affect growth. Our main results are summarized as follows. First, we find the strongest evidence for the robustness of five determinants, namely, initial income, investment, life expectancy, inflation, and aid. The robustness of initial income is consistent with the conditional convergence hypothesis. In addition, several other variables that have been used in "ad hoc" growth regressions in the literature, are generally not found to be robust. Second, we identify significant differences of our results compared to existing literature that addresses model uncertainty but fails to account for dynamics and/or endogeneity. These differences underscore the importance of addressing dynamics and endogeneity in addition to model uncertainty in growth empirics, and that LIBMA may be a useful tool for this investigation.

In the continuing investigation of the empirics of growth, increasing attention is being given to the implications of model uncertainty. A growing number of growth researchers are turning to BMA methods which provide a solid theoretical foundation for addressing model uncertainty. While there is a growing literature focusing on improving and refining the BMA techniques—including on the impact of the choice of priors—the work on BMA and its applications has underscored that failing to properly account for model uncertainty results in overconfident and often fragile inferences. Potentially, this has important implications for policy makers seeking to use findings of growth analyses to offer policy advice, suggesting that policy analysis and recommendations should not be conditioned on a specific model but rather should reflect model uncertainty.

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Appendix A1: Monte Carlo experiment results

This Appendix describes the Monte Carlo simulations intended to assess the performance of LIBMA when a reduced instrument count is used. We compute posterior model probabilities, inclusion probabilities for each variable in the universe considered, and parameter statistics.

We consider the case where the universe of potential explanatory variables contains 12 variables, namely, 5 exogenous variables (out of which 2 are time invariant), 6 endogenous variables and the lagged dependent variable which is predetermined. Throughout our simulations we keep the number of periods constant, that is, $T = 6$ and we vary the number of individuals, $N = 50$, 75, 90,and 100. We examine three cases of instrument sets, with using (i) all lags of instruments, (ii) 2 lags of the instruments, and (iii) 1 lag of the instruments. For all three cases we use both collapsed and non-collapsed forms of the instruments. As a result, for the three sets for the full (collapsed) forms, we have the moment conditions as follows: (i) for the "all" lags set, we have 119 (51) moment conditions; (ii) for 2 lags 95 (36) moment conditions; and (iii) for 1 lag 73 (29) moment conditions. Table A lists the moment conditions for a variety of m, q, and T also relative to the sample size N.

We generate 500 instances of the data generating process with time invariant variables ι_{it}, regular exogenous variables x_{it}, endogenous variables w_{it}, and parameter values $(\alpha \quad \theta)'$. Further, we assume that both the random error term v_{it} and the individual effect η_i are drawn from a Normal distribution, $v_{it} \sim N\left(0, \sigma_v^2\right)$ and $\eta_i \sim N\left(0, \sigma_\eta^2\right)$, respectively, and consider the case where $\sigma_v^2 = 0.10$, and $\sigma_\eta^2 = 0.10$. Appendix A2 discusses the data generating process in detail and presents the results of the analysis.

Table A1 reports the inclusion probability (defined as the sum of all the posterior probabilities for each model that contains that particular variable) for each variable considered, along with the true model in the second column of the table, for various N and instrument transformations.[14] Given the assumptions made relative to the model priors, the prior probability of inclusion for each variable is the same and equal to 0.50. Comparing the collapsed and non-collapsed cases, it is immediately clear that collapsing the instruments improves the inclusion probabilities dramatically for both the included and non-included variables. This is particularly the case for smaller N where the inclusion probabilities in many cases improve by a factor of 1.5 or more. As the sample size increases, the posterior inclusion probabilities approach 1 for all the relevant variables. For the variables not contained in the true model the median posterior probability of inclusion decreases with the sample size. A comparison among the collapsed forms for various lags suggests that overall, using 1 or 2 lags rather than the full set of lags gives higher inclusion probabilities, particularly for the endogenous variables and for lower values of N, but there is no clear distinction between the choice between 1 or 2 lags. For higher values of N selecting fewer lags among the collapsed does not improve the results dramatically.

We turn now to the parameter estimates and examine how the estimated values compare with the true parameter values. Table A2 presents the median values of the estimated parameters compared to the parameters of the true model (discussed in the previous section). As in the case of inclusion probabilities, collapsing the instruments always improves the

[14] A value of 1(0) in column 2 indicates that the true model contains (excludes) that variable.

parameter estimation, with both the bias and variance decreasing (and with even more improvements as the sample gets larger). Again, as in the case of the inclusion probabilities, using 1 or 2 lags rather than all lags among the stacking options is preferred.

While it is beyond the scope of our approach, we also present results in terms of model selection. Table A3 presents relevant statistics for the posterior probability of the true model; the ratio of the posterior model probability of the true model to the highest posterior probability of all the other models (excluding the true model); and how often our methodology recovers the true model by reporting how many times the true model has the highest posterior probability. Stacking instruments gives better results, particularly for the recovery of the true model. Importantly, even with poorer results in terms of model selection (e.g. cases where the recovery rate of the true model is poor or the true model receives low posterior probability), the BMA is able to differentiate among the relevant and non-relevant variables, as it can be seen from Tables A1 and A2.

In summary, there is clear evidence that collapsing the instruments improves the results, both in terms of inclusion probabilities, parameter estimates, and model selection. This is particularly due to the fact that collapsing the instruments reduces the ratio of instruments to sample size, $\frac{G}{N}$. Once collapsed, further reducing the number of lags yields some further improvements which disappear as the ratio of $\frac{G}{N}$ becomes smaller. So, while in the case of $N = 75$ using 1 or 2 lags rather than the full set of lags gives better results, comparing cases like $N = 75$ collapsed 1 lag, with $N = 90$ collapsed 2 lags, and $N = 100$ collapsed all lags (all of which have $\frac{G}{N}$ between 0.4 and 0.5) yields similar results.

Table A. Instruments for various options of $T = 6, m = 5$, and $q = 6$

	Instruments	$N = 50$	$N = 75$	$N = 90$	$N = 100$
Instrument options		$\frac{G}{N}$	$\frac{G}{N}$	$\frac{G}{N}$	$\frac{G}{N}$
Uncollapsed full	119	2.38	1.59	1.32	1.19
Uncollapsed 2 lags	95	1.90	1.27	1.06	0.95
Uncollapsed 1 lag	73	1.46	0.97	0.81	0.73
Collapsed full	51	1.02	0.68	0.57	0.51
Collapsed 2 lags	36	0.72	0.48	0.40	0.36
Collapsed 1 lag	29	0.58	0.39	0.32	0.29

Appendix A2: Monte Carlo data generating process

Consider the case where the universe of potential explanatory variables contains 12 variables, namely, 5 exogenous variables (out of which 2 are time invariant), 6 endogenous variables and the lagged dependent variable.

We begin by generating the two time invariant exogenous variables for every individual i and period t, as follows

$$\begin{aligned}&\begin{pmatrix}\iota_{it}^1 & \iota_{it}^2\end{pmatrix} = r_i^\iota,\\ &\text{with } \Pr\left[r_i^\iota = \begin{pmatrix}m\sqrt{3/2} & n\sqrt{3/2}\end{pmatrix}\right] = 1/9,\\ &\text{for } i = 1, \ldots, N; m = 0, 1, 2; n = 0, 1, 2.\end{aligned}$$

where r_i^ι is a vector random variable with two independent and uniformly distributed elements with discrete support $\{0, \sqrt{3/2}, 2\sqrt{3/2}\}$. We select the size of support so that variance of the resultant random variable is 1.

Next, we generate three exogenous variables by sampling from a normal distribution,

$$\begin{aligned}&(x_{it}^1 \quad x_{it}^2 \quad x_{it}^3) = r_t^x\\ &\quad\text{with } r_t^x \sim N(0, I_3),\\ &\quad\quad\text{for } t = 0, 1, \ldots, T; i = 1, \ldots, N,\end{aligned}$$

where I_3 is the three dimensional identity matrix.

Similarly, for the endogenous variables, $\begin{pmatrix}w_{it}^1 & \cdots & w_{it}^6\end{pmatrix}$, we have the following data generating process

$$\begin{aligned}&(w_{it}^1 \quad \cdots \quad w_{it}^6) = 0.4055(w_{it}^1 \quad \cdots \quad w_{it}^6) - 0.2454v_{it}\imath + r_{it}^w, \text{ for } t = 1, \ldots, T\\ &(w_{i0}^1 \quad \cdots \quad w_{i0}^6) = -0.2454v_{it}\imath + r_{i0}^w,\\ &\quad\text{with } v_{it} \sim N(0, \sigma_v^2), r_{it}^w \sim N(0, I_6).\end{aligned}$$

Here $\imath$ denotes the vector of 1's with appropriate dimension. As the data generating process for the endogenous variables indicates, the overall error term v_{it} is assumed to be distributed normally here.

For $t = 0$, the dependent variable is generated by

$$\begin{aligned}&y_{i0} = \frac{1}{1-\alpha}\Big((\iota_{i0} \quad x_{i0} \quad w_{i0})\,\theta\mathfrak{m} + \eta_i + v_{i0}\Big)\\ &\text{with } v_{i0} \sim N(0, \sigma_v^2) \text{ and } \eta_i \sim N(0, \sigma_\eta^2).\end{aligned}$$

where $\theta = 0.23$, $\iota_{i0} = \begin{pmatrix}\iota_{i0}^1 & \iota_{i0}^2\end{pmatrix}$, $x_{i0} = \begin{pmatrix}x_{i0}^1 & x_{i0}^2 & x_{i0}^3\end{pmatrix}$, and $w_{i0} = \begin{pmatrix}w_{i0}^1 & \cdots & w_{i0}^6\end{pmatrix}$. In addition, $\mathfrak{m} = (1 \quad 0 \quad 1 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0)'$ is the model selection vector. It indicates that we choose the model with 1 time invariant variable, 2 regular exogenous variables, and 3 endogenous variables as the true model.

For $t = 1, 2, ..., T$ the data generating process is given by

$$\begin{aligned}&y_{it} = \alpha y_{i,t-1} + (\iota_{it} \quad x_{it} \quad w_{it})\,\theta\mathfrak{m} + \eta_i + v_{it},\\ &\text{with } v_{it} \sim N\left(0, \sigma_v^2\right),\ and \eta_i \sim N\left(0, \sigma_\eta^2\right).\end{aligned}$$

The theoretical R^2 of the generated models varies between 0.50 and 0.60.

Table 1. “Ad hoc” and “kitchen sink” growth regressions to be avoided
Fragility of parameter estimates and significance for various model specifications

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(initial income)	-0.0172**	0.00692	-0.00406	-0.0126	-0.0223***	-0.0159**	-0.0090	-0.0165*	-0.0251**	-0.0118
	(0.0068)	(0.0205)	(0.0069)	(0.0097)	(0.0074)	(0.0065)	(0.0072)	(0.0096)	(0.0113)	(0.0072)
Log(investment)	0.0256**	0.0339	0.0274		0.0168	0.0195	0.0282**	0.0342**	0.0308**	0.0255***
	(0.0098)	(0.0213)	(0.0172)		(0.0122)	(0.0098)	(0.0115)	(0.0150)	(0.0131)	(0.00899)
Log(population growth)	0.0118	-0.00501	-0.0278		0.0478*	0.0149	-0.0120	-0.0354*	-0.0076	0.0001
	(0.0243)	(0.0715)	(0.0579)		(0.0247)	(0.0247)	(0.0216)	(0.0193)	(0.0291)	(0.0225)
Log(years of education)	0.0063	0.000003	-0.0045		0.0107	0.0016	0.0015	0.0035	0.0199	-0.0024
	(0.0093)	(0.0137)	(0.0102)		(0.0094)	(0.0072)	(0.0120)	(0.0139)	(0.0129)	(0.0073)
Life expectancy	-0.0005	-0.0013			-0.0007	-0.0005	-0.0005	0.0002	-0.0004	-0.0007*
	(0.0004)	(0.0023)			(0.0005)	(0.0005)	(0.0010)	(0.0008)	(0.0008)	(0.0004)
Terms of Trade	-0.0159			-0.0035	-0.0291	-0.0381*	-0.0113	-0.0079	-0.0361*	-0.0180
	(0.0252)			(0.0180)	(0.0246)	(0.0229)	(0.0280)	(0.0246)	(0.0210)	(0.0230)
Sub-Saharan Africa	0.0013			-0.0056	-0.0033	-0.0065	-0.0010	0.0207	0.0054	
	(0.0110)			(0.00749)	(0.0116)	(0.0136)	(0.0151)	(0.0144)	(0.0148)	
Ethnic heterogeneity	-0.0133			-0.0025	-0.0158	0.0006	-0.0056			-0.0048
	(0.0105)			(0.0136)	(0.0145)	(0.0158)	(0.0097)			(0.0143)
Aidgdp	-0.0988**			-0.0885**	-0.1340***	-0.0890		-0.1120*	-0.1160**	-0.0939**
	(0.0476)			(0.0432)	(0.0448)	(0.0553)		(0.0580)	(0.0563)	(0.0417)
Polity	0.0012**			0.0012***	0.0019***	0.0006	0.0004			0.0010*
	(0.0006)			(0.0004)	(0.0006)	(0.0005)	(0.0005)			(0.0005)
War	-0.0037			-0.0071*	-0.0038	-0.0029	0.0010			
	(0.0037)			(0.0040)	(0.0062)	(0.0053)	(0.0052)			
Tropics	-0.0041			-0.0145	-0.0126	-0.0174*	-0.0031			-0.0163*
	(0.0079)			(0.0113)	(0.0087)	(0.0100)	(0.0080)			(0.0092)
Log(inflation)	-0.0191**			-0.0111	-0.0173*	-0.0198***	-0.0173***	-0.0103	-0.0038	-0.0170**
	(0.0077)			(0.0127)	(0.0101)	(0.0068)	(0.0062)	(0.0116)	(0.0122)	(0.0074)
Log(governm. spending)	0.0071			0.0040	0.0042	0.0033	-0.0021	0.0080	0.0077	0.0077
	(0.0130)			(0.0130)	(0.0121)	(0.0181)	(0.0138)	(0.0118)	(0.0113)	(0.0157)
Debt	-0.0065**			-0.0064**	-0.0043	-0.0061**	-0.0068***	-0.0042	-0.0054	-0.0046
	(0.0029)			(0.0029)	(0.0027)	(0.0026)	(0.0022)	(0.0038)	(0.0042)	(0.0030)
Overvaluation Index	0.0087			0.0104	0.0102	0.0175**	0.0108	0.0119	0.00114	0.0109
	(0.0083)			(0.0075)	(0.0070)	(0.0089)	(0.0101)	(0.0108)	(0.0113)	(0.0075)
Advanced Economies	-0.0079			-0.0062	0.0020	-0.0010	-0.0131			-0.0080
	(0.0086)			(0.0097)	(0.0087)	(0.0104)	(0.0101)			(0.0089)
Openness	0.0014			0.0115*	0.0001		-0.0022	-0.0005	-0.0019	0.0023
	(0.0042)			(0.0061)	(0.0057)		(0.0043)	(0.0047)	(0.0058)	(0.0051)
Panel 1976	-0.00002	-0.0007	-0.0005	-0.0033		0.0031	-0.0023	0.0013		-0.0003
	(0.0044)	(0.0035)	(0.0033)	(0.0038)		(0.0057)	(0.0040)	(0.0037)		(0.0049)
Panel 1984	-0.0070	-0.0160***	-0.0171***	-0.0165**		-0.0049	-0.0113*	-0.0096*		-0.0089
	(0.0068)	(0.0052)	(0.0041)	(0.0068)		(0.0071)	(0.0061)	(0.0057)		(0.0063)
Panel 1992	0.0033	-0.0093	-0.0127**	-0.0086		0.0082	-0.0016	-0.00003		0.0017
	(0.0082)	(0.0094)	(0.0056)	(0.0090)		(0.0079)	(0.0085)	(0.0074)		(0.0069)
Panel 2000	0.0059	-0.0021	-0.0052	-0.0062		0.0124	0.0050	0.0036		0.0065
	(0.0096)	(0.0095)	(0.0063)	(0.0099)		(0.0082)	(0.0094)	(0.0104)		(0.0077)
Panel 2008	-0.0065	-0.0164*	-0.0190***	-0.0220**		0.0006	-0.0100	-0.0120		-0.0074
	(0.0111)	(0.0091)	(0.0067)	(0.0110)		(0.0097)	(0.0105)	(0.0119)		(0.0084)
Constant	0.0946	-0.0327	0.0479	0.1370	0.1090	0.1150	0.1040**	0.1020	0.1510	0.0940
	(0.0800)	(0.2140)	(0.1520)	(0.1160)	(0.1070)	(0.0967)	(0.1140)	(0.1020)	(0.1130)	(0.0868)
Observations	416	578	580	464	416	416	417	457	457	420
Countries	105	125	126	121	105	105	105	115	115	105
Hansen	0.61	0.18	0.16	0.36	0.22	0.54	0.88	0.45	0.18	0.56
AR1 p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR2 p-value	0.43	0.82	0.92	0.29	0.79	0.35	0.34	0.28	0.94	0.44

Notes:
1. Estimated using Arellano-Bond systems GMM.

Table 2. Robustness of growth determinants using LIBMA
Marginal evidence of importance sorted by the inclusion probability

	Variables	Posterior P(inclusion)	Posterior Mean	Posterior St. Error
1	Log(initial income)	0.86	-0.036	0.050
2	Panel 2008	0.72	-0.011	0.021
3	Log(investment)	0.65	0.019	0.044
4	Life expectancy	0.65	0.001	0.004
5	Panel 1992	0.64	0.005	0.015
6	Aidgdp	0.58	-0.133	0.328
7	Panel 2000	0.53	0.006	0.016
8	Log(inflation)	0.53	-0.031	0.075
9	Panel 1976	0.51	0.003	0.012
10	Log(population growth)	0.45	-0.030	0.096
11	Tropics	0.45	-0.008	0.037
12	Advanced economies	0.40	0.011	0.041
13	Polity	0.40	0.000	0.002
14	Panel 1984	0.39	-0.002	0.013
15	Debt	0.37	-0.002	0.013
16	Overvaluation Index	0.36	-0.004	0.032
17	Openness	0.35	0.004	0.028
18	Log(government spending)	0.34	-0.005	0.038
19	Ethnic heterogeneity	0.31	-0.005	0.067
20	Log(years of education)	0.27	-0.003	0.035
21	Sub-Saharan Africa	0.26	-0.005	0.043
22	War	0.26	-0.004	0.026
23	Terms of Trade	0.24	-0.010	0.149

Notes:
1. Sorted by the posterior inclusion probability.
2. Variables above the line have inclusion probabilities above 0.50.

Table 3. LIBMA comparison with BACE and FLS

Marginal evidence of importance

	FLS prior 1				FLS prior 9				BACE			
	Variables	P(incl.)	Post. Mean	Post. St. Error	Variables	P(incl.)	Post. Mean	Post. St. Error	Variables	P(incl.)	Post. Mean	Post. St. Error
1	Log(initial income)*	1.00	-0.016	0.002	Log(initial income)*	1.00	-0.016	0.002	Log(initial income)*	1.00	-0.016	0.002
2	Debt	1.00	-0.007	0.001	Life expectancy*	1.00	-0.007	0.001	Life expectancy*	1.00	-0.007	0.001
3	Life expectancy*	0.99	0.001	0.000	Debt	0.99	0.001	0.000	Debt	0.99	0.001	0.000
4	Overvaluation Index	0.95	0.010	0.004	Log(investment)*	0.94	0.010	0.004	Log(investment)*	0.95	0.010	0.004
5	Openness	0.64	0.004	0.003	Overvaluation Index	0.56	0.003	0.003	Overvaluation Index	0.66	0.004	0.003
6	Log(investment)*	0.53	0.003	0.003	Openness	0.44	0.002	0.003	Openness	0.54	0.003	0.003
7	Log(population growth)	0.25	-0.003	0.006	War	0.18	-0.002	0.005	War	0.26	-0.003	0.006
8	Log(years of education)	0.23	0.001	0.002	Log(years of education)	0.17	0.001	0.002	Aidgdp*	0.24	0.001	0.002
9	Polity	0.22	0.000	0.000	Polity	0.14	0.000	0.000	Polity	0.23	0.000	0.000
10	War	0.16	-0.001	0.003	Aidgdp*	0.11	-0.001	0.003	Log(years of education)	0.16	-0.001	0.003
11	Tropics	0.13	0.000	0.001	Terms of Trade	0.08	0.000	0.001	Terms of trade	0.14	0.000	0.001
12	Terms of Trade	0.12	-0.005	0.020	Log(governm. spending)	0.07	-0.003	0.016	Log(governm. spending)	0.13	-0.005	0.021
13	Aidgdp*	0.11	0.002	0.012	Ethnic heterogeneity	0.07	0.001	0.010	Ethnic heterogeneity	0.11	0.002	0.012
14	Advanced economies	0.11	0.000	0.002	Tropics	0.06	0.000	0.001	Tropics	0.11	0.000	0.002
15	Ethnic heterogeneity	0.10	0.000	0.002	Advanced economies	0.06	0.000	0.002	Sub-Saharan Africa	0.11	0.000	0.002
16	Sub-Saharan Africa	0.10	0.000	0.001	Log(population growth)	0.06	0.000	0.001	Advanced economies	0.10	0.000	0.002
17	Log(inflation)*	0.09	0.000	0.002	Log(inflation)*	0.06	0.000	0.002	Log(inflation)*	0.10	0.000	0.002
18	Log(governm. spending)	0.09	0.000	0.001	Sub-Saharan Africa	0.05	0.000	0.001	Log(population growth)	0.10	0.000	0.001

Notes:

1. Sorted by the posterior inclusion probability. Variables above the line have inclusion probabilities above 0.50.

2. Starred variables are those identified as robust by LIBMA in Table 2.

Table 4. LIBMA comparison with BACE and FLS (panel data format)

Marginal evidence of importance

		FLS prior 1				FLS prior 9				BACE		
	Variables	P(incl.)	Post. Mean	Post. St. Error		P(incl.)	Post. Mean	Post. St. Error		P(incl.)	Post. Mean	Post. St. Error
1	Log(initial income)*	1.00	-0.014	0.089	Log(initial income)*	1.00	-0.014	0.089	Log(initial income)*	1.00	-0.014	0.089
2	Overvaluation Index	1.00	0.018	0.144	Overvaluation Index	1.00	0.018	0.144	Overvaluation Index	1.00	0.018	0.144
3	Life expectancy*	1.00	0.001	0.011	Life expectancy*	1.00	0.001	0.011	Life expectancy*	1.00	0.001	0.011
4	Log(investment)*	1.00	0.013	0.124	Log(investment)*	1.00	0.013	0.124	Log(investment)*	1.00	0.013	0.124
5	Debt	1.00	-0.006	0.051	Debt	1.00	-0.006	0.050	Debt	1.00	-0.006	0.051
6	Log(inflation)*	1.00	-0.018	0.209	Log(inflation)*	1.00	-0.018	0.209	Log(inflation)*	1.00	-0.018	0.209
7	Log(population growth)	0.83	0.014	0.211	Log(population growth)	0.82	0.014	0.208	Log(population growth)	0.83	0.014	0.212
8	Sub-Saharan Africa	0.72	0.008	0.150	Sub-Saharan Africa	0.70	0.007	0.147	Sub-Saharan Africa	0.72	0.008	0.150
9	Panel 1984	0.69	-0.006	0.111	Panel 1984	0.68	-0.006	0.110	Panel 1984	0.69	-0.006	0.111
10	Panel 2008*	0.57	-0.006	0.126	Panel 2008*	0.55	-0.005	0.124	Panel 2008*	0.58	-0.006	0.127
11	Panel 2000*	0.44	0.003	0.084	Panel 2000*	0.44	0.003	0.084	Panel 2000*	0.44	0.003	0.084
12	Panel 1976*	0.38	0.003	0.096	Panel 1976*	0.38	0.003	0.095	Panel 1976*	0.38	0.003	0.096
13	Panel 1992*	0.26	-0.001	0.070	Panel 1992*	0.24	-0.001	0.067	Panel 1992*	0.27	-0.001	0.071
14	Polity	0.17	0.000	0.004	Polity	0.15	0.000	0.004	Polity	0.17	0.000	0.004
15	War	0.16	-0.001	0.070	War	0.14	-0.001	0.067	War	0.16	-0.001	0.071
16	Log(governm. spending)	0.10	0.000	0.038	Log(governm. spending)	0.09	0.000	0.036	Log(governm. spending)	0.10	0.000	0.038
17	Log(years of education)	0.07	0.000	0.036	Log(years of education)	0.06	0.000	0.034	Log(years of education)	0.07	0.000	0.036
18	Tropics	0.06	0.000	0.037	Tropics	0.05	0.000	0.035	Tropics	0.06	0.000	0.037
19	Advanced economies	0.06	0.000	0.048	Advanced economies	0.05	0.000	0.045	Advanced economies	0.06	0.000	0.048
20	Aidgdp*	0.05	0.000	0.230	Aidgdp*	0.05	0.000	0.216	Aidgdp*	0.05	0.000	0.230
21	Terms of Trade	0.05	0.000	0.266	Terms of Trade	0.05	0.000	0.252	Terms of Trade	0.05	0.000	0.266
22	Ethnic heterogeneity	0.05	0.000	0.073	Ethnic heterogeneity	0.04	0.000	0.069	Ethnic heterogeneity	0.05	0.000	0.074
23	Openness	0.05	0.000	0.025	Openness	0.04	0.000	0.024	Openness	0.05	0.000	0.025

Notes:

1. Sorted by the posterior inclusion probability. Variables above the line have inclusion probabilities above 0.50.

2. Starred variables are those identified as robust by LIBMA in Table 2.

Table A1. Model recovery: medians and variances of posterior inclusion probabilities for each variable
True model vs. BMA posterior inclusion probability for various N ($\alpha = 0.50$, $\sigma_v^2 = 0.1$)

	Lags	All lags used				1 lag used				2 lags used			
	Instruments	Not stacked		Stacked		Not stacked		Stacked		Not stacked		Stacked	
	True model	Median	Variance	Median	Variance	Median	Variance	Median	Variance	Median	Variance	Median	Variance
N=50													
yt-1	1	0.3483	0.0039	0.5560	0.0229	0.4466	0.0128	0.7192	0.0394	0.3663	0.0055	0.6704	0.0288
x1	1	0.3292	0.0026	0.5019	0.0141	0.4174	0.0098	0.6556	0.0288	0.3458	0.0039	0.5785	0.0233
x2	0	0.3121	0.0011	0.3523	0.0032	0.3632	0.0057	0.3371	0.0047	0.3223	0.0024	0.3393	0.0043
x3	1	0.3446	0.0036	0.5729	0.0185	0.4686	0.0116	0.7786	0.0293	0.3685	0.0047	0.6971	0.0240
x4	1	0.3444	0.0038	0.5720	0.0181	0.4707	0.0109	0.7747	0.0287	0.3702	0.0052	0.6993	0.0259
x5	0	0.3119	0.0011	0.3622	0.0034	0.3632	0.0046	0.3336	0.0049	0.3225	0.0017	0.3417	0.0044
w1	1	0.3250	0.0025	0.4044	0.0183	0.4050	0.0103	0.4792	0.0329	0.3369	0.0032	0.4506	0.0288
w2	1	0.3238	0.0018	0.3925	0.0177	0.3884	0.0093	0.4323	0.0338	0.3382	0.0036	0.4191	0.0254
w3	1	0.3250	0.0020	0.3952	0.0169	0.3972	0.0104	0.4455	0.0330	0.3404	0.0033	0.4191	0.0265
w4	0	0.3279	0.0022	0.4160	0.0122	0.4036	0.0085	0.4466	0.0223	0.3423	0.0034	0.4296	0.0173
w5	0	0.3290	0.0019	0.4209	0.0110	0.4019	0.0078	0.4245	0.0199	0.3446	0.0026	0.4346	0.0157
w6	0	0.3284	0.0015	0.4208	0.0119	0.3978	0.0070	0.4430	0.0229	0.3449	0.0025	0.4463	0.0170
N=75													
yt-1	1	0.3582	0.0063	0.9316	0.0317	0.7818	0.0421	0.9422	0.0312	0.5010	0.0216	0.9527	0.0297
x1	1	0.3421	0.0050	0.8546	0.0373	0.7077	0.0363	0.9137	0.0310	0.4618	0.0177	0.9080	0.0314
x2	0	0.3093	0.0023	0.2840	0.0077	0.3032	0.0079	0.2823	0.0089	0.3286	0.0042	0.2821	0.0089
x3	1	0.3723	0.0064	0.9438	0.0207	0.8281	0.0313	0.9681	0.0227	0.5323	0.0179	0.9694	0.0200
x4	1	0.3687	0.0059	0.9471	0.0249	0.8227	0.0308	0.9738	0.0215	0.5547	0.0177	0.9719	0.0211
x5	0	0.3106	0.0018	0.2893	0.0074	0.2987	0.0073	0.2834	0.0091	0.3306	0.0047	0.2868	0.0081
w1	1	0.3240	0.0050	0.4935	0.0744	0.4321	0.0550	0.5323	0.0702	0.3563	0.0202	0.5252	0.0767
w2	1	0.3207	0.0048	0.4814	0.0758	0.4359	0.0522	0.5256	0.0718	0.3535	0.0178	0.5025	0.0774
w3	1	0.3265	0.0047	0.5317	0.0752	0.4454	0.0534	0.5694	0.0677	0.3689	0.0189	0.5592	0.0759
w4	0	0.3293	0.0032	0.3556	0.0277	0.3775	0.0191	0.3596	0.0281	0.3620	0.0093	0.3468	0.0260
w5	0	0.3286	0.0037	0.3836	0.0276	0.3966	0.0248	0.3732	0.0298	0.3661	0.0094	0.3609	0.0306
w6	0	0.3275	0.0040	0.3616	0.0293	0.3827	0.0245	0.3493	0.0253	0.3656	0.0120	0.3497	0.0269
N=90													
yt-1	1	0.6051	0.0327	0.9873	0.0150	0.9558	0.0282	0.9875	0.0215	0.7862	0.0357	0.9912	0.0157
x1	1	0.5322	0.0286	0.9575	0.0206	0.8974	0.0333	0.9663	0.0196	0.6946	0.0358	0.9716	0.0168
x2	0	0.3000	0.0062	0.2676	0.0079	0.2729	0.0095	0.2635	0.0107	0.2879	0.0082	0.2680	0.0088
x3	1	0.6272	0.0290	0.9927	0.0054	0.9679	0.0197	0.9958	0.0148	0.8080	0.0283	0.9958	0.0074
x4	1	0.6311	0.0263	0.9929	0.0054	0.9700	0.0201	0.9959	0.0118	0.8228	0.0269	0.9958	0.0075
x5	0	0.2960	0.0070	0.2750	0.0110	0.2707	0.0094	0.2696	0.0108	0.2871	0.0094	0.2692	0.0106
w1	1	0.3559	0.0355	0.6744	0.0967	0.5071	0.0879	0.6429	0.0851	0.4163	0.0597	0.6343	0.0942
w2	1	0.3521	0.0322	0.6000	0.0954	0.4939	0.0915	0.6418	0.0875	0.4188	0.0577	0.6520	0.0924
w3	1	0.3758	0.0296	0.6493	0.0933	0.5340	0.0857	0.6595	0.0799	0.4450	0.0567	0.6899	0.0889
w4	0	0.3538	0.0141	0.3169	0.0296	0.3426	0.0283	0.3173	0.0320	0.3747	0.0223	0.3134	0.0276
w5	0	0.3561	0.0150	0.3293	0.0319	0.3468	0.0338	0.3449	0.0345	0.3711	0.0240	0.3323	0.0312
w6	0	0.3573	0.0140	0.3304	0.0276	0.3464	0.0286	0.3229	0.0254	0.3581	0.0211	0.3264	0.0270
N=100													
yt-1	1	0.7954	0.0403	0.9969	0.0089	0.9888	0.0155	0.9956	0.0137	0.9272	0.0291	0.9980	0.0066
x1	1	0.6915	0.0381	0.9859	0.0145	0.9573	0.0249	0.9879	0.0124	0.8514	0.0346	0.9895	0.0075
x2	0	0.2848	0.0082	0.2517	0.0070	0.2592	0.0118	0.2487	0.0080	0.2654	0.0079	0.2427	0.0083
x3	1	0.8291	0.0302	0.9985	0.0049	0.9927	0.0092	0.9990	0.0111	0.9415	0.0216	0.9993	0.0041
x4	1	0.8290	0.0278	0.9989	0.0061	0.9937	0.0088	0.9990	0.0076	0.9412	0.0203	0.9994	0.0036
x5	0	0.2754	0.0109	0.2522	0.0110	0.2558	0.0097	0.2558	0.0116	0.2676	0.0122	0.2480	0.0125
w1	1	0.4299	0.0611	0.7393	0.0955	0.6063	0.1076	0.7640	0.0829	0.4812	0.0814	0.7949	0.0971
w2	1	0.4232	0.0606	0.7216	0.1081	0.5961	0.1027	0.7010	0.0900	0.4673	0.0798	0.7177	0.1026
w3	1	0.4229	0.0644	0.7143	0.0982	0.5712	0.1037	0.6850	0.0843	0.4794	0.0812	0.7487	0.0939
w4	0	0.3423	0.0266	0.3136	0.0298	0.3281	0.0374	0.3003	0.0301	0.3342	0.0315	0.3030	0.0284
w5	0	0.3449	0.0240	0.3106	0.0274	0.3256	0.0351	0.3044	0.0308	0.3499	0.0277	0.2952	0.0235
w6	0	0.3552	0.0244	0.3179	0.0298	0.3301	0.0329	0.3004	0.0258	0.3486	0.0273	0.3162	0.0293

Notes:
1. A value of 1 (0) in the second column indicates that a variable is included (excluded) in the true model.

Table A2. Model recovery: medians and variances of estimated parameter values

True model vs. BMA coefficients' estimated values for various N (α = 0.50, σ_v^2 = 0.1)

	Lags	All lags used				1 lag used				2 lags used			
	Instruments	Not stacked		Stacked		Not stacked		Stacked		Not stacked		Stacked	
	True value	Median	Variance	Median	Variance	Median	Variance	Median	Variance	Median	Variance	Median	Variance
N=50													
yt-1	0.50	0.2156	0.0025	0.3314	0.0138	0.2711	0.0073	0.4181	0.0212	0.2254	0.0032	0.3976	0.0169
x1	0.23	0.1186	0.0010	0.1580	0.0030	0.1401	0.0021	0.1733	0.0055	0.1190	0.0012	0.1634	0.0037
x2	0.00	-0.0019	0.0011	-0.0006	0.0009	-0.0012	0.0011	-0.0015	0.0006	0.0001	0.0011	-0.0006	0.0006
x3	0.23	0.0755	0.0004	0.1316	0.0019	0.1042	0.0010	0.1810	0.0026	0.0810	0.0005	0.1602	0.0023
x4	0.23	0.0747	0.0004	0.1280	0.0020	0.1049	0.0012	0.1759	0.0025	0.0826	0.0006	0.1611	0.0025
x5	0.00	-0.0007	0.0002	0.0008	0.0003	-0.0001	0.0002	0.0003	0.0002	-0.0006	0.0002	0.0008	0.0002
w1	0.23	0.0878	0.0012	0.1105	0.0107	0.1094	0.0060	0.1308	0.0161	0.0921	0.0013	0.1156	0.0127
w2	0.23	0.0844	0.0010	0.1022	0.0090	0.1030	0.0039	0.1133	0.0211	0.0879	0.0014	0.1085	0.0116
w3	0.23	0.0837	0.0011	0.1000	0.0088	0.1074	0.0047	0.1150	0.0174	0.0863	0.0013	0.1104	0.0094
w4	0.00	-0.0024	0.0010	-0.0049	0.0073	-0.0027	0.0034	-0.0020	0.0171	-0.0042	0.0013	-0.0049	0.0097
w5	0.00	-0.0036	0.0008	-0.0030	0.0077	-0.0030	0.0029	-0.0017	0.0135	-0.0036	0.0011	-0.0028	0.0096
w6	0.00	-0.0034	0.0009	-0.0039	0.0070	-0.0020	0.0030	-0.0060	0.0158	-0.0038	0.0011	-0.0028	0.0107
N=75													
yt-1	0.50	0.2283	0.0030	0.5047	0.0170	0.4507	0.0185	0.5052	0.0154	0.3117	0.0102	0.5174	0.0155
x1	0.23	0.1216	0.0012	0.1949	0.0046	0.1765	0.0043	0.2051	0.0042	0.1427	0.0028	0.2004	0.0038
x2	0.00	-0.0014	0.0006	0.0000	0.0002	-0.0004	0.0004	-0.0001	0.0004	-0.0031	0.0006	0.0001	0.0003
x3	0.23	0.0811	0.0005	0.2212	0.0021	0.1928	0.0025	0.2238	0.0018	0.1207	0.0015	0.2261	0.0019
x4	0.23	0.0815	0.0005	0.2211	0.0022	0.1896	0.0025	0.2244	0.0018	0.1250	0.0015	0.2248	0.0018
x5	0.00	-0.0003	0.0001	0.0004	0.0001	0.0008	0.0002	0.0004	0.0001	0.0005	0.0001	0.0004	0.0001
w1	0.23	0.0936	0.0015	0.1285	0.0096	0.1231	0.0100	0.1401	0.0123	0.1010	0.0052	0.1354	0.0132
w2	0.23	0.0895	0.0017	0.1211	0.0115	0.1185	0.0123	0.1298	0.0168	0.0957	0.0060	0.1229	0.0128
w3	0.23	0.0967	0.0017	0.1370	0.0116	0.1258	0.0102	0.1452	0.0149	0.1058	0.0072	0.1435	0.0129
w4	0.00	-0.0029	0.0012	-0.0008	0.0054	0.0012	0.0055	-0.0011	0.0093	-0.0018	0.0029	0.0001	0.0065
w5	0.00	0.0001	0.0015	-0.0003	0.0043	0.0008	0.0074	-0.0009	0.0093	0.0007	0.0035	-0.0003	0.0059
w6	0.00	-0.0024	0.0014	-0.0012	0.0068	-0.0008	0.0077	-0.0005	0.0112	-0.0041	0.0054	-0.0023	0.0076
N=90													
yt-1	0.50	0.3724	0.0155	0.5249	0.0083	0.5170	0.0143	0.5218	0.0106	0.4613	0.0161	0.5228	0.0080
x1	0.23	0.1542	0.0034	0.2089	0.0028	0.1998	0.0044	0.2114	0.0033	0.1800	0.0039	0.2106	0.0024
x2	0.00	0.0005	0.0004	-0.0001	0.0001	-0.0003	0.0002	-0.0003	0.0002	-0.0002	0.0003	-0.0003	0.0001
x3	0.23	0.1458	0.0024	0.2319	0.0007	0.2239	0.0017	0.2320	0.0013	0.1856	0.0023	0.2325	0.0008
x4	0.23	0.1435	0.0022	0.2309	0.0007	0.2249	0.0018	0.2314	0.0010	0.1924	0.0022	0.2314	0.0007
x5	0.00	0.0000	0.0001	0.0004	0.0001	0.0002	0.0001	0.0005	0.0001	0.0002	0.0001	0.0003	0.0001
w1	0.23	0.1040	0.0071	0.1616	0.0092	0.1239	0.0124	0.1625	0.0108	0.1149	0.0095	0.1601	0.0092
w2	0.23	0.0968	0.0050	0.1524	0.0074	0.1278	0.0090	0.1541	0.0116	0.1102	0.0084	0.1587	0.0079
w3	0.23	0.1071	0.0068	0.1543	0.0073	0.1363	0.0123	0.1601	0.0104	0.1267	0.0088	0.1644	0.0078
w4	0.00	-0.0030	0.0037	0.0002	0.0019	-0.0002	0.0033	0.0004	0.0081	-0.0018	0.0044	-0.0003	0.0033
w5	0.00	-0.0007	0.0024	-0.0005	0.0022	-0.0001	0.0045	0.0004	0.0057	-0.0012	0.0030	-0.0008	0.0030
w6	0.00	0.0007	0.0025	-0.0001	0.0031	-0.0007	0.0039	-0.0006	0.0040	0.0013	0.0033	-0.0007	0.0034
N=100													
yt-1	0.50	0.4662	0.0186	0.5270	0.0061	0.5335	0.0085	0.5232	0.0073	0.5186	0.0147	0.5267	0.0046
x1	0.23	0.1789	0.0050	0.2117	0.0020	0.2048	0.0031	0.2143	0.0023	0.1909	0.0044	0.2134	0.0015
x2	0.00	0.0007	0.0003	0.0002	0.0001	0.0002	0.0001	-0.0003	0.0001	0.0003	0.0002	0.0000	0.0000
x3	0.23	0.1945	0.0027	0.2329	0.0006	0.2314	0.0010	0.2317	0.0009	0.2196	0.0019	0.2326	0.0005
x4	0.23	0.1905	0.0025	0.2340	0.0007	0.2330	0.0009	0.2326	0.0007	0.2205	0.0020	0.2346	0.0004
x5	0.00	0.0001	0.0001	0.0002	0.0000	0.0003	0.0001	0.0002	0.0001	0.0001	0.0001	0.0001	0.0000
w1	0.23	0.1131	0.0068	0.1758	0.0091	0.1444	0.0094	0.1820	0.0116	0.1185	0.0090	0.1873	0.0092
w2	0.23	0.1087	0.0098	0.1691	0.0082	0.1378	0.0084	0.1703	0.0085	0.1228	0.0079	0.1705	0.0074
w3	0.23	0.1069	0.0074	0.1654	0.0070	0.1324	0.0083	0.1653	0.0072	0.1245	0.0081	0.1794	0.0067
w4	0.00	-0.0027	0.0026	0.0000	0.0015	-0.0004	0.0022	-0.0003	0.0043	-0.0010	0.0024	-0.0007	0.0011
w5	0.00	-0.0017	0.0031	0.0003	0.0014	0.0002	0.0032	0.0008	0.0055	0.0000	0.0031	0.0006	0.0013
w6	0.00	-0.0011	0.0031	0.0004	0.0020	-0.0003	0.0031	0.0002	0.0032	-0.0002	0.0028	0.0001	0.0017

Notes:

1. The second column indicates the true parameter values.

Table A3. Posterior probability of the true model and ratio of true model/best among the other models
Summary statistics for various N ($\alpha = 0.50$, $\sigma_v^2 = 0.1$)

	All lags used		1 lag used		2 lags used	
	Not stacked	Stacked	Not stacked	Stacked	Not stacked	Stacked
	Posterior probability of the true model					
N=50						
Mean	0.000	0.002	0.003	0.008	0.001	0.005
Variance	0.000	0.000	0.002	0.000	0.000	0.000
Q1	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.000	0.002	0.000	0.001
Q3	0.000	0.001	0.000	0.007	0.000	0.004
N=75						
Mean	0.001	0.025	0.011	0.029	0.003	0.028
Variance	0.000	0.002	0.001	0.002	0.000	0.002
Q1	0.000	0.001	0.000	0.001	0.000	0.001
Median	0.000	0.005	0.001	0.008	0.000	0.007
Q3	0.000	0.022	0.007	0.038	0.001	0.033
N=90						
Mean	0.006	0.043	0.026	0.048	0.014	0.052
Variance	0.001	0.004	0.003	0.004	0.001	0.004
Q1	0.000	0.002	0.000	0.004	0.000	0.004
Median	0.000	0.012	0.003	0.020	0.001	0.020
Q3	0.003	0.054	0.022	0.072	0.009	0.080
N=100						
Mean	0.017	0.055	0.034	0.063	0.024	0.060
Variance	0.002	0.005	0.004	0.005	0.003	0.005
Q1	0.000	0.002	0.001	0.005	0.000	0.005
Median	0.002	0.020	0.007	0.032	0.003	0.029
Q3	0.008	0.087	0.035	0.103	0.021	0.095

	All lags used		1lag used		2 lags used	
	Not stacked	Stacked	Not stacked	Stacked	Not stacked	Stacked
	Ratio of true model/best among the other models					
N=50						
Mean	0.023	0.098	0.104	0.218	0.041	0.151
Variance	0.008	0.075	1.527	0.169	0.050	0.107
Q1	0.001	0.003	0.001	0.009	0.001	0.007
Median	0.004	0.016	0.003	0.041	0.003	0.035
Q3	0.013	0.052	0.012	0.202	0.012	0.132
N=75						
Mean	0.036	0.319	0.164	0.392	0.066	0.376
Variance	0.050	0.360	0.155	0.397	0.066	0.378
Q1	0.001	0.007	0.002	0.015	0.001	0.010
Median	0.002	0.064	0.016	0.110	0.006	0.087
Q3	0.010	0.288	0.104	0.485	0.026	0.447
N=90						
Mean	0.117	0.456	0.302	0.563	0.199	0.582
Variance	0.169	0.498	0.364	0.562	0.241	0.632
Q1	0.002	0.021	0.004	0.041	0.002	0.033
Median	0.007	0.127	0.030	0.197	0.014	0.204
Q3	0.047	0.566	0.209	0.819	0.105	0.805
N=100						
Mean	0.222	0.525	0.359	0.680	0.262	0.587
Variance	0.341	0.548	0.464	0.681	0.340	0.573
Q1	0.002	0.020	0.006	0.047	0.004	0.036
Median	0.017	0.169	0.064	0.282	0.029	0.218
Q3	0.111	0.730	0.340	1.061	0.197	0.915

Notes:

1. See Appendices A1 and A2 for details.

Table B1. Sample dataset

Variable definitions and sources

		Variable	Source	Definition
Dependent Variable				
		Growth	Penn World Table 6.2	Growth of real GDP per capita (2000 US dollars at PPP)
Explanatory Variables				
1	Solow determinants			
	1	Log(initial income)	Penn World Table 6.2	Logarithm of initial real GDP per capita (2000 US dollars at PPP)
	2	Log(investment)	Penn World Table 6.2	Logarithm of real investment as ratio to GDP (2000 US dollars at PPP)
	3	Log(population growth)	Penn World Table 6.2	Logarithm of annual population growth rate plus 005
2	Human capital			
	4	Log(years of education)	Barro and Lee dataset	Logarithm of total average stock of years of primary and secondary education
	5	Life expectancy	World Development Indicators	Life expectancy at birth (total) with filled in years
3	Macroeconomic stability			
	6	Log(inflation)	International Financial Statistics (IMF)	Logarithm of one plus the inflation rate
	7	Log(Government spending)	Penn World Table 6.2	Logarithm of real government consumption as ratio to GDP (2000 US dollars at PPP)
	8	Debt	Authors' caclulations	Classfication 0-4 based on percentiles of debtgdp: 0=unreported, 1<25 perc, 2=25-49perc, 3=50-74perc, 4>75perc
	9	Overvaluation Index	Penn World Table 6.2	Ln of index of over/undervaluation
4	Trade regime			
	10	Openness	Penn World Table 6.2	Exports plus Imports as share of GDP (2000 US dollars at PPP)
5	External environment			
	11	Terms of Trade	World Economic Outlook (IMF)	Terms of trade (goods and services) growth
	12	Aidgdp	Global Development Finance	Foreign aid as percentage of GDP
6	Internal environment: resources			
	13	Ethnic heterogeneity	Sambanis 2001 extended	Ethnic heterogeneity (Vanhanen's measure): sum of racial, linguistic, and religious division rescaled 0-1
	14	Relative investment price	Penn World Table 6.2	Relative investment price level (PI/PC) (2000 US dollars at PPP)
	15	War	Sambanis (2004); Doyle and Sambanis (2006)	War prevalence
7	Institutions and governance			
	15	Civil Liberties	Freedom House	1 to 7, with 1 being highest degree of freedom, Freedom House
	16	Polity	Polity IV	Aggregate index of autocracy and democracy
8	Fixed Factors: Geography/Physical Factors			
	18	Tropics	Gallup, Mellinger, Sachs (CID datasets)	% Land area in geographical tropics
9	Fixed Factors: Regional characteristics and heterogeneity			
	19	Sub-Saharan Africa	Authors' caclulations	Sub-Saharan Africa dummy variable
	20	Advanced economies	Authors' caclulations	Advanced economy dummy variable
	21	Panel 1976	Authors' caclulations	Time dummy variable
	22	Panel 1984	Authors' caclulations	Time dummy variable
	23	Panel 1992	Authors' caclulations	Time dummy variable
	24	Panel 2000	Authors' caclulations	Time dummy variable
	25	Panel 2008	Authors' caclulations	Time dummy variable