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Endogeneity and Panel Data in Growth Regressions: A Bayesian Model Averaging Approach*

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Abstract. Bayesian model averaging (BMA) has been successfully applied in the empirical growth literature as a way to overcome the sensitivity of results to different model specifications. In this paper, we develop a BMA technique to analyze models that differ in the set of instruments, exogeneity restrictions, or the set of controlling regressors. Our framework allows for both cross-section regressions with instrumental variables and for the commonly used panel data model with fixed effects and endogenous or predetermined regressors. The large model space that typically arises can be effectively analyzed using a Markov Chain Monte Carlo algorithm. We apply our technique to the dataset used by Burnside and Dollar (2000) who investigated the effect of international aid on GDP growth. We show that BMA is an effective tool for the analysis of panel data growth regressions in cases where the number of models is large and results are sensitive to model assumptions.

Keywords: Bayesian Model Averaging, Instrumental variables, Panel Data, Empirics of Growth, Effectiveness of Aid.

JEL Classification: O1, O2, O4, C30, C11

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1 Introduction

The technique of Bayesian model averaging (BMA) was popularized as a method to overcome model uncertainty in growth regressions by Fernández et al. (2001b) and Sala-i-Martín et al. (2004). It was proposed as a method to overcome the sensitivity of results with respect to the set of controlling variables in a regression. Since then, BMA has been applied widely in the empirical growth literature (e.g., Durlauf et al., 2008; Prüfer and Tondl, 2008; Winford and Papageorgiou, 2008; Ciccone and Jarocinski, 2010; Crespo-Cuaresma et al., 2011) and in other areas of economics (e.g., Koop and Tole, 2003; Tobias and Li, 2004). Recent papers have contributed towards the development of summary measures of the output (Ley and Steel, 2007; Doppelhofer and Weeks, 2009); led to greater understanding of prior assumptions (e.g., Ley and Steel, 2009; 2011); and extended the technique in ways that are relevant to growth regressions such as threshold models (Crespo-Cuaresma and Doppelhofer, 2007), heteroscedasticity (Doppelhofer and Weeks, 2008), endogeneity (Cohen-Cole et al., 2009; Lenkoski et al., 2011; Koop et al., 2011; Karl and Lenkoski, 2012), and panel data models (León-González and Montolio, 2004; Moral-Benito, 2010; 2012, Chen et al. 2011).

As has been well documented, growth regressions may be subject to the important drawback of potential endogeneity in some regressors. However, while most previous research in growth regressions has dealt with uncertainty regarding the set of controlling regressors, little attention has been given to the uncertainty regarding the choice of instruments and exogeneity restrictions. In this sense it is also notorious that empirical results can be greatly affected by the choice and number of instruments that are used to tackle the endogeneity problem, as we further illustrate in Section 5. Moreover, although in a panel data context, instruments can be easily constructed using lags, it has been argued that it is not good practice to use the whole set of available instruments (e.g., see Roodman, 2009a). As a consequence, there are no clear guidelines to choose among models with different sets of identifying restrictions.

In this paper we develop a new BMA strategy to deal with a model space that includes models that differ in the set of regressors, instruments, and exogeneity restrictions in a panel data context. To deal with the large number of models that arise in a typical application (in our application, we deal with approximately 2^{52} models) we use the reversible jump algorithm developed by Koop et al. (2011, KLS henceforth) for BMA in the instrumental variable regression model. We show how this framework can be adapted to deal with dynamic panel data models with endogenous (or predetermined) regressors and the large instrument set that typically arises in the GMM estimation of these models (e.g., Arellano and Bond, 1991).

Our empirical application uses the original dataset of Burnside and Dollar (2000, BD henceforth), as extended by Easterly et al. (2004, ELR henceforth), who used instrumental variable regression to analyze the impact of international aid (an endogenous regressor) on the per capita GDP growth of developing countries. The work of BD generated a lot of interest and was followed by a large number of papers that (using different estimation methods, set of control variables/instruments, definition of variables, slightly different datasets, etc.) found similar (e.g., Collier and Dollar, 2002) and sometimes different results (e.g., Hansen and Tarp, 2001). Furthermore, it still generates open debate in the aid effectiveness literature today[1]. Note that it is not our purpose to investigate the general question of whether aid really increases the growth rate of per capita GDP. Our ultimate purpose is to find out what we can learn from the approach adopted in BD if we appropriately consider the problem of model uncertainty in the set of regressors, in the exogeneity restrictions, and in the choice of instruments used in growth regressions. Therefore, our contribution extends to the general literature that investigates the determinants of economic growth.

The paper is organized as follows. Section 2 describes the model space in the context of cross-country growth regressions with instrumental variables. Section 3 explains how this framework can be adapted to deal with panel data models with endogenous regressors. Section 4 briefly presents the main concepts regarding prior/posterior probabilities and computation. Section 5 presents an empirical application to aid effectiveness, and finally, Section 6 concludes.

[1]For a broad review of this literature, see for example, the meta-analysis produced by Doucouliagos and Paldam (2009, 2010).

2 Model Space in Cross-Country Growth Regressions

Let the GDP growth rate, g_i, depend on exogenous regressors (x_i) and a set of (possibly) endogenous regressors (y_i):

$$g_i = \gamma' y_i + \beta' x_i + u_i, \tag{1}$$

where $g_i : 1 \times 1$, $y_i : m \times 1$, $x_i : k_{1j} \times 1$, and $i = 1, ..., N$. We assume that the equation for g_i is part of a system of equations whose reduced form for y_i takes the form:

$$y_i = \Pi_{2x} x_i + \Pi_{2z} z_i + v_i, \tag{2}$$

where $z_i : k_{2j} \times 1$. The errors are normal with zero means and are uncorrelated over i. We assume that x_i and z_i are exogenous:

$$E\left(x_i \begin{pmatrix} u_i \\ v_i \end{pmatrix}'\right) = 0 \text{ and } E\left(z_i \begin{pmatrix} u_i \\ v_i \end{pmatrix}'\right) = 0.$$

The subindex j stands for the j^{th} model, and j varies from 1 to N^{mod}, where N^{mod} is the total number of models. For simplicity of notation, we do not attach j subindices to parameter matrices (Π_{2x}, Π_{2z}, β) although their dimension varies over models. We define the model space by imposing first the restriction $k_{2j} \geq m$ (so models are just or over identified) and consider all models that differ in the following.

- Set of instruments: the variables in z_i are a subset of a larger group of potential instruments denoted by Z^*. There is uncertainty as to which subset of Z^* should be entered in the model, and hence, uncertainty about the column dimension of matrix Π_{2z}. We let Z^* be formed by two disjoint subsets: $Z^* = Z_1^* \cup Z_2^*$. The first subset Z_1^* consists of variables that are allowed to be entered in the model either in x_i or in z_i, whereas the variables in Z_2^* are only allowed to be entered in the model as part of z_i.

- Variables in x_i: x_i is a subset of $Z_1^* \cup X^*$, where X^* is the set of all potential regressors that are not allowed to be instruments. Uncertainty about what variables are to be entered in x_i implies uncertainty over the elements of β.

- Restrictions on the coefficients of endogenous regressors: some coefficients in γ might be restricted to be zero. A zero restriction on γ implies that the corresponding regressor in y_i does not have an impact on g_i.
- Exogeneity: some of the covariances between u_i and v_i might be zero. A zero covariance implies that the corresponding regressor in y_i is exogenous.

Note that X^* is the set of exogenous variables that the researcher is certain cannot be instruments. In contrast, Z_2^* is the set of exogenous variables the researcher is certain cannot be regressors. However, usually, it is interesting to check the validity of some exclusion restrictions (i.e., restrictions that instruments do not enter the structural equation), and for this reason, we let x_i be a subset of $Z_1^* \cup X^*$.

As shown in KLS, the number of models in the model space when $Z^* = Z_1^*$ is $2^{2m} N^A$, where N^A is defined as[2]

$$N^A = \sum_{j=m}^{k_{Z1}^T} 2^{k_X^T + k_{Z1}^T - j} C_j^{k_{Z1}^T},$$

where k_{Z1}^T is the number of elements in Z_1^* and k_X^T is the number of elements in X^*. In the empirical analysis of Section 5, which uses the dataset of BD as extended by ELR, for the cross-section regressions we will have four endogenous regressors (in y, and so $m = 4$), 10 potential instruments (all of them included in Z_1^*) and 17 exogenous regressors (X^*). Thus, the number of models can be calculated to be approximately 2^{37}.

3 Dealing with Fixed Effects and Endogeneity

In the panel data context, we first introduce a fixed effect f_i in equation (1):

$$g_{it} = f_i + \gamma' y_{it} + \beta' x_{it} + u_{it} \qquad t = 1, ..., T. \tag{3}$$

[2] C_a^b denotes the combinatorial number $\begin{pmatrix} b \\ a \end{pmatrix}$.

In order to eliminate the fixed effect, we use the forward orthogonal deviations operator (Arellano, 2003; p. 17), which applied to a variable u_{it} gives by definition

$$u_{it}^* = \left(\frac{T-t}{T-t+1}\right)^{1/2}\left[u_{it} - \frac{1}{T-t}(u_{i,(t+1)} + ... + u_{iT})\right].$$

Applying this operator to equation (3) yields

$$g_{it}^* = \gamma' y_{it}^* + \beta' x_{it}^* + u_{it}^* \qquad t = 1, ..., T-1. \tag{4}$$

An advantage of this transformation over taking first differences is that if u_{it} is homoskedastic with no serial correlation, so is u_{it}^*. We show in the appendix that from a Bayesian perspective, this transformation arises from integrating out the individual effects from the posterior density using a flat prior for f_i. Hayashi and Sims (1982) used this transformation in a time series model and proposed instrumental variable estimation with predetermined instruments. A predetermined instrument z_{it}^p is assumed to be uncorrelated with current and future values of u_{it} (and therefore, uncorrelated also with u_{it}^*), but allowed to be correlated with past values of u_{it} (and u_{it}^*). This correlation affects neither the consistency nor the asymptotic variance of the instrumental variable estimator. Thus, for our purposes, we use the Bayesian analogue of the 2SLS estimator by adding auxiliary equations for y_{it}^* as follows:

$$\begin{aligned} g_{it}^* &= \gamma' y_{it}^* + \beta' x_{it}^* + u_{it}^*, \\ y_{it}^* &= \Pi_{2x} x_{it}^* + \Pi_{2z} z_{it}^* + \Pi_{2z^p} z_{it}^p + v_{it}^*, \end{aligned} \tag{5}$$

where z_{it}^* are strictly exogenous instruments (in forward orthogonal deviations)[3] and z_{it}^p are predetermined instruments. Even though our instrument set includes predetermined instruments, we form the likelihood function of the model defined by equations in (5) (which we refer to as the pseudo-likelihood function, as in Gourieroux et al. 1984) as if (z_{it}^*, z_{it}^p) were uncorrelated with $(u_{it}^*,\ v_{it}^*)$ contemporaneously and at all lags and leads. The limited information maximum likelihood (LIML) estimator that maximizes the pseudo-likelihood of equation (5) has been proposed by Alonso-Borrego

[3]Strictly exogenous instruments are those that are uncorrelated with $(u_{it}\ ,v_{it})$ at all lags and leads.

and Arellano (1999) to obtain estimates in the dynamic linear panel data model.

The predetermined instruments z_{it}^p are normally chosen to be lags of y_{it}. If y_{it} is, for instance, the initial value of GDP then we have that $cov(y_{it}, u_{it}^*) = 0$ and one could choose $z_{it}^p = y_{it}$. If y_{it} is, however, international aid, we might have that $cov(y_{it}, u_{it}^*) \neq 0$ but still be able to assume that $cov(y_{i,(t-1)}, u_{it}^*) = 0$. In that case, we can fix $z_{it}^p = y_{i,(t-1)}$. This is the method suggested by Anderson and Hsiao (1982) to select instruments. However, later work suggested that more efficient estimates might be obtained by using a larger number of moment conditions. Various studies basically used further lags as instruments in a GMM framework (e.g., Holtz-Eakin et al. (1988) and Arellano and Bond (1991)). However, using further lags in our framework might imply loosing time observations. To avoid this, we follow the strategy in Roodman (2009b), and define GMM-style predetermined instruments as follows:
$Zy_{it}^{2,0} = y_{i,t}$ if $t = 2$, and 0 otherwise;
$Zy_{it}^{2,1} = y_{i,t-1}$ if $t = 2$, and 0 otherwise;
$Zy_{it}^{3,0} = y_{i,t}$ if $t = 3$, and 0 otherwise;
$Zy_{it}^{3,1} = y_{i,t-1}$ if $t = 3$, and 0 otherwise;
$Zy_{it}^{3,2} = y_{i,t-2}$ if $t = 3$, and 0 otherwise;
and in general,
$Zy_{it}^{h,l} = y_{i,t-l}$ if $t = h$, and 0 otherwise, for $h = 2, ..., T$ and $l = 0, ..., T-1$.

The use of these instruments mimics the common practice in GMM of creating a moment condition $E(u_{it}^* y_{it-l}) = 0$ separately for each period t and for each lag l. To see this, note that our likelihood embeds the assumption $E(u_{it}^* Zy_{it}^{h,l}) = 0$, whose sample analogue is

$$\sum_{i,t} u_{it}^* Zy_{it}^{h,l} = \sum_i u_{ih}^* y_{i,h-l} = 0,$$

which is also the sample analogue of the GMM moment condition. As for the model space, it is defined in the same way as before, with the exception that we now have a new set of potential predetermined regressors (Z^{*p}), given as follows.

- Strictly exogenous instruments z_{it} are a subset of $Z^* = Z_1^* \cup Z_2^*$. The predetermined instruments z_{it}^p are a subset of Z^{*p}.
- The strictly exogenous regressors x_{it} are a subset of $Z_1^* \cup X^*$. Note that predetermined instruments are not allowed to be entered in x.

- Restrictions on the coefficients of endogenous regressors: some coefficients in γ might be restricted to be zero.
- Exogeneity: some of the covariances between u_{it}^* and v_{it} might be zero.

In Section 5, for the panel data regressions, we use 35 GMM-style predetermined instruments: 20 using current values and lags of *gdp* (i.e., initial log GDP per capita) and 15 using lags of *eda* (i.e., international aid over GDP). In the case that Z_1^* is an empty set (and thus, $Z^* = Z_2^*$), the number of models can be calculated as $2^{2m}N^B$, where N^B is defined as

$$N^B = 2^{k_X^T} \sum_{j=m}^{k_{Z2}^T + k_{ZP}^T} C_j^{k_{Z2}^T + k_p^T},$$

where k_{Z2}^T is the number of elements in Z_2^* and k_{ZP}^T is the number of elements in Z^{*p}. Moreover, we will then have 5 endogenous regressors (in y, and thus, $m = 5$), 42 potential instruments (all of them in Z^{*p}), and 9 exogenous regressors (X^*). Note that the instruments z_{it}^p are entered into the system of equations (5) without being transformed into orthogonal deviations. We now have fewer regressors than in cross-section regressions because some of these are time-invariant and drop out when we take orthogonal deviations. Even then, because of the larger number of instruments, the number of models turns out to be now larger than in the cross-sectional case and approximately equal to 2^{52}.

4 Bayesian Model Averaging: Priors, Posterior Model Probabilities, and Computation

The prior for parameter θ within a model M_j is denoted by $\pi(\theta)$ and involves normal and inverted Wishart densities (see the technical appendix for details) such that the marginal likelihood for model M_j is defined as

$$\pi(M_j|Y) = \int \pi(Y|\theta, M_j)\pi(\theta|M_j)d\theta,$$

where Y represents all observed data and $\pi(Y|\theta, M_j)$ is the likelihood. The weights for Bayesian model averaging are equal to the posterior model probabilities, which are defined as

$$\Pr(M_j|Y) = \frac{\pi(M_j)\pi(M_j|Y)}{\sum_j \pi(M_j)\pi(M_j|Y)}, \tag{6}$$

where $\pi(M_j)$ is the prior probability of model M_j and the summation is over the whole model space. For simplicity, in our empirical application, we treat all models as equally likely a priori, but if desired, prior model probabilities could also be constructed by first defining the prior probability that an exogenous regressor should be entered in a model as part of x (see Ley and Steel, 2009; 2011 for the theory on how to construct prior probabilities in a robust manner), and similar prior probabilities created for instruments and exogeneity restrictions.

There are two challenges regarding computation. First, the number of models in our empirical application is approximately 2^{37} when using equations (1)–(2) (i.e., without fixed effects) and 2^{52} when using equation (5) (i.e., with fixed effects). Second, there is no analytical expression for the marginal likelihood $\pi(M_j|Y)$, which could only be calculated using computationally intensive numerical methods. That is, not only the number of terms to be calculated in the denominator of equation (6) is too large but also the calculation of each term is computationally expensive. To surmount these problems, we use the reversible jump algorithm proposed by KLS. This algorithm is a Markov Chain algorithm that iteratively samples values for parameter θ and model M_j. Given arbitrarily fixed initial values for (θ, M_j), after a sufficient number of iterations, the generated values can be used as a sample from the posterior of (θ, M_j). This sample is used to calculate quantities of interest such as posterior model probabilities (using the proportion of times that the chain visits a particular model) and confidence intervals for parameters.

5 Aid, Policies, and Economic Growth

The impact of foreign aid and (macro)economic policies on economic growth is still an interesting and open debate, in both developing countries (recipients) and developed countries (donors). The seminal work by BD became influential because of the policy implications of their results, which could be summarized as follows: donor countries should direct aid to developing countries that behave under the same parameters as developed ones, that is, those with "good" macroeconomic policies (fiscal, monetary, and trade policies).

The "policy selectivity" result in BD has been questioned by various authors and for different reasons: i) data issues; ii) selection of regressors and of instrumental variables (when endogeneity of aid is accounted for); and iii) the econometric technique chosen. As Roodman (2007) states, "*The diversity of conclusions within this literature, arising from roughly similar specifications applied within the same data universe, alone suggests that many of the results in question are fragile. That should concern policymakers and researchers alike. Yet among research papers favoring one story or another, robustness testing is rare.*" Therefore, from our point of view, the issue of foreign aid and policy effectiveness is perfectly suited for the application of the new BMA approach developed in the previous sections, our empirical exercise being an independent replication of previous studies with an important improvement on the econometric methodology employed.

For this purpose, we use the data from ELR, who updated the original dataset from BD from 1970-93 to 1970-97, as well as fill in missing data for the original period, 1970-93. Thus, we are using 7 four-year periods. Table A.1 in the data appendix gives the variable/instrument definitions and the group to which they belong (i.e., Z^*, Z^{*p}, X^*, or y). In addition to all the regressors in BD, we also include two more regressors proposed by Dalgaard and Hansen (2001): the policy index (see below for its definition) squared and aid squared. As for instruments, we use the set of instruments in BD and we add predetermined instruments using lags of aid and log GDP per capita for the panel regressions (see Table A.1 for details). We run BMA first without accounting for fixed effects, pooling all four-year periods to estimate equations (1)–(2). Then, we run BMA accounting for fixed effects using equation (5). In the BMA estimation without fixed effects, we include all potential instruments in Z_1^* (i.e., they could be entered in x or z, or not be entered in the model at all), but when we include fixed effects, we include all the (time-variant) instruments in Z^{*p} (and hence none of the instruments are transformed into orthogonal deviations). In the BMA estimation with fixed effects we force the time dummies to be entered in the model[4]. We run each BMA separately for the whole sample and for the sample of low income countries. Following BD, for the latter sample, we select those countries whose real GDP per capita in the year 1970 was below USD 1,900 (in constant 1985 dollars) and also Nicaragua[5]. Hence, in the full sample, there are

[4]Note that system (5) does not include a constant and hence we proceed as such to avoid the model with no explanatory variables and no constant being visited by the algorithm.

[5]Although the GDP per capita of Nicaragua was over USD 1,900 in 1970, it then

63 countries (with 359 country-period observations), and in the low-income sample there are 44 countries (with 244 country-period observations).

Regarding the policy index (pol), we construct it following the methodology proposed by BD. BD create an index covering aspects of fiscal, monetary, and trade policies. Fiscal policy is measured by the budget surplus over GDP (bb). The success or failure of monetary policy is measured by the level of inflation (infl), while trade policy is represented by a binary (0/1) openness indicator (sacw) constructed by Sachs and Warner (1995). To avoid collinearity problems, BD create an index using a weighted average of the three measures. The weights for the policy index are the estimated coefficients in a regression of GDP growth on the three measures and other exogenous regressors. Following this methodology, we construct two policy indices: one for the whole sample and another for the sample of low-income countries[6]. The index of policy is increasing with budget surplus and trade openness but decreasing with inflation.

Before we apply the BMA methodology, we show an example of the sensitivity of results to model specification. Table 1 contains estimates for four models without fixed effects and shows that the p-value of the coefficient of aid can vary between (0.00) and (0.39) by changing the set of regressors or instruments. Table 2 corresponds to the GMM estimation of the dynamic panel model with fixed effects and shows that the p-value of the coefficient of aid changes from (0.00) to (0.19) when we increase the number of lags that are used as instruments from 1 to 2.

<INSERT TABLE 1 AROUND HERE >

We run the proposed reversible jump algorithm for 600,000 iterations after discarding the initial 40,000 iterations. As one of the checks for convergence, we estimate the total visited probability (George and McCulloch, 1997), which is an estimate of the proportion of the total probability mass that is visited by the algorithm[7]. This is over 99% in all cases, indicating good convergence. In addition to calculating the posterior model probabilities using the relative frequency of visits of the algorithm, we construct it

decreased over time and was below USD 1,900 in 1982. For this reason, BD included Nicaragua in the low-income sample.

[6]Given that our dataset, as previously noted, differs slightly from the original BD dataset, our policy index is also slightly different from the original one.

[7]See the technical appendix for details of how this total visited probability is actually constructed.

by numerically calculating the marginal likelihood of each model visited by the algorithm. As a measure of convergence (Fernandez et al., 2001b), we calculate the correlation between the two measures and it is over 99%, again indicating good convergence. We also carry out several runs with randomly chosen initial values and obtain the same results. We perform some sensitivity analysis with respect to the prior density of parameters and the results that we report below do not change qualitatively (please see the technical appendix for further details).

<INSERT TABLE 2 AROUND HERE >

We first report the BMA estimates of the first derivative of the growth rate with respect to aid (g_A), policy index (g_P), and the logarithm of the initial GDP per capita ($g_{initial}$) in Table 3 (using equations (1)–(2) without fixed effects) and in Table 4 (using equation (5) with fixed effects). Because some potential regressors are defined as interactions of other regressors, these partial derivatives might depend on several parameters in the model. The posterior probability of g_A being zero is higher than 95% in all cases, while in contrast, the posterior probability of g_P being positive is greater than 95% in all cases.

<INSERT TABLE 3 AROUND HERE >

When using the whole sample and no fixed effects, there is strong evidence that $g_{initial}$ is positive, indicating that countries are conditionally diverging. However, when we include fixed effects, $g_{initial}$ is zero with high posterior probability (at least 87%), indicating a lack of conditional convergence or divergence. We also report g_{AP}, which is the cross derivative of growth with respect to aid and policies. This derivative measures the extent to which a higher policy index increases the effectiveness of aid. The posterior probability of g_{AP} being equal to 0 is higher than 99% in all cases. The results are similar to those found by Eris (2008) who applied BMA to the dataset of BD assuming all regressors to be exogenous in a pooled regression.

The marginal impacts presented in Tables 3 and 4 are consistent for the two subsamples used: all countries and low-income countries. Therefore, our estimates seem to point out that aid is not effective with respect to the GDP growth rate, not even when interacted with the so-called “good policies.” Indeed, what matters for economic growth are good policies themselves; good policies in the spirit of BD. Given that one of the main results of our empirical exercise is that what really matters for economic growth is sound macroeconomic policy making, we perform a final robust estimation. Table 8 presents the BMA estimates for a reduced form equation for growth in which the policy index components are entered as separate regressors. Note that the signs are as expected and that the two policy variables with higher posterior probabilities of inclusion are inflation and trade openness. Thus, good policies in our context should be mostly understood as policies that relate not so much to budget surplus but to inflation and trade openness[8].

<INSERT TABLE 4 AROUND HERE >

Tables 5 to 7 show more detailed output from the BMA estimation (which was used to compute the marginal effects in Tables 3 and 4). BMA has a preference for parsimony. In BMA without fixed effects (Table 5), the only two regressors with posterior probability of inclusion near to one are policy squared (pol2) and initial GDP (gdp). However, with the full sample, two of the potential instruments are more likely to belong to x_i than to z_i. These are the logarithm of population (lpop) and the interaction of this variable with the policy index (polpop), with posterior probabilities of inclusion in the growth equation of 73% and 81%, respectively, and positive coefficients. This indicates that population should not be used as an instrument in growth regressions. Although BD used population as an instrument for aid, subsequent literature has included the population level as one of the potential determinants of growth (e.g., Moral-Benito 2010; 2012 and Sala-i-Martin et al. 2004) to capture the inherent increasing returns to scale in endogenous growth models.

<INSERT TABLE 5 AROUND HERE >

When using BMA with fixed effects (Table 6), the regressors with posterior inclusion probability close to one are policy (pol), policy squared (pol2), and m21 (lag M2 over GDP). The coefficient of m21 is clearly negative, and this might be capturing the negative impact of high inflation rates on the economy. Recall also that the policy index is decreasing in inflation and

[8]As a robustness check, we also constructed a policy index using the weights from the BMA analysis of Table 8. The results do not change qualitatively if this policy index is used.

that $g_P > 0$. Thus, inflation also reduces per capita GDP growth through the policy index. The significance of the policy index squared indicates that the impact of inflation (and budget deficit) is non-linear, possibly capturing threshold effects.

<INSERT TABLE 6 AROUND HERE >

In Table 7, we observe that out of the large number of potential instruments, only a few are chosen, and among these very few were constructed with lags. The GMM-style instruments that are chosen are the nearest available lags ($Zgdp^{6,0}$, $Zgdp^{6,1}$ and $Zeda^{4,1}$), which are normally more strongly correlated (with the endogenous regressors) than further lags. This fits well with recent literature that concludes that models that use fewer but strong instruments are better for inference (e.g., see Roodman, 2009a for a review of this literature).

<INSERT TABLE 7 AROUND HERE>
<INSERT TABLE 8 AROUND HERE>

6 Conclusions

BMA has been widely used in the empirical growth literature but the focus has been mostly on uncertainty regarding the set of control variables. However, typical growth regressions use panel data with endogenous regressors, where the available instrument set tends to be very large. Although results could be sensitive to the instrument set chosen, there are currently no clear guidelines on how to choose the instruments. The purpose of the present paper is to develop a new BMA methodology that allows panel regression with fixed effects and endogenous regressors, while simultaneously allowing uncertainty regarding the set of instruments, regressors, and exogeneity restrictions. In our empirical application, we show that the large model space that typically arises can be effectively analyzed with the reversible jump algorithm proposed by Koop et al. (2011) and that the BMA methodology selects models with fewer but stronger instruments.

This methodology is then applied to perform an independent replication in a widely debated area of the empirics of economic growth—the impact of foreign aid on the economic growth of developing countries. By using well-known datasets, we obtain that once all the model uncertainty in growth regressions has been accounted for, foreign aid has no impact on the growth rate of recipient countries. Moreover, aid has no impact when interacted with the index of good policies proposed by BD. From our BMA results, it emerges that it is macroeconomic policy making that has a higher posterior probability of inclusion in a growth regression, and hence, a greater potential for explaining the GDP growth rates of developing countries.

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Data Appendix

The dataset comes from Easterly, Levine and Roodman (2004), who revised and extended the dataset of Burnside and Dollar (2000). In addition to variables related to foreign aid (eda and functions of eda) and GDP (gdp, gdpg, and interactions), the dataset includes variables to control for political instability of the recipient country: ethnic fractionalization (ethnf) and assassinations (assas), and their interaction (eth_a). Moreover, the variable icrge accounts for institutional quality and it is an index based on the evaluation of five different institutional indicators. It is constructed by the private international investment risk service "International Country Risk Guide." The five indicators are as follows: Quality of Bureaucracy, Corruption in Government, Rule of Law, Expropriation Risk, and Repudiation of Contracts by Government (for more details, see Knack and Keefer, 1995). The proxy for the development of financial markets is broad money relative to GDP (m2) while the lagged value of the share of imported arms on all imports (arms) accounts for the possible existence of conflicts in recipient countries. The dataset also includes the country's population (lpop and interactions) and dummy variables for location: Sub-Saharan Africa (ssa), East Asia (easia), Central America (centam), Egypt and Franc zone (frz).

Table A.1: Variables used		
Name	Brief Description	Type
gdpg	Real GDP per capita growth (%)	g
eda	Aid (% of GDP)	y
eda2	Squared Aid	y
polaid	Aid*policy index	y
aid2pol	Aid2*policy index	y
gdp	log of real GDP per capita, beginning of period	X^* or[a] y
ethnf	Ethnic fractionalization	X^*
assas	Assassinations	X^*
icrge	Institutional quality	X^*
m2	Lagged M2 (% of GDP)	X^*
ssa	Sub Saharan Africa Dummy	X^*
easia	East Asia Dummy	X^*
eth_a	ethnf*assas	X^*
pol	Policy index	X^*
pol2	Squared policy index	X^*
dum3 to dum8	Time dummies	X^*
lpop	ln of population	Z^* or[b] Z^{*p}
egypt	Egypt dummy	Z^* or[c] out
centam	Central America Dummy	Z^* or[c] out
arms	Lagged Armed Imports (% of all imports)	Z^* or[b] Z^{*p}
frz	Franc Zone Dummy	Z^* or[c]out.
polarms	policy*arms	Z^* or[b] Z^{*p}
polpop	policy*lpop	Z^* or[b] Z^{*p}
polpop2	policy*(lpop)^2	Z^* or[b] Z^{*p}
polgdp	policy*gdp	Z^* or[b] Z^{*p}
polgdp2	policy*(gdp)^2	Z^* or[b] Z^{*p}
$Zgdp^{h,l}$	gdp if $h = t$ and 0 otherwise. For $l = 0, ..., h-2$	Z^{*p}
$Zeda^{h,l}$	eda if $h = t$ and 0 otherwise. For $l = 1, ..., h-2$	Z^{*p}

[a] *gdp* belongs to X^* in the analysis without fixed effects, but belongs to y when we include fixed effects.

[b] instrument belongs to Z^* in the analysis without fixed effects, but belongs to Z^{*p} when we include fixed effects.

[c] instrument belongs to Z^* in the analysis without fixed effects, but it is not used when we include fixed effects, because it is time-invariant.

Technical Appendix

Prior specification and convergence diagnostic

Several priors for the incomplete simultaneous equation model have been proposed in the Bayesian econometrics literature. Although the KLS algorithm can be used for many of those priors, here we have used a prior using the parameterization in Drèze (1976). Let $\gamma_{\widetilde{E}}$ be a $d_{\widetilde{E}} \times 1$ vector containing the non-zero elements of γ. We define the following.

$$\Pi_x = \begin{pmatrix} \gamma'\Pi_{2x} + \beta' \\ \Pi_{2x} \end{pmatrix} = \begin{pmatrix} \pi_{1x} \\ \Pi_{2x} \end{pmatrix}, \tag{7}$$

$$\Pi_z = \begin{pmatrix} \pi_{1z} \\ \Pi_{2z} \end{pmatrix} = \begin{pmatrix} \gamma' \\ I_m \end{pmatrix} \Pi_{2z}, \qquad \Sigma = E\left(\begin{pmatrix} u_i \\ v_i \end{pmatrix} \begin{pmatrix} u_i \\ v_i \end{pmatrix}' \right),$$

$$\Omega = \begin{pmatrix} 1 & \gamma' \\ 0 & I_m \end{pmatrix} \Sigma \begin{pmatrix} 1 & 0 \\ \gamma & I_m \end{pmatrix} = \begin{bmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & \Omega_{22} \end{bmatrix},$$

$$\omega_{11\cdot 2} = var(v_{1i}|v_{2i}) = \omega_{11} - \omega_{12}\Omega_{22}^{-1}\omega_{21},$$

$$\widetilde{\omega}_{21} = \Omega_{22}^{-1}\omega_{21}.$$

We specify a normal prior on $(\gamma'_{\widetilde{E}}, vec(\Pi_x)', vec(\Pi_{2z})')'$ such that $vec\,(\Pi_x)\,|\Omega \sim N(0, \underline{g}\underline{V}_{\Pi_x} \otimes \Omega)$, $\gamma_{\widetilde{E}}|\Omega \sim N(0, \underline{g}\omega_{11\cdot 2}\underline{A})$, and $vec(\Pi_{2z})|\Omega \sim N(0, \underline{g}\underline{D} \otimes \Omega_{22})$, where $(\underline{g}, \underline{g}^e, \underline{V}_{\Pi_x}, \underline{A}, \underline{D})$ are prior hyper-parameters. We set $\underline{A} = I_{d_{\widetilde{E}}}$, $\underline{S}_{22} = \underline{g}^{-1}I_m$, and $\underline{v}_{22} = m + 1$. Further, we set $\underline{V}_{\Pi_x}$ as the inverse of the cross-products of exogenous regressors in the model, and $\underline{D}$ as the inverse of the cross-products of the instruments.

Regarding the variance-covariance matrix, we fix the following prior specification on $(\widetilde{\omega}_{21}, \Omega_{22}, \omega_{11\cdot 2})$:

$$\begin{aligned} \widetilde{\omega}_{21} &\sim N(0, \underline{g}^e\omega_{11\cdot 2}I_m), \\ \Omega_{22} &\sim IW_m(\underline{S}_{22}, \underline{v}_{22}), \\ p(\omega_{11\cdot 2}) &\propto |\omega_{11\cdot 2}|^{-1}, \end{aligned} \tag{8}$$

where $IW_m(\underline{S}_{22}, \underline{v}_{22})$ represents the inverted Wishart distribution with degrees of freedom equal to $\underline{v}_{22}$ and parameter matrix $\underline{S}_{22}$ (Bauwens et al., 1999, p. 305). We set $\underline{v}_{22} = m + 1$ and $\underline{S}_{22}$ equal to the identity matrix.

In our empirical applications, we set $\underline{g} = \underline{g}^e$, and repeat BMA for several values of it: N, N^2, and N^3. The marginal likelihoods were bigger when $\underline{g}$ was smaller, indicating that smaller values of $\underline{g}$ are preferable. For this reason, the results we report are those corresponding to $\underline{g} = \underline{g}^e = N$. However, empirical results were qualitatively the same for other values of $\underline{g}$.

In order to calculate the total visited probability (George and McCulloch, 1997), we first define a large set of models A that contains the models visited by algorithm B. We then calculate the marginal likelihood for each model in A, so that we could obtain the estimated total visited probability as the joint posterior probability of B over that of A.

Integrating out the individual effect to obtain forward orthogonal deviations

Let us now show that when all instruments are strictly exogenous, equations in (5) can be obtained by first specifying a dynamic panel data model in levels and then integrating out the fixed effects from the posterior density. To see this, first complete equation (3) for g_{it} with auxiliary equations for y_{it}:

$$\begin{aligned} g_{it} &= f_i + \gamma' y_{it} + \beta' x_{it} + u_{it} \qquad t = 1, ..., T, \\ y_{it} &= f_i^y + \Pi_{2x} x_{it} + \Pi_{2z} z_{it} + v_{it}, \end{aligned} \tag{9}$$

and calculate the reduced form of equations in (9) as

$$h_{it} = \begin{pmatrix} g_{it} \\ y_{it} \end{pmatrix} = \Pi_x x_{it} + \Pi_z z_{it} + f_i^r + \varepsilon_{it}, \tag{10}$$

where Π_x and Π_z are defined as in (7), and $(f_i^r, \varepsilon_{it})$ are defined as

$$\varepsilon_{it} = \begin{pmatrix} 1 & \gamma' \\ 0 & I_m \end{pmatrix} \begin{pmatrix} u_{it} \\ v_{it} \end{pmatrix}, \qquad f_i^r = \begin{pmatrix} 1 & \gamma' \\ 0 & I_m \end{pmatrix} \begin{pmatrix} f_i \\ f_i^y \end{pmatrix}.$$

Since the variance-covariance matrix of ε_{it} is Ω, the likelihood function can be written as

$$|\Omega|^{-N/2} |2\pi|^{-NT/2} \exp\left(-\frac{1}{2} \sum_{i=1}^{N} \sum_{t=1}^{T} tr[\Omega^{-1} (\widetilde{h}_{it} - f_i^r)(\widetilde{h}_{it} - f_i^r)'] \right),$$

where $\widetilde{h}_{it} = h_{it} - \Pi_x x_{it} - \Pi_z z_{it}$. Using a flat prior on f_i^r, we can integrate this expression with respect to f_i^r and obtain

$$|\Omega|^{-N/2} |2\pi|^{-N/2} \exp\left(-\frac{1}{2} \sum_{i=1}^{N} tr[\Omega^{-1} \widetilde{h}_i' Q \widetilde{h}_i] \right), \tag{11}$$

where $\widetilde{h}_i = (\widetilde{h}_{i1}, ..., \widetilde{h}_{iT})'$, Q is the within-group operator (Arellano 2003, p. 15) $Q = I - (1/T)ii'$, i is a $T \times 1$ vector of ones, and I is the identity matrix. To see that this is the likelihood of the model defined by the equations in (5), first note that Q can be written as $Q = A'A$, where A is a $(T-1) \times T$ matrix known as the forward orthogonal operator (Arellano 2003, p. 17), such that $\widetilde{h}_i' Q \widetilde{h}_i = (A\widetilde{h}_i)' A\widetilde{h}_i$. Hence, expression (11) can be written as

$$|\Omega|^{-N/2} |2\pi|^{-N/2} \exp\left(-\frac{1}{2}\sum_{i=1}^{N} tr[\Omega^{-1}\widetilde{h}_i^{*\prime}\widetilde{h}_i^{*}]\right), \tag{12}$$

where

$$\widetilde{h}_i^{*} = A\widetilde{h}_i = A\begin{pmatrix} \widetilde{h}_{i1}' \\ \vdots \\ \widetilde{h}_{iT}' \end{pmatrix} = A\left[\begin{pmatrix} h_{i1}' \\ \vdots \\ h_{iT}' \end{pmatrix} - \begin{pmatrix} x_{i1}' \\ \vdots \\ x_{iT}' \end{pmatrix}\Pi_x' - \begin{pmatrix} z_{i1}' \\ \vdots \\ z_{iT}' \end{pmatrix}\Pi_z'\right].$$

Note also that A is a $(T-1)\times T$ matrix and hence $\widetilde{h}_i^{*} = A\widetilde{h}_i$ is a $(T-1)\times 1$ vector with the forward orthogonal deviations of h_i^{*}:

$$\widetilde{h}_i^{*} = \begin{pmatrix} \widetilde{h}_{i1}^{*\prime} \\ \vdots \\ \widetilde{h}_{iT-1}^{*\prime} \end{pmatrix} = \begin{pmatrix} g_{i1}^{*} & y_{i1}^{*\prime} \\ \vdots & \vdots \\ g_{iT-1}^{*} & y_{iT-1}^{*\prime} \end{pmatrix} - \begin{pmatrix} x_{i1}^{*\prime} \\ \vdots \\ x_{iT-1}^{*\prime} \end{pmatrix}\Pi_x' - \begin{pmatrix} z_{i1}^{*\prime} \\ \vdots \\ z_{iT-1}^{*\prime} \end{pmatrix}\Pi_z'.$$

Using the properties for the trace operator, it is possible to write expression (12) as

$$\begin{aligned} & |\Omega|^{-N/2} |2\pi|^{-N/2} \exp\left(-\frac{1}{2}\sum_{i=1}^{N} tr[\widetilde{h}_i^{*}\Omega^{-1}\widetilde{h}_i^{*\prime}]\right) \\ = \; & |\Omega|^{-N/2} |2\pi|^{-N/2} \exp\left(-\frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T-1}[\widetilde{h}_{it}^{*\prime}\Omega^{-1}\widetilde{h}_{it}^{*}]\right), \end{aligned} \tag{13}$$

which is clearly the likelihood of the model defined by the equations in (5).

	Model 1		Model 2		Model 3		Model 4	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
eda	-0.3	(0.23)	4.9	(0.39)	-0.8	(0.00)	-0.6	(0.13)
polaid	0.9	(0.05)	0.2	(0.46)	0.2	(0.23)	0.1	(0.35)
aid2pol	-0.2	(0.05)	Exc		Exc		Exc	
eda2	Exc		-0.8	(0.37)	Exc		Exc	
gdp	-0.6	(0.18)	0.8	(0.62)	Exc		Exc	
ethnf	-0.8	(0.39)	-0.5	(0.81)	Exc		Exc	
assas	-0.4	(0.19)	-0.5	(0.41)	-0.4	(0.02)	-0.4	(0.01)
icrge	0.2	(0.07)	0.3	(0.32)	0.2	(0.20)	0.2	(0.11)
m21	0	(0.16)	0.1	(0.35)	Exc		Exc	
ssa	-0.9	(0.16)	-1.9	(0.27)	Exc		-0.8	(0.27)
easia	1.6	(0.02)	2.2	(0.24)	Exc		Exc	
eth_a	0	(0.97)	0.4	(0.76)	Exc		Exc	
pol	0.5	(0.07)	0.3	(0.78)	1.3	(0.00)	1.2	(0.00)
pol2	Exc		0.0	(0.92)	Exc		Exc	
dum3	0.7	(0.31)	0	(0.99)	Exc		Exc	
dum4	-0.7	(0.34)	-1.8	(0.36)	Exc		Exc	
dum5	-2.3	(0.00)	-5.2	(0.13)	Exc		Exc	
dum6	-1.4	(0.06)	-4.5	(0.22)	Exc		Exc	
dum7	-1.6	(0.03)	-3.5	(0.22)	Exc		Exc	
dum8	-1.0	(0.17)	-2.4	(0.30)	Exc		Exc	
_cons	6.7	(0.04)	-5.9	(0.69)	-3.7	(0.02)	-2.9	(0.09)
lpop	Inst		Inst		Inst		Inst	
egypt	Inst		Inst		Inst		Inst	
centam	Inst		Inst		Inst		Inst	
arms1	Inst		Inst		Inst		Inst	
frz	Inst		Inst		Inst		Inst	
polarms	Inst		Inst		2.4	(0.00)	2.1	(0.01)
polpop	Inst		Inst		Inst		Inst	
polpop2	Inst		Inst		Inst		Inst	
polgdp	Inst		Inst		Inst		Inst	
polgdp2	Inst		Inst		Inst		Inst	
Diagnostic Tests								
Anderson *p*	(0.00)		(0.16)		(0.00)		(0.00)	
Sargan *p*	(0.22)		(0.16)		(0.22)		(0.26)	

Table 1: LIML Estimates and Diagnostic Tests under Four Model Specifications. *p*-values in brackets. '*Exc*' means the variable was not used in the estimation; '*Inst*' means it was used as an instrument. '*Sargan p*' is the *p*-value for the Sargan (1958) test of overidentifying restrictions. '*Anderson p*' is the *p*-value for the Anderson (1951) test of underidentification.

	Model 1		Model 2		Model 3		Model 4	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
gdp	-8.7	(0.00)	-8.6	(0.00)	-9.1	(0.00)	-8.7	(0.00)
eda	1.2	(0.00)	0.5	(0.19)	0.5	(0.10)	0.6	(0.06)
polaid	0.0	(0.93)	-0.2	(0.46)	-0.2	(0.32)	Exc	
pol	1.2	(0.06)	1.5	(0.01)	1.4	(0.00)	1.1	(0.00)
Diagnostic Test								
Hansen p	(0.10)		(0.09)		(0.08)		(0.07)	
Sargan p	(0.00)		(0.00)		(0.00)		(0.00)	
Number of moment conditions	12		21		37		37	
STATA command								
Model 1	xtabond2 gdpg gdp eda polaid pol, gmm(gdp l.eda, laglimits(1 1)) iv(pol) nolevel robust							
Model 2	xtabond2 gdpg gdp eda polaid pol, gmm(gdp l.eda, laglimits(1 2)) iv(pol) nolevel robust							
Model 3	xtabond2 gdpg gdp eda polaid pol, gmm(gdp l.eda) iv(pol) nolevel robust							
Model 4	xtabond2 gdpg gdp eda pol, gmm(gdp l.eda) iv(pol) nolevel robust							

Table 2: One-Step-Difference GMM Estimates and Diagnostic Tests Under Three Model Specifications. *p*-values in brackets. '*Sargan p*' and '*Hansen p*' are the *p*-values for alternative tests of over-identifying restrictions (Sargan, 1958 and Hansen, 1982). Model 1 uses at most one lag of (gdp, eda) as instruments for each period. Model 2 uses at most two lags. Models 3 and 4 use as many lags as available.

	All Countries				Low Income Countries			
	Median	$Pr < 0$	$Pr = 0$	$Pr > 0$	Median	$Pr < 0$	$Pr = 0$	$Pr > 0$
g_A	0.00	0.002	0.995	0.003	0.00	0.004	0.994	0.002
g_{AP}	0.00	0.001	0.997	0.002	0.00	0.001	0.998	0.001
g_P	1.45	0.000	0.000	1.000	1.67	0.000	0.000	1.000
$g_{Initial}$	0.58	0.007	0.000	0.993	0.38	0.179	0.000	0.821

Table 3: Marginal Impacts: BMA Estimation with no Fixed Effects. The column '*Median*' gives the posterior median and ($Pr < 0$, $Pr = 0$,$Pr > 0$) give the posterior probability of being smaller, equal and greater than 0. g_A is the first derivative of the growth rate with respect to aid. g_{AP} is the second derivative with respect to Aid and the policy index. g_P is the first derivative with respect to policy index. $g_{Initial}$ is the first derivative with respect to the initial value of log GDP per capita. Marginal derivatives are evaluated at sample means.

	All Countries				Low Income Countries			
	Median	$Pr < 0$	$Pr = 0$	$Pr > 0$	Median	$Pr < 0$	$Pr = 0$	$Pr > 0$
g_A	0.00	0.00	0.960	0.040	0.00	0.002	0.970	0.028
g_{AP}	0.00	0.00	0.996	0.004	0.00	0.000	0.996	0.004
g_P	0.70	0.01	0.000	0.990	0.61	0.050	0.000	0.950
$g_{Initial}$	0.00	0.12	0.870	0.01	0.00	0.060	0.930	0.010

Table 4: Marginal Impacts: BMA Estimation with Fixed Effects. Meaning of labels as in Table (3)

	All Countries						Low Income					
	Pr≠ 0	Endg	Inst	2.5	50	97.5	Pr≠ 0	Endg	Inst	2.5	50	97.5
eda	0.00	0.00		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
polaid	0.00	0.00		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
aid2pol	0.00	0.00		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
eda2	0.00	1.00		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
constant	1.00			-13.6	-7.22	0.50	1.00			-10.7	-1.45	4.68
gdp	1.00			0.10	0.58	1.05	1.00			-0.44	0.40	1.23
ethnf	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
assas	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
icrge	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
m21	0.08			-0.01	0.00	0.00	0.79			-0.03	0.00	0.02
ssa	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
easia	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
eth_a	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
pol	0.00			0.00	0.00	0.00	0.17			0.00	0.00	2.08
pol2	1.00			-0.02	0.07	0.17	1.00			-0.01	0.08	0.17
dum3	0.30			0.00	0.00	2.94	0.01			0.00	0.00	0.00
dum4	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
dum5	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
dum6	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
dum7	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
dum8	0.00			0.00	0.00	0.00	0.00			0.00	0.00	0.00
lpop	0.73		0.27	0.00	0.30	0.58	0.10		0.90	0.00	0.00	0.47
egypt	0.00		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
centam	0.00		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
arms1	0.04		0.96	0.00	0.00	1.66	0.01		0.15	0.00	0.00	0.00
frz	0.00		0.01	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
polarms	0.01		0.99	0.00	0.00	0.00	0.02		0.98	0.00	0.00	0.00
polpop	0.81		0.17	0.00	0.09	0.12	0.44		0.29	0.00	0.00	0.14
polpop2	0.01		0.01	0.00	0.00	0.00	0.19		0.09	0.00	0.00	0.01
polgdp	0.18		0.82	0.00	0.00	0.69	0.17		0.78	0.00	0.00	0.27
polgdp2	0.06		0.94	-0.06	0.00	0.00	0.05		0.93	0.00	0.00	0.03

Table 5: BMA estimation with no fixed effects. Pr≠ 0 is the posterior probability of entering in the model as a regressor (in y_2 or x). '*Endg*' is the posterior probability of being endogenous. '*Inst*' is the posterior probability of entering in the model as an instrument (in z). The (2.5%, 50%, 97.5%) percentiles of the posterior distribution are under the corresponding headings.

	All Countries					Low Income				
	Pr≠ 0	Endg	2.5	50	97.5	Pr≠ 0	Endg	2.5	50	97.5
eda	0.02	0.03	0.00	0.00	0.00	0.01	0.04	0.00	0.00	0.00
polaid	0.00	0.03	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00
aid2pol	0.00	0.53	0.00	0.00	0.00	0.00	0.73	0.00	0.00	0.00
eda2	0.02	0.54	0.00	0.00	0.00	0.01	0.60	0.00	0.00	0.00
gdp	0.13	1.00	-4.11	0.00	0.00	0.06	1.00	-2.06	0.00	0.00
assas	0.00		0.00	0.00	0.00	0.00		0.00	0.00	0.00
m21	0.99		-0.09	-0.04	0.02	1.00		-0.11	-0.06	-0.01
etha	0.00		0.00	0.00	0.00	0.00		0.00	0.00	0.00
pol	1.00		0.00	0.70	1.40	1.00		-0.17	0.62	1.40
pol2	1.00		-0.12	-0.01	0.11	1.00		-0.10	0.00	0.11
dum4	1.00		-2.21	-1.21	-0.17	1.00		-2.09	-0.95	0.19
dum5	1.00		-3.42	-2.42	-1.41	1.00		-3.19	-2.08	-0.97
dum6	1.00		-2.31	-1.31	-0.32	1.00		-2.07	-0.97	0.13
dum7	1.00		-2.09	-1.12	-0.15	1.00		-2.72	-1.65	-0.58

Table 6: BMA estimation with fixed effects. Pr≠ 0 is the posterior probability of entering in the model as a regressor (in y_2 or x). '*Endg*' is the posterior probability of being endogenous. The (2.5%, 50%, 97.5%) percentiles of the posterior distribution are under the corresponding headings.

	All Countries	Low Income
lpop	1.00	1.00
arms1	0.01	0.00
polarms	1.00	1.00
polpop	0.95	0.69
polpop2	0.05	0.48
polgdp	1.00	0.88
polgdp2	1.00	0.95
$Zgdp^{3,0}$	0.01	0.00
$Zgdp^{3,1}$	0.00	0.00
$Zgdp^{4,0}$	0.00	0.01
$Zgdp^{4,1}$	0.00	0.00
$Zgdp^{4,2}$	0.00	0.00
$Zgdp^{5,0}$	0.00	0.00
$Zgdp^{5,1}$	0.00	0.00
$Zgdp^{5,2}$	0.00	0.00
$Zgdp^{5,3}$	0.00	0.00
$Zgdp^{6,0}$	0.40	0.98
$Zgdp^{6,1}$	0.13	0.49
$Zgdp^{6,2}$	0.01	0.00
$Zgdp^{6,3}$	0.00	0.00
$Zgdp^{6,4}$	0.01	0.00
$Zgdp^{7,0}$	0.01	0.04
$Zgdp^{7,1}$	0.00	0.00
$Zgdp^{7,2}$	0.00	0.01
$Zgdp^{7,3}$	0.00	0.00
$Zgdp^{7,4}$	0.00	0.00
$Zgdp^{7,5}$	0.00	0.00
$Zeda^{3,1}$	0.00	0.00
$Zeda^{4,1}$	1.00	1.00
$Zeda^{4,2}$	0.00	0.00
$Zeda^{5,1}$	0.00	0.03
$Zeda^{5,2}$	0.01	0.00
$Zeda^{5,3}$	0.00	0.00
$Zeda^{6,1}$	0.00	0.00
$Zeda^{6,2}$	0.00	0.00
$Zeda^{6,3}$	0.00	0.00
$Zeda^{6,4}$	0.00	0.01
$Zeda^{7,1}$	0.00	0.00
$Zeda^{7,2}$	0.00	0.00
$Zeda^{7,3}$	0.00	0.00
$Zeda^{7,4}$	0.00	0.00
$Zeda^{7,5}$	0.00	0.00

Table 7: BMA with Fixed Effects: Posterior Probability of Being an Instrument.

	All Countries		Low Income	
	mean	$Pr \neq 0$	mean	$Pr \neq 0$
constant	0.1	0.13	0.26	0.18
icrge	0.3	0.95	0.37	0.87
m21	0.0	0.06	0	0.1
ssa	-1.3	0.96	-1.51	0.96
easia	1.6	0.9	1.93	0.91
bb	0.3	0.08	0.1	0.07
infl	-2.2	1.00	-2.75	1.00
sacw	1.2	0.87	0.82	0.62
ethnf	0.0	0.07	-0.01	0.07
gdp	0.0	0.12	0.02	0.16
assas	-0.1	0.36	-0.43	0.65
eth_a	-0.1	0.17	-0.04	0.11
dum2	1.3	0.81	0.7	0.47
dum3	1.7	0.96	1.2	0.73
dum4	0.0	0.07	0.03	0.08
dum5	-1.2	0.83	-0.41	0.35
dum6	0.0	0.07	-0.01	0.07
dum7	0.0	0.07	-0.31	0.29
dum8	0.0	0.08	0.11	0.15

Table 8: BMA when policy variables (i.e. bb, infl and sacw) enter as separate regressors in a reduced-form regression on growth. $Pr \neq 0$ is the posterior probability that the coefficient is different from 0. *mean* is the posterior mean of the coefficient. All regressors are assumed to be exogenous. The sample sizes were 396 (all countries) and 262 (low-income).