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Abstract

This paper considers panel growth regressions in the presence of model uncertainty and reverse causality concerns. For this purpose, my econometric framework combines Bayesian Model Averaging with a suitable likelihood function for dynamic panel models with weakly exogenous regressors and fixed effects. An application of this econometric methodology to a panel of countries over the 1960-2000 period indicates that there is no robust determinant of economic growth and that the rate of conditional convergence is indistinguishable from zero.

Keywords: growth regressions, panel data, model uncertainty, bayesian model averaging.

JEL classification: O40, C23, C11.

Resumen

En este documento se estiman regresiones de crecimiento económico *a la Barro* teniendo en cuenta, simultáneamente, los problemas de endogeneidad e incertidumbre de modelo. A tal fin, se combinan métodos de estimación de modelos de panel por máxima verosimilitud con técnicas Bayesianas de promediado de modelos. Aplicando la técnica propuesta a un panel de países en el período 1960-2000, los resultados empíricos contrastan con el consenso previo en la literatura de crecimiento empírico: por un lado, no se encuentra evidencia de convergencia condicional entre los países, y por otro lado, ninguna variable parece predecir de forma robusta el crecimiento económico a largo plazo.

Palabras clave: regresiones de crecimiento, datos de panel, incertidumbre de modelo, promediado Bayesiano de modelos.

Códigos JEL: O40, C23, C11.

1 Introduction

Empirical growth research has evolved around two major questions (e.g. Durlauf et al. (2005)), namely, which factors - if any - can explain cross-country differences in income per capita? And, are cross-county differences in growth rates transient in the long run?

Satisfactory answers to these questions must account for two important challenges, model uncertainty and endogeneity of potentially relevant determinants of income per capita levels. Model uncertainty arises because different growth theories are logically consistent with another (Brock and Durlauf (2001)). As a result, different combinations of growth theories represent legitimate empirical growth specifications. To deal with model uncertainty, growth researchers have increasingly adopted Bayesian Model Averaging —henceforth BMA— (e.g. Fernández et al. (2001); Sala-i-Martin et al. (2004); Masanjala and Papageorgiou (2008); Magnus et al. (2010)). However, most BMA approaches have been developed for single cross-sections of countries under the assumption of exogenous growth determinants. These studies can therefore not address a second main challenge to growth econometricians, the endogeneity of growth determinants.[1] In principle some of these issues can be dealt with in a panel data context, which allows including country-specific fixed effects in the empirical model and accounting for feedback from economic growth to the regressors.

To deal with the dual challenges of model uncertainty and endogenous regressors, this paper combines BMA techniques with a suitable likelihood function for panel data models with fixed effects that allow for feedback from economic growth to the regressors. To do so I extend the approach in Moral-Benito (2012a) by allowing for weakly exogenous regressors.[2] In particular, I combine the likelihood in Moral-Benito (2012b), which is based on the same identifying assumptions as well-known panel GMM estimators of the type discussed in Arellano and Bond (1991), with BMA techniques using the unit information prior on the parameter space as suggested by Raftery (1995).

As an application of my econometric framework incorporating both weak exogeneity and model uncertainty in a panel setting, I revisit the determinants of economic growth over the 1960-2000 period for a large sample of countries. In contrast to the previous literature, the point estimate of the speed of convergence is relatively low, and its associated posterior variance renders this estimate statistically indistinguishable from zero. This result leads to the conclusion that the

[1]Durlauf et al. (2008, 2012) and Eicher et al. (2012) consider endogenous regressors in the BMA setting for certain growth determinants. In particular, these authors consider weighted averages of two-stage least squares estimates using BIC-inspired weights. Since the formal justification of these approaches remains an open issue, Koop et al. (forthcoming) propose a fully Bayesian approach to deal with endogenous regressors in the BMA framework based on cross-sectional data with an application to returns-to-schooling equations.

[2]Note that weakly exogenous regressors are also known as predetermined regressors in the panel data terminology.

hypothesis of no conditional convergence cannot be rejected given the evidence obtained in this paper. This finding casts doubt on what has often been considered the main prediction of the neoclassical growth model (Ramsey (1928); Solow (1956)); in contrast, it provides evidence in favor of endogenous growth models such as Romer (1987, 1990) and Aghion and Howitt (1992) which do not predict conditional convergence. I also conclude that no other variable can robustly predict long run economic growth. In particular, uncertainty surrounding estimation seems to be large enough to preclude us from labeling any of the regressors as a robust determinant of economic growth. One possible interpretation of this finding is that the fragility of growth regressions is high enough to cast doubt on the validity of this approach to identify the sources of long-run economic growth.[3]

The combination of panel approaches with BMA represents an open line of research, especially in the context of growth empirics. Mirestean and Tsangarides (2009) and Leon-Gonzalez and Montolio (2012) consider GMM-type approaches to panel data (e.g. Arellano and Bond (1991); Alonso-Borrego and Arellano (1999)) combined with model averaging techniques under weak exogeneity of the regressors. However, the combination of frequentist GMM parameter estimates with BMA methods remains controversial from the perspective of the philosophical foundations of statistics as noted by Durlauf et al. (2008). Alternatively, Moral-Benito (2012a) combines the BMA methodology with dynamic panel data models under the assumption of strictly exogenous regressors based on the suitable likelihood function developed in Alvarez and Arellano (2003). This paper contributes to this strand of the literature by combining BMA with a proper likelihood function for dynamic panel models under weak exogeneity of the regressors.

The rest of the paper is organized as follows. Section 2 describes the econometric framework. Section 3 and 4 present the empirical application and findings. Section 5 concludes.

2 Econometric Methodology

The literature on the empirical determinants of economic growth is interested in estimating:

$$\Upsilon_i = c \ln y_{i0} + \beta x_i + \epsilon_i \tag{1}$$

where $\Upsilon_i = t^{-1}(\ln y_{it} - \ln y_{i0})$ represents the growth rate of GDP per worker between 0 and t. x_i is a vector of variables that determine the log run income level (e.g. Barro (1991)). This estimating equation can be derived from a generic one sector growth model, in either the Solow-Swan —e.g. Solow (1956); Swan (1956)— or the Ramsey-Cass-Koopmans —e.g. Ramsey (1928); Cass (1965); Koopmans (1965)— variants.

[3] In any case, note that the results in this paper are conditional on the model space considered, and thus should be interpreted with caution.

2.1 Growth Empirics and Panel Data

Cross-country growth regressions are commonly estimated from small-T panels using the Heston et al. (2006, 2009, 2011) data sets of worldwide aggregate series. Although these datasets span around forty years (from 1960 to 2000), the data are typically split into five- or ten-year intervals to focus on long run economic growth. In particular, a panel variant of the baseline empirical growth regression in (1) is usually considered:

$$\ln y_{it} = \alpha \ln y_{it-1} + \beta x_{it} + \eta_i + \zeta_t + v_{it} \qquad (i = 1, ..., N)(t = 1, ..., T) \tag{2}$$

where $\alpha = (1 + c)$, η_i is a country-specific fixed effect that allows considering unobservable heterogeneity across countries, and ζ_t is a period-specific shock common to all countries.

On the grounds of two main arguments, the use of panel data in growth empirics may be preferable to cross-sectional data. On the one hand, the prospects for reliable generalizations in cross-country growth regressions are often constrained by the limited number of countries available, therefore, the use of within-country variation to multiply the number of observations is a natural response to this constraint. On the other hand, the use of panel data methods allows solving the inconsistency of empirical estimates arising due to the existence of omitted country specific effects which, if not uncorrelated with other regressors, lead to a misspecification of the underlying dynamic structure.

In the panel setting, weak exogeneity implies that current values of the regressors are uncorrelated with future realizations of the shocks to economic growth. However, past shocks to the dependent variable can be correlated with current regressors so that feedback from GDP to growth determinants is allowed. As a result, weak exogeneity, also known as predeterminedness in the panel data terminology, represents a natural assumption to address reverse causality concerns in the growth context. The weak exogeneity assumption can be formalized as follows:

$$E\left(v_{it} \mid y_i^{t-1}, x_i^t, \eta_i\right) = 0 \qquad (i = 1, ..., N)(t = 1, ..., T) \tag{3}$$

where $y_i^{t-1} = (y_{i0}, ..., y_{it-1})'$ and $x_i^t = (x_{i0}, ..., x_{it})'$. Note also that right-hand-side variables are allowed to be correlated with the country-specific effects η_i.

Moment conditions implied by assumption (3) are commonly exploited within a method-of-moments perspective. First-differenced GMM estimators discussed in Arellano and Bond (1991) are the best example in this category. In the growth empirics context, Caselli et al. (1996) and Benhabib and Spiegel (2000) are two examples of such an approach. However, an important caveat of these panel GMM estimators is the lack of formal statistical justification for combining them with Bayesian approaches such as BMA.

On the other hand, since the number of countries is limited, the cross-section dimension in growth data sets is not very large so that finite sample performance of "fixed T, large N" consistent estimators such as first-differenced GMM may be a cause of concern (e.g. Bond et al. (2001)). The reason is that, as Blundell and Bond (1998) pointed out, lagged levels may be only weak instruments for the equation in first-differences with persistent series such as GDP.[4]

2.2 Likelihood Function for Panel Data Models with Weakly Exogenous Regressors

In a recent paper, Moral-Benito (2012b) develops a likelihood function for panel data models with fixed effects and weakly exogenous regressors. Therefore, feedback from economic growth to the regressors (i.e. reverse causality) can be accommodated using this likelihood-based approach. Also, the availability of such a likelihood function allows combining the Bayesian apparatus (e.g. BMA) with this type of panel models. As a side benefit, based on the identifying assumption in (3), the resulting maximum likelihood estimator is shown to outperform panel GMM estimators in terms of finite sample performance, especially in the presence of weak instruments.

Moral-Benito (2012b) develops the implications of the model in (2)-(3) for the first and second moments of the observed variables in order to set up a likelihood function based on a multivariate regression model with restrictions on the covariance matrix. For this purpose, the structural equation (2) is augmented with additional reduced form equations capturing the unrestricted feedback process as follows:

$$x_{it} = \gamma_{t0} y_{i0} + ... + \gamma_{t,t-1} y_{i,t-1} + \Lambda_{t1} x_{i1} + ... + \Lambda_{t,t-1} x_{i,t-1} + c_t \eta_i + \vartheta_{it} \tag{4}$$

where c_t is a vector of parameters of order $k \times 1$, and, for $h < t$, γ_{th} is the $k \times 1$ vector $\gamma_{th} = (\gamma^1_{th}, \ldots, \gamma^k_{th})'$ with $h = 0, \ldots, T-1$. Moreover, Λ_{th} is a matrix of parameters of order $k \times k$, and ϑ_{it} is a $k \times 1$ vector of prediction errors.

On the other hand, the mean vector and covariance matrix of the joint distribution of the initial observations (y_{i0}, x_{i1}) and the individual effects η_i are unrestricted given the following reduced form equation:

$$y_{i0} = c_0 \eta_i + v_{i0} \tag{5}$$

where c_0 is a scalar.

[4] In order to solve this weak-instruments problem, Bond et al. (2001) proposed, in the context of growth regressions, the use of the so-called system-GMM estimator introduced by Arellano and Bover (1995). However, this estimator requires the additional assumption of mean stationarity of the variables which might not be appropriate in data sets starting at the end of a war as argued by Barro and Sala-i-Martin (2003).

Given the complete model in (2) and (4)-(5), the log-likelihood under Gaussian errors can be written as:

$$\log f(data|\theta) \propto \frac{N}{2}\log\det(B^{-1}D\Sigma D'B'^{-1}) - \frac{1}{2}\sum_{i=1}^{N}\left\{R_i'(B^{-1}D\Sigma D'B'^{-1})^{-1}R_i\right\} \tag{6}$$

where $R_i = (y_{i0}, x_{i1}', y_{i1}, \ldots, x_{iT}', y_{iT})'$ and $U_i = (\eta_i, v_{i0}, \vartheta_{i1}', v_{i1}, \ldots, \vartheta_{iT}', v_{iT})'$ are the vectors of observed variables (data) and errors respectively. $\Sigma = diag\{\sigma_\eta^2, \sigma_{v_0}^2, \Sigma_{\vartheta_1}, \sigma_{v_1}^2, ..., \Sigma_{\vartheta_T}, \sigma_{v_T}^2\}$ is the block-diagonal variance-covariance matrix of U_i. Moreover, θ is the vector of parameters to be estimated that augments the parameters of interest (α, β) from equation (2) with auxiliary parameters $\left(c_0, \sigma_\eta^2, \sigma_{v_0}^2, \{c_t, \gamma_{th}, vec(\Lambda_{th}), \sigma_{v_t}^2, vech(\Sigma_{\vartheta_t})\}_{t=1}^{t=T}\right)$. Note also that, in order to avoid notational clutter, I do not use model-specific subindices although θ will vary over models as discussed below (given model uncertainty, different combinations of regressors will result in different models to be considered).

Finally, B and D are matrices of coefficients given by:

$$B = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & \ldots & 0 & 0 & 0 \\ -\gamma_{10} & I_k & 0 & 0 & 0 & \ldots & 0 & 0 & 0 \\ -\alpha & -\beta' & 1 & 0 & 0 & \ldots & 0 & 0 & 0 \\ -\gamma_{20} & -\Lambda_{21} & -\gamma_{21} & I_k & 0 & \ldots & 0 & 0 & 0 \\ 0 & 0 & -\alpha & -\beta' & 1 & \ldots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & 0 & 0 & 0 \\ -\gamma_{T0} & -\Lambda_{T1} & -\gamma_{T1} & -\Lambda_{T2} & -\gamma_{T2} & \ldots & -\gamma_{T,T-1} & I_k & 0 \\ 0 & 0 & 0 & 0 & 0 & \ldots & -\alpha & -\beta' & 1 \end{pmatrix}$$

$$D = \begin{pmatrix} (c_0 \quad c_1' \quad 1 \qquad c_2' \qquad 1 \quad \ldots \quad c_T' \quad 1) \\ I_{T(k+1)} \end{pmatrix}$$

The Gaussian likelihood in (6) allows combining Bayesian approaches such as BMA with panel data models under correlated random effects and weakly exogenous regressors. On the other hand, the maximizer of $\log f(data|\theta)$ is a consistent and asymptotically normal estimator regardless of non-normality. More concretely, the resulting estimator is asymptotically equivalent to the Arellano and Bond (1991) GMM estimator augmented with the moments discussed in Ahn and Schmidt (1995) given by the lack of autocorrelation in the errors as implied by assumption (3). More details about the properties of this maximum likelihood approach can be found in Moral-Benito (2012b).

2.3 Growth Empirics and Model Uncertainty

Model uncertainty in growth empirics arises due to the lack of clear theoretical guidance on the choice of regressors to include in the vector x_{it}. This results in the existence of potentially many empirical models, each given by a different combination of regressors. In particular, if we have k possible explanatory variables, we will have 2^k possible combinations of regressors, that is to say, 2^k different models - indexed by M_j for $j = 1, ..., 2^k$- which all seek to explain the *data*.

As a result, researcher's uncertainty about the value of the parameter of interest in a growth regression exists at distinct two levels. The first one is the uncertainty associated with the parameter conditional on a given empirical growth model. This level of uncertainty is of course assessed in virtually every empirical study. What is not fully assessed is the uncertainty associated with the specification of the empirical growth model. It is typical for a given paper that the specification of the growth regression is taken as essentially known; while some variations of a baseline model are often reported, via different choices of control variables, standard empirical practice does not systematically account for the sensitivity of claims about the parameter of interest to model choice.

Provided a suitable likelihood function is available, BMA represents a natural alternative to deal with model uncertainty.[5] In a nutshell, BMA entails three main steps: (i) choose prior distributions on the model and parameter spaces; (ii) determine the likelihood function of the data under each model and parameter value; (iii) compute the full posterior distribution of the coefficients using Bayes' theorem.

More formally, the posterior distribution of any quantity of interest, say Θ, is a weighted average of the posterior distributions of Θ under each of the models under consideration:

$$f(\Theta|data) = \sum_{j=1}^{2^K} P\left(M_j|data\right) f(\Theta|data, M_j) \tag{7}$$

where $P\left(M_j|data\right)$ is the posterior model probability of model j, and $f(\Theta|data, M_j)$ represents the posterior distribution of Θ conditional on model j.

In this paper, each model-specific posterior is given by a normal distribution with mean at the MLE and dispersion matrix equal to the inverse of the Fisher information. The Bernstein-von Mises theorem, which can be interpreted as the "Bayesian central limit theorem", states that a Bayesian posterior is well approximated by this distribution. Berger (1985) provides an in-depth analysis and an illustration of the Bernstein-von Mises theorem.

[5] There also exists a frequentist approach to model averaging (e.g. Claeskens and Hjort (2003); Hansen (2007)).

On the other hand, posterior model probabilities are given by:

$$P(M_j|data) = \frac{P(M_j) f(data|M_j)}{\sum_{i=1}^{2^K} P(M_i) f(data|M_i)} \tag{8}$$

where $f(data|M_j)$ is the marginal likelihood for model j given by $\int f(data|\Theta, M_j) g(\Theta|M_j) d\Theta$.

The likelihood in (6) allows computing this quantity and thus considering BMA together with dynamic panel data models under weakly exogenous regressors and correlated effects. In this setting, each of the models being considered comprise the same set of simultaneous equations. Therefore, model-specific marginal likelihoods refer to the joint density of the dependent variable and all the weakly exogenous regressors. In order to guarantee comparability of these likelihoods, this is so even when some of the regressors are not "included" in the model, i.e. a given regressor is excluded from a particular model by simply restricting to zero its β coefficient in the structural equation (2). Therefore, the full set of reduced form equations in (4)-(5) is common to all the models under consideration.

BMA also allows computing the posterior probability (PIP) that a particular variable h is included in the regression. In particular, this probability is an indicator of the weighted average goodness-of-fit of models containing a particular variable relative to models not containing that variable. The PIP of variable h is calculated as the sum of the posterior model probabilities for all of the models including that particular variable.

Regarding prior assumptions, I consider the unit information prior (UIP) on the parameter space. This prior is a multivariate normal with mean the MLE of the parameters and variance the inverse of the expected Fisher information matrix for one observation. Note also that this particular choice of parameters' prior is equivalent to the Schwarz asymptotic approximation as discussed in Kass and Wasserman (1995). Moral-Benito (2012a) provides some discussion on the use of this prior in the panel data setting.

Regarding the model prior distributions to be elicited, I consider the uniform prior, i.e. all models are equally probable a priori so that $P(M_j) = 1/2^K \ \forall j$. This prior is the result of assuming a Binomial distribution for the model size with prior inclusion probability of a given variable equal to 0.5, or equivalently, prior expected model size equal to $k/2$.[6]

Eicher et al. (2011) conclude that the unit information prior combined with the uniform model prior outperforms any other possible combination of priors previously considered in the BMA literature in terms of cross-validated predictive performance. This combination of priors also identifies the largest set of growth determinants.

[6]Moreover, the main findings in this paper are robust to the use of the random model prior suggested by Ley and Steel (2009).

3 Growth Determinants

The augmented Solow-Swan model can be taken as the baseline empirical growth model. It consists of four determinants of economic growth, initial income, rates of physical and human capital accumulation, and population growth. In addition to those four determinants, Durlauf et al. (2005)'s survey of the empirical growth literature identifies 43 distinct growth theories and 145 proposed regressors as proxies; each of these theories is found to be statistically significant in at least one study.

The set of growth determinants considered in this paper is only a subset of that identified by Durlauf et al. (2005). Also, this set is smaller than that of previous BMA-growth studies. Four main reasons are behind this choice: (i) Data availability in the panel data context for the postwar period 1960-2000 is smaller than in the cross-sectional case. For instance, the fraction of GDP in mining or the fraction of Muslim population (both considered in previous BMA literature with cross-sectional data) are available only for the year 1960. (ii) Ciccone and Jarocinski (2010) and Moral-Benito (2012a) show that the fewer the potential growth determinants considered, the smaller the sensitivity of the results. According to this finding, it is advisable to avoid the inclusion of several proxies for the same growth theory. For instance, I only include one proxy for human capital, the stock of years of secondary education in the total population. (iii) Related to the previous argument, Durlauf et al. (2008) argue that the different candidate growth determinants should be grouped by growth theories in order to account for interdependencies among them when eliciting model priors, i.e. the so-called dilution priors. Alternatively, I select one variable for each theory as a type of dilution prior with only one proxy in each group/theory. (iv) Last but not least, computational burden is also an important limitation in this respect. The number of models to be estimated increases exponentially with the number of regressors considered and, given the panel likelihood considered in this paper, it is necessary to resort to numerical optimization methods. As a result, the problem would be computationally intractable if I include too many candidates.

All in all, the following candidate growth determinants are considered to form the model space:

- Initial GDP: One of the main features of the neoclassical growth model is the prediction of a low (less than one) coefficient on initial GDP (i.e. it predicts conditional convergence). If the other explanatory variables are held constant, then the economy tends to approach (or not) its long-run position at the rate indicated by the magnitude of the coefficient.

- Investment Ratio: The ratio of investment to output represents the saving rate in the neoclassical growth model. In this model, a higher saving rate raises the steady-state level of output per effective worker and therefore increases the growth rate for a given starting value of

GDP. Many empirical studies such as DeLong and Summers (1991) have found an important positive effect of the investment ratio on economic growth.

- Education: In the neoclassical growth model, since the seminal work of Lucas (1988), the concept of capital is usually broadened from physical capital to include human capital. Education is the form of human capital that has generated most of the empirical work. In spite of the positive theoretical effect, many empirical studies have failed in finding such an effect. In particular, I consider here the years of secondary education from Barro and Lee (2000).

- Life Expectancy: Another commonly-considered form of human capital is health. In particular, the log of life expectancy at birth at the start of each period is typically used as an indicator of health status. There is a growing consensus that improving health can have a large positive impact on economic growth. For example, Gallup and Sachs (2001) argue that wiping out malaria in sub-Saharan Africa could increase per capita GDP growth by 2.6% a year.

- Population Growth: The steady-state level of output per effective worker in the neoclassical growth model is negatively affected by a higher rate of population growth because a portion of the investment is devoted to new workers rather than to raise capital per worker. However, this implication is not always confirmed when estimating empirical growth models.

- Investment Price: Since the seminal work of Agarwala (1983), it is often argued that distortions of market prices impact negatively on economic growth. Given the connection between investment and growth, such market interferences would be especially important if they apply to capital goods. Therefore, following Barro (1991) and Easterly (1993) among others, I consider the investment price level as a proxy for the level of distortions of market prices that exists in the economy.

- Trade Openness: The trade regime/external environment is captured by the degree of openness measured by the trade openness, imports plus exports as a share of GDP. It is often argued that a higher degree of trade openness increases the opportunity set of profitable investments and therefore promotes economic growth. Many authors such as Levine and Renelt (1992) and Frankel and Romer (1999) have considered this ratio.

- Government Consumption: Since the seminal work of Barro (1991), many authors have considered the ratio of government consumption to GDP as a measure of distortions in the economy. The argument is that government consumption has no direct effect on private productivity but lower saving and growth through the distorting effects from taxation or government-expenditure programs.

- Polity Measure: The role of democracy in the process of economic growth has been the source of considerable research effort. However, there is no consensus about how the level of democracy in a country affects economic growth. Some researchers believe that an expansion of political rights (i.e. more democracy) fosters economic rights and tends thereby to stimulate growth. Others think that the growth-retarding aspects of democracy such as the heightened concern with social programs and income redistribution may be the dominant effect. Many authors such as Barro (1996) and Tavares and Wacziarg (2001) have empirically investigated this issue. In this paper, I consider the Polity IV index of democracy/autocracy for analyzing the overall effect of democracy on growth.

- Population: Romer (1987, 1990) and Aghion and Howitt (1992) among others, developed theories of endogenous growth that imply some benefits from larger scale. In particular, if there are significant setup costs at the country level for inventing or adapting new products or production techniques, then the larger economies would, on this ground, perform better. This countrywide scale effect is tested by considering country's population in millions of people.

4 Empirical Results

Considering a balanced panel for 73 countries, I combine BMA with dynamic panel data models under weak exogeneity of the regressors and correlated country-specific effects. The sample period is 1960-2000 at 10-years intervals so that the number of time-series observations is $T = 4$. Table 1 presents some moments of the coefficients' posterior distributions computed following equation (7). In particular, posterior distribution moments reported in Table 1 are marginalized over all the models considered. The interest on conditional or unconditional moments depends on the prior held by the researcher regarding the inclusion of a particular variable. If the researcher is certain that a given variable belongs to the model, the conditional moments provide the estimates of interest. However, if this is not the case, unconditional versions are more appropriate.[7]

The first two columns of Table 1 present the mean and standard deviation (s.d.) of the coefficients' BMA posterior distributions. While the exact distribution of the ratio of BMA posterior mean to posterior s.d. is not known, several interpretations of this ratio are available in the litera-

[7]The relationship between unconditional and conditional posterior mean and s.d. is given by $E(\theta|data)_{cond} = E(\theta|data)_{uncond}/PIP$ and $V(\theta|data)_{uncond} = [V(\theta|data)_{cond} + E^2(\theta|data)_{cond}] \times PIP - E^2(\theta|data)_{uncond}$.

Table 1: Growth Regressions using Panel BMA under Weak Exogeneity

	Posterior Mean	Posterior s.d.	PIP	BMA Posterior Percentiles		
				2.5%	50%	97.5%
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable is ln(GDP$_t$)					
ln(GDP$_{t-1}$)	0.918	0.106	–	0.716	0.914	1.137
Investment	0.063	0.062	77%	−0.031	0.080	0.199
Education	0.031	0.071	72%	−0.122	0.045	0.194
Pop. Growth	0.018	0.052	71%	−0.091	0.025	0.143
Population	0.121	0.079	98%	−0.032	0.122	0.274
Invest. Price	−0.033	0.043	66%	−0.136	−0.049	0.035
Trade Openness	0.034	0.032	77%	−0.012	0.043	0.103
Gov. Consumption	−0.013	0.086	75%	−0.212	−0.016	0.177
ln(life expect)	0.086	0.095	86%	−0.078	0.097	0.294
Democracy	−0.056	0.052	68%	−0.165	−0.083	0.020

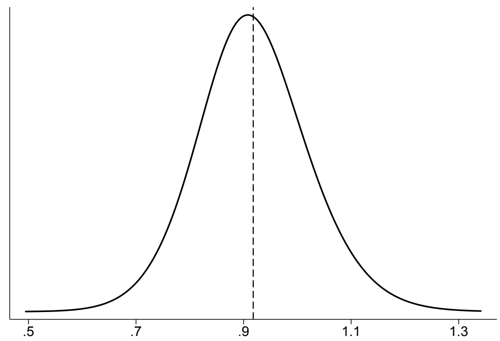
Notes: The sample covers 73 countries over the period 1960 to 2000 — divided in 10-years sub periods resulting in $T = 4$ time-series observations. All regressors have been standardized. Columns (1) and (2) report the BMA posterior mean and standard error respectively. Column (3) reports the posterior inclusion probability. Finally, columns (4), (5) and (6) present, respectively, the 2.5%, 50% and 97.5% percentiles of the coefficients' BMA posterior distributions. Results in this table are based on the unit information prior for the parameter space and the uniform priors for the model space.

ture. Raftery (1995) suggested that for a variable to be considered as effective the ratio of mean/s.d. (in absolute value) must exceed 1, which from a frequentist viewpoint implies that the regressor improves the power of the regression. Masanjala and Papageorgiou (2008) are more stringent and consider a threshold value of the mean/s.d. ratio of 1.3, which approximately corresponds to a 90% confidence interval in frequentist approaches. Finally, Sala-i-Martin et al. (2004) set this threshold at 2 since they argue that having a mean/s.d. ratio of 2 in absolute value indicates an approximate 95% Bayesian coverage region that excludes zero. According to the estimates in columns (1) and (2) of Table 1, four coefficients (investment, population, trade openness and democracy) present a ratio of mean/s.d. larger than 1 in absolute value. Among them, only the population coefficient has a ratio larger than 1.3 in absolute value. However, none of the variables considered in Table 1 presents a ratio larger than 2 in absolute value. Finally, note that the mean/s.d. ratio for the convergence coefficient (ln(GDP$_{t-1}$)) is 8.66 for the null $\alpha = 0$. However, given that the null of lack of conditional convergence is $\alpha = 1$ in this framework, the mean/s.d. ratio of interest would take the value -0.77, which does not exceed any of the three thresholds above.

Column (3) of Table 1 reports the BMA posterior inclusion probability (PIP) of each regressor. According to Raftery (1995), evidence for a regressor with a PIP from $50-75\%$ is called weak, from $75-95\%$ positive, from $95-99\%$ strong, and $> 99\%$ very strong. The PIPs presented in Table 1 indicate that very strong evidence is not obtained for any of the regressors considered. However, strong evidence is found in favor of the population variable, and positive evidence for the variables investment, trade openness and life expectancy. The evidence in favor of the remaining regressors is only weak according to the Raftery (1995) scale. Finally, note that PIP is not reported for the convergence coefficient because theory offers strong guidance in favor of the inclusion of intial GDP in growth regressions (see Durlauf et al. (2005)). Therefore, I include initial GDP (i.e. the lagged dependent variable) in all models under consideration.

BMA posterior percentiles are also reported in columns (4)-(6) of Table 1. In particular, I report the 2.5%, 50% and 97.5% percentiles as a summary of the BMA posterior distributions. While the sign of the 50% percentile coincides in all cases with that of the mean in column (1), the magnitude is quite different for those coefficients with lower mean/s.d. ratio in absolute value. Moreover, the 2.5% and the 97.5% percentiles have opposite signs for all the growth determinants analyzed in Table 1. Regarding the issue of convergence, the 2.5% percentile of the posterior distribution for α implies a convergence rate of an economy to its steady state of 3.3% while the 97.5% percentile would no longer predict conditional convergence at all.[8]

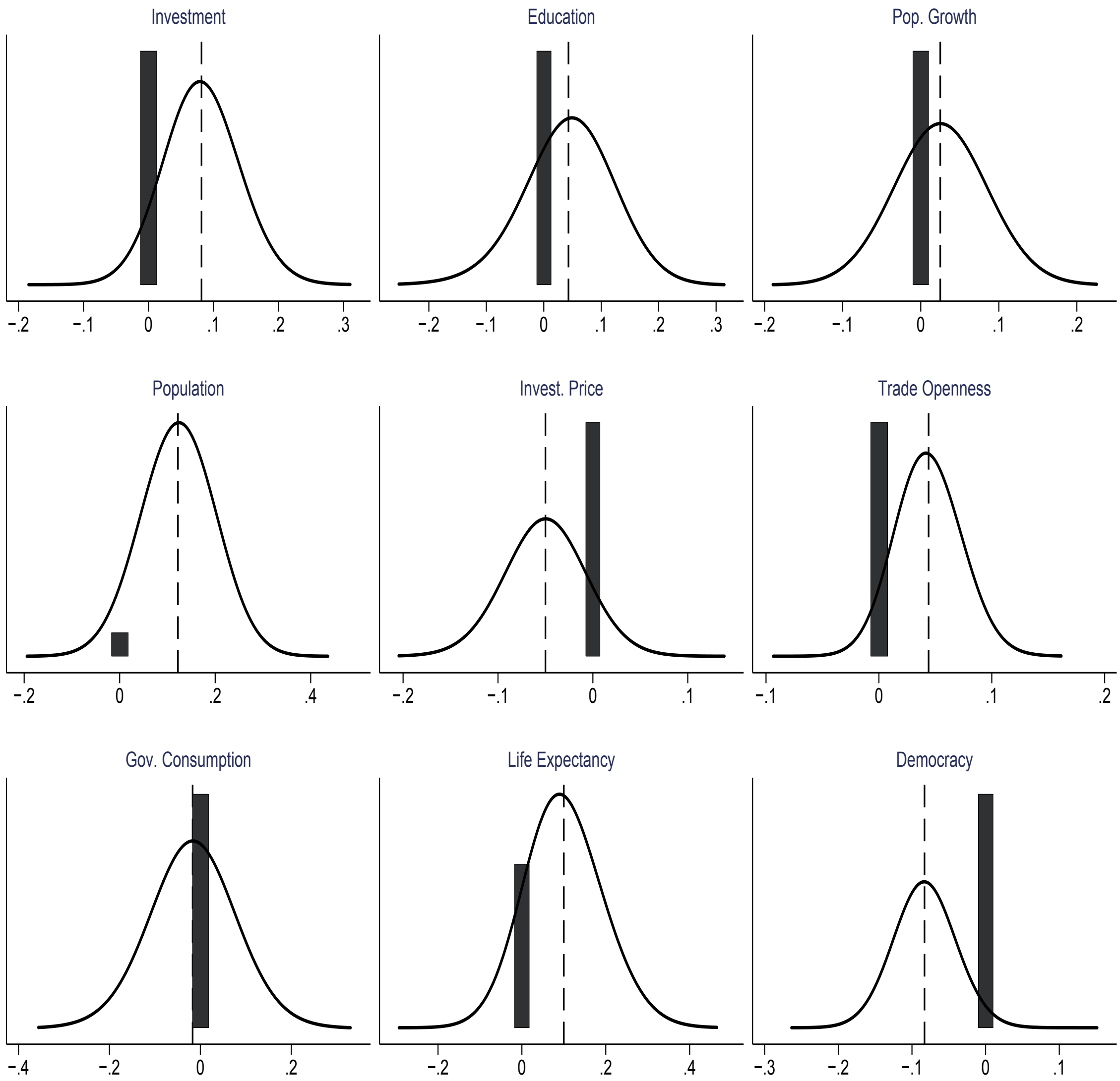
Figure 1: Posterior Distribution of the Convergence Coefficient



This Figure presents the marginal posterior distribution of the convergence coefficient (α). A dashed vertical line indicates the posterior mean presented in Table 1.

[8]Note that the rate of convergence (λ) can be computed as $\lambda = \frac{\ln \alpha}{-\tau}$ where $\tau = 10$ years, and α is the coefficient on $\ln(y_{t-1})$.

Figure 2: Posterior Distributions of Growth Determinants' Coefficients



This Figure presents the marginal posterior distributions of the regression coefficients. In particular, each plot presents (i) a gauge at zero which shows the probability that a variable is not inc1uded in the regression (given by one minus the posterior inc1usion probability), and (ii) the normal mixture density for each coefficient's posterior distribution. A dashed vertical line indicates the posterior mean presented in Table 1.

Posterior summary statistics such as the mean and the s.d. can be too reductive and potentially misleading due to the often irregular shapes of BMA posterior distributions. Therefore, Figures 1 and 2 present the full BMA posterior distributions for each coefficient. These posteriors have two parts, (i) a gauge located at 0 on the x-axis which represents the posterior probability of the models that exclude the variable (i.e. one minus the PIP); (ii) a continuous part describing the posterior distribution of the coefficient conditional on inclusion. Looking at these plots one can simultaneously analyze (i) whether a particular variable significantly contributes to improve the explanatory power of the empirical model, and (ii) how the posterior distribution looks assuming that the variable is included in the model. Interestingly enough, Figures 1 and 2 point to BMA posterior distributions with approximately Gaussian shapes for all the coefficients under consideration. Moreover, posterior modes are in all cases quite close to the posterior means reported as our preferred point estimate. Therefore, one can interpret that the results presented in Table 1 represent an accurate summary of the full BMA posterior distributions.

Putting all these findings together, I now discuss the implications for the two major questions in the growth empirics literature, namely, the convergence debate and the identification of growth determinants. Regarding the issue of convergence, I find no evidence of conditional convergence in panel growth regressions once model uncertainty and reverse causality concerns are accounted for. The point estimate for the rate of convergence is 0.85% looking at the mean of the BMA posterior distribution, and 0.90% and 0.96% if we look at the median and the mode respectively. In all the three cases, our point estimate for the convergence rate is substantially lower than previous panel studies ignoring model uncertainty such as Caselli et al. (1996) who estimated a convergence rate of around 12%. Moroever, analyzing the full posterior distribution of the convergence coefficient, I conclude that the rate of convergence is statistically indistinguishable from zero.[9] This finding casts doubt on the conventional wisdom of conditional convergence as a strong empirical regularity in the country level data (e.g. Barro and Sala-i Martin (1992); Caselli et al. (1996)). For example, early versions of endogenous growth theories such as Romer (1987, 1990) and Aghion and Howitt (1992) were criticized because in contrast to the neoclassical growth model, they no longer predicted conditional convergence.

The identification of growth determinants is the other question of interest in the growth regressions literature. In this respect, despite I find mild evidence in favor of the population variable, which would imply empirical support for the increasing returns to scale in endogenous growth models (e.g. Romer (1987, 1990); Aghion and Howitt (1992)), the dispersion of the posterior distributions is generally large enough to render the estimated effects statistically indistinguishable from zero. This evidence would lead to the conclusion that there is no variable unambiguously related to economic growth according to the robustness-checking method considered in the paper; hence there may not be universal rules about what makes countries grow. However, a more prudent

[9] This result was also found in Moral-Benito (2012a), where both model uncertainty and predeterminedness of the lagged dependent variable were considered. However, in contrast to the present paper, Moral-Benito (2012a) considered a panel likelihood function under the assumption of strictly exogenous regressors.

interpretation of this evidence is that the fragility of cross-country growth regressions casts doubt on the validity of this approach to identify the sources of long-run economic growth. Finally, it is worth emphasizing that one should be aware of the limitations in this paper. On the one hand, the results discussed above are conditional on the reduced model space considered; on the other hand, important issues such as parameter heterogeneity (see Eicher et al. (2007)) are absent.

5 Concluding Remarks

Two of the main challenges in growth econometrics are model uncertainty and endogeneity of the determinants of long run income per capita levels. Model uncertainty arises because many growth models are compatible with each other. Endogeneity concerns arise in the form of omitted variables (e.g. country-specific effects) and reverse causality between economic growth and the regressors.

BMA methods have enjoyed an increasing popularity in the growth empirics literature as a solution to model uncertainty (e.g. Fernández et al. (2001); Masanjala and Papageorgiou (2008)). Moreover, panel data approaches such as first-differenced GMM are commonly considered to address omitted variables and reverse causality concerns in the framework of growth regressions (e.g. Caselli et al. (1996); Benhabib and Spiegel (2000)). Leon-Gonzalez and Montolio (2012) and Mirestean and Tsangarides (2009) combine this type GMM-type (or pseudo-likelihood) approaches to panel data with model averaging techniques using BIC-based weights. However, the formal Bayesian justification of these approaches remains an open debate (e.g. Durlauf et al. (2008)).

In this paper, I combine BMA with a suitable likelihood function for panel data models with country-specific effects and weakly exogenous regressors. This allows me to address model uncertainty as well as omitted variables and reverse causality concerns in a unified econometric framework with proper statistical foundations.

Once model uncertainty and weakly exogenous regressors are accounted for, empirical findings are in stark contrast to the previous consensus in the literature. First, the estimated convergence rate is not statistically distinguishable from zero. This result casts doubt on conditional convergence, which has often been seen as the main prediction of the neoclassical model of growth. Second, there is no variable unambiguously related to economic growth. Hence, economic growth does not appear to be robustly related to the determinants proposed in the literature so far.

A Data Appendix

Table A1: Variable Definitions and Sources

Variable	Source	Definition
GDP	PWT 6.2	Logarithm of GDP per capita (2000 US dollars at PP)
I/GDP	PWT 6.2	Ratio of real domestic investment to GDP
Education	Barro and Lee (2000)	Stock of years of secondary education in the total population
Pop. Growth	PWT 6.2	Average growth rate of population
Population	PWT 6.2	Population in millions of people
Inv. Price	PWT 6.2	Purchasing-power-parity numbers for investment goods
Trade Openness	PWT 6.2	Exports plus imports as a share of GDP
G/GDP	PWT 6.2	Ratio of government consumption to GDP
ln (life expect)	WDI 2005	Logarithm of the life expectancy at birth
Polity	Polity IV Project	Composite index given by the democracy score minus the autocracy score. Original range -10,-9,...,10, normalized 0-1.

Notes: All variables are available for all the countries in the sample (see table below) and for the whole period 1960-2000. PWT 6.2 refers to Penn World Tables 6.2 and it can be fount at http://pwt.econ.upenn.edu/. WDI 2005 refers to World Development Indicators 2005. Data from Barro and Lee (2000) is available at http://www.cid.harvard.edu/ciddata/ciddata.html. Finally, data from the Polity IV Project can be downloaded from http://www.systemicpeace.org/polity/polity4.htm.

Table A2: List of Countries

Algeria	France	Mali	Singapore
Argentina	Ghana	Mauritius	South Africa
Australia	Greece	Mexico	Spain
Austria	Guatemala	Mozambique	Sri Lanka
Belgium	Honduras	Nepal	Sweden
Benin	India	Netherlands	Switzerland
Bolivia	Indonesia	New Zealand	Syria
Brazil	Iran	Nicaragua	Thailand
Cameroon	Ireland	Niger	Togo
Canada	Israel	Norway	Trinidad & Tobago
Chile	Italy	Pakistan	Turkey
China	Jamaica	Panama	Uganda
Colombia	Japan	Paraguay	United Kingdom
Costa Rica	Jordan	Peru	United States
Denmark	Kenya	Philippines	Uruguay
Dom. Republic	Lesotho	Portugal	Venezuela
Ecuador	Malawi	Rwanda	Zambia
El Salvador	Malaysia	Senegal	Zimbabwe
Finland			

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