Rough and Lonely Road to Prosperity: A reexamination of the sources of growth in Africa using Bayesian Model Averaging*

Winford H. Masanjala
Department of Economics, University of Malawi
Population Studies Center, University of Pennsylvania

Chris Papageorgiou†
Research Department, International Monetary Fund
Department of Economics, Louisiana State University

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Abstract

This paper takes a fresh look into Africa's dismal growth performance by using the Bayesian Model Averaging (BMA) methodology. We estimate the posterior probability of a large number of potential explanatory variables and cross-country regression models. In large, we find that determinants of growth in Africa are strikingly different from the rest of the world. In addition, growth regression models that best explain global growth do poorly in explaining African growth, and conversely.

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†Send correspondence to Chris Papageorgiou, Research Department, International Monetary Fund, 700 19th St. N.W, Washington, DC 20431, email: cpapageorgiou@imf.org, tel: (202) 623-7503, fax: (202) 589-7503.

1 Introduction

Recent empirical work on the determinants of economic growth has generated an almost universally pessimistic consensus about economic prospects in sub-Saharan Africa (see, e.g. Bloom and Sachs, 1998; Collier and Gunning, 1999b; Acemoglu, Johnson and Robinson, 2001; Artadi and Sala-i-Martin, 2003).[1] This consensus, originally due to Barro's (1991) finding of a negative African dummy, has since been fortified by Easterly and Levine's (1997) dramatic depiction in "Africa's Growth Tragedy" which shows that African economic performance has been markedly worse than that of other regions. However, despite this consensus, little is known about the determinants of economic growth in Africa. This paper investigates Africa's growth tragedy from two perspectives. First, what are the determinants of growth in Africa. Second, given these determinants and compared to the rest of the world, does Africa grow differently?

On the first question, a number of studies have recently asserted that determinants of growth in Africa are the same as the rest of the world, so that Africa's slow growth is partly explicable in terms of particular variables that are globally important for the growth process but are low in Africa (see, e.g. Sachs and Warner 1997; Rodrik, 1998). As a result, in much of the empirical literature on economic growth, sub-Saharan Africa exists primarily as a regional dummy (see, e.g. Barro, 1991; Barro and Lee, 1993; Easterly and Levine, 1997; Collier and Gunning, 1999a; Sala-i-Martin, 1997; Sachs and Warner, 1997). However, African growth may partly be explicable in terms of the distinctive effects of the variables in Africa (see, e.g. Temple, 1998; Collier and Gunning, 1999a). More recent evidence suggests that the determinants of growth, their marginal impacts and the mechanism through which those factors affect growth may be different in Africa from the rest of the world (see, e.g. Block, 2001; Tsangarides, 2005).

On the second question, even among those who believe that African growth can be explained using globally relevant variables, there is little agreement on the proximate causes of Africa's growth tragedy. Owing primarily to the lack of reliable data, evidence on economic development in Africa has mostly been anecdotal. Although the last decade has witnessed a proliferation of possible explanatory variables, there is little guidance from economic theory regarding which variables to include in growth regressions. Traditionally, Africa's slow growth in per capita incomes has been explained in terms of the peculiarity of its geography (see, e.g. Sachs and Warner, 1995; Diamond,

[1] For the remainder of the paper, Africa is used generically for sub-Saharan Africa.

1997; Landes, 1998). According to this view, since geographical and ecological variables shape economic development directly, by influencing productivity, and indirectly, by influencing the choice of political and economic institutions, there appears to be a positive correlation between tropical climate and slow economic growth (see Gallup, Sachs and Mellinger, 1998; Sachs, 2001).

However, following work by Acemoglu, Johnson and Robinson (2002), Rodrik, Subramanian and Trebbi (2002), and Easterly and Levine (2003) argue that the role of geography in explaining cross-country variations in growth patterns of per capita income operates predominantly or exclusively through the choice of institutions, with little direct effect from geography. Another strand of orthodoxy, following Frankel and Romer (1999), emphasizes the role of macroeconomic policy and the degree of integration in international trade in affecting economic growth. The lack of consensus on the key determining factors of African growth underscores the problem of *model uncertainty* (that has plagued much of the empirical growth literature) and highlights the need for a methodology that resolves this problem, and helps answer the central questions posed above.[2]

This paper explicitly addresses the questions raised above using a Bayesian Model Averaging framework (BMA) following Fernàndez, Ley and Steel (2001). This framework allows us to do two things. First, given a set of potential explanatory variables, BMA allows us to separately identify growth models that are pertinent to explaining observed growth patterns in Africa and the rest of the world, by allowing for any subset of the explanatory variables to combine in a growth regression and to estimate the posterior probability of any such combination of regressors. Second, conditional on the model posterior probabilities, we can resolve the issue of model uncertainty in African growth regressions by estimating the posterior probabilities of all possible explanatory variables commonly used in cross-country growth regressions for which data are available.

Our main results can be summarized as follows: First, using the posterior probability for individual regressors we show that, except for initial output, variables flagged as important in explaining the global pattern of economic growth lose their significance when the same exercise is conducted on an Africa-only sample. In addition, variables which were insignificant in explaining global growth are found to be very significant in explaining African growth. Second, the combinations of variables (models) with the highest posterior probabilities in the global context are shown to be very different from those for Africa. Put differently, the growth regression models that best explain global growth

[2]For an excellent survey on the key econometric problems that have plagued the robustness of cross-country regressions, not the least being model uncertainty, see Durlauf and Quah (1999).

do poorly in explaining African growth, and vice versa.

These results may have notable implications for the growth literature in general, and African growth in particular. First, using the BMA methodology we resolve the model uncertainty problem inherent in existing growth regressions. In particular, we rank and show which individual regressors, and combinations thereof, have the most explanatory power according to their posterior probabilities in explaining African growth. Second, our results contribute to the ongoing debate between the primacy of geography, institutions or economic policy in explaining Africa's growth tragedy. By ranking variables based on their probability of inclusion, we try to shed some light on the difficult problem of delineating the school of thought to which the majority of these significant regressors belong. Third, regarding policy, our results provides a justification of why reforms that have been effective elsewhere may have been less effective in Africa. Finally, implications of our results to future research are sizable to both theoretical and empirical work.

The rest of the paper is organized as follows. Section 2 motivates our estimation exercise by taking a closer look at the data. Section 3 presents a brief summary of the Bayesian Model Averaging (BMA) methodology used in our econometric estimation. In section 4 we present and examine the results of the BMA estimation. In particular, we discuss the regressor and model posterior probabilities, and growth regression estimates in relation to the existing literature. Section 5 presents robustness analyses of our results to an alternative model averaging methodology and an alternative model specification. Section 6 concludes and offers directions for future research.

2 A First Look at the Data

We begin by briefly describing the data used in our estimation.

2.1 Data

Our estimation exercises use a subset of the data first utilized in Sala-i-Martin (1997). We chose the Sala-i-Martin (1997) dataset for two reasons. First, we found that this dataset is the most comprehensive for the research at hand, both in terms of the number of variables and time periods available for sub-Sahara African countries. This dataset includes a relatively large number of variables without entailing loss of African observations compared to most other cross-country datasets in the literature. Second, we want to compare results obtained from exercises using an Africa-only sample to results obtained from the benchmark "global" sample (see Fernàndez, Ley and Steel, 2001; henceforth, FLS). To reduce the possibility that differences in posterior probabilities of our exercise and the benchmark study by FLS are due to differences in the data used, we use the Sala-i-Martin (1997) dataset from which FLS drew part of their sample. Although the most ideal situation would be to use exactly the same data as FLS, this proved impractical because in constructing their dataset, FLS excluded most sub-Sahara African countries due to data unavailability for most of their additional variables and ended up with only 18 sub-Sahara African countries in their sample of 72 countries.[3]

Table 1 presents the variables that will be used in our baseline estimation. By many accounts, these are the most frequently used variables in cross-country growth regression exercises as they have been found (in various degrees) to matter for growth. The dependent variable, per capita GDP growth, is measured as the difference in the natural logarithm of per capita GDP between 1960 and 1992 from Summers and Heston's (1991) purchasing power parity adjusted in chained dollars. The 25 potential regressors are as presented in Sala-i-Martin (1997) and FLS; for each country, the data points represent a cross-section of average values measured over the 1960-1992 period.[4] Tables A1 and A2 in the appendix present a list of the countries and the definitions of variables (accompanied with their sources) used in this paper, respectively.

2.2 Descriptive Statistics

Table 1 compares the means and standard deviation values of our baseline variables for Africa and the rest of the world. To summarize the most important trends, we note that Africa appears to have started from a more disadvantaged position than the rest of the world. In 1960 the level of per capita GDP in Africa was half as much the level of per capita GDP in the rest of the world, life expectancy at birth was only 41 years in Africa compared to 61 years in the world and primary school enrollment was only 41 percent compared to 89 percent in the rest of the world. At the same time, African economies were almost three times as reliant on output from mining and while primary commodities comprised about 61 percent of exports in the rest of the world, in Africa they accounted for 88 percent of the exports.

[3] In his study, Sala-i-Martin (1997) estimated the probability of inclusion of 62 variables of which he flagged 22 as important. FLS estimated the posterior probability of 42 variables, including the 22 variables previously flagged as important by Sala-i-Martin (1997).

[4] Due to lack of data for most African countries in our dataset for equipment and non-equipment investment, we use the ratio of investment to GDP from Summers and Heston's Real National Accounts as our investment measure. Sala-i-Martin (1997) notes that substituting the investment share of GDP with equipment and non-equipment investment does not critically alter his model's qualitative implications.

Table 1: Descriptives statistics

	Regressor	**Africa**		**Rest of World**	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
1	ln GDP per capita, 1960	6.630	0.531	8.376	0.695
2	Fraction of Mining in GDP	0.072	0.106	0.026	0.033
3	Primary Exports, 1970	0.884	0.148	0.605	0.308
4	Primary School Enrolment, 1960	0.409	0.278	0.892	0.164
5	Life Expectancy, 1960	40.90	5.339	60.74	9.853
6	Investment	0.092	5.598	0.210	0.071
7	Years Economy Open	0.083	0.185	0.545	0.327
8	Outward Orientation	0.432	0.502	0.326	0.474
9	Exchange Rate Distortion	161.6	41.06	106.7	22.64
10	Economic Organization	3.000	1.886	3.788	0.893
11	Population Growth	0.027	0.006	0.018	0.010
12	French Colony Dummy	0.378	0.492	0.038	0.194
13	British Colony Dummy	0.432	0.502	0.250	0.437
14	Fraction Speaking English	0.005	0.019	0.103	0.277
15	Fraction Speaking Foreign Language	0.064	0.188	0.449	0.421
16	Ethnolinguistic Fractionalization	0.649	0.250	0.272	0.251
17	Revolutions and Coups	0.268	0.252	0.178	0.248
18	War Dummy	0.405	0.500	0.403	0.495
19	Political Rights	5.689	1.269	2.767	1.635
20	Civil Liberties	5.438	1.098	2.840	1.489
21	Absolute Latitude	10.71	7.567	29.68	17.27
22	Fraction Protestant	0.157	0.138	0.174	0.282
23	Fraction Muslim	0.299	0.318	0.077	0.236
24	Fraction Catholic	0.197	0.167	0.522	0.418
25	Area (Scale Effect)	624.4	611.4	1098	2375

Notes: The mean and standard deviation values of the 25 variables presented above are computed from our baseline Africa sample that consists of 37 sub-Sahara African countries. We use data from Sala-i-Martin (1997) which in turn were obtained from various sources. A list of these countries appear in Table A1 in the appendix. A brief description of the variables and their respective sources appear in Table A2 in the appendix.

African countries were on average less open to international trade. Interestingly, African countries had been “open” for only 8 percent of the entire 1960-1992 period, whereas the rest of the world was open for 55 percent. In addition, although Africa had fewer countries that leaned socialist (outward orientation), it implemented more protectionist policies (low economic organization) over the same period and exchange rates were grossly misaligned.

As Table 1 shows, Africa suffers from natural disadvantages as well. For example, a larger fraction of its land area lies in the tropics, it has three times as many landlocked countries, it has a higher degree of ethnolinguistic fractionalization, and it consists of countries that are relatively small making it difficult to benefit from economies of scale. Africa may also be constrained in its uptake of information and new technologies from the developed world. This is because although 43 and 38 percent of African countries are former British and French colonies, respectively, only 0.5 percent and 6.4 percent of the African population speaks English or any European language as a first language, respectively. Finally, Africa scores worse on institutions of government that are conducive to investment and private enterprise. Our descriptive statistics show that African citizens enjoyed a lower level of political rights and civil liberties than did the rest of the world, and that African countries were twice as likely to change holders of executive office through unconstitutional means (revolutions and coups).

3 Estimation Methodology

A frequent objection to empirical work on economic growth is the model uncertainty problem (see, e.g. Temple, 1999; Brock and Durlauf, 2001; Durlauf, 2001). The central cause of this problem is that several models may seem reasonable, but lead to different conclusions about the parameters of interest. Edward Leamer (1978) was one of the first to emphasize this difficulty. More recently, due to the proliferation of possible explanatory variables in cross-country regressions and the relative lack of guidance from economic theory as to which variables to include, considerable attention has been devoted to appropriately incorporating model uncertainty into empirical growth analyses. Levine and Renelt (1992) investigate the robustness of cross-country regressions using extreme bounds analysis (pioneered by Leamer, 1983) and find that few variables pass the test. In contrast, Sala-i-Martin (1997), using a less restrictive test, identifies a relatively large number of variables to which he assigns some level of confidence for inclusion in growth regressions.

The above papers share two serious limitations. First, they restrict the set of regressors to always contain certain key variables.[5] However, fixing the number of regressors that always appear in the regression affects the size of the estimated coefficients (see Leon-Gonzalez and Montolio, 2003). Second, they are not anchored on any sound statistical theory. The extreme bound analysis is subject to another limitation in that it usually is excessively harsh and biased towards selecting very few "effective" regressors (see Sala-i-Martin, 1997; and Doppelhofer, Miller and Sala-i-Martin, 2004).

To overcome these limitations, we use the emerging Bayesian Model Averaging (BMA) methodology. BMA allows for any subset of regressors to appear in the model and more importantly it is based on a sound statistical theory rendering it superior to previous model averaging methodologies.

While an early contribution on model averaging in economics can be found in Moulton (1991) and Palm and Zellner (1992), it is fairly recent that the literature has employed BMA in a variety of economic applications. BMA has been applied to economic data in the analysis of consumer demand systems, optimal pricing, cross-country regressions, and income convergence (see, e.g. Chua et al., 2001; Bunning et al., 2002; FLS and Sala-i-Martin, Doppelhofer and Miller, 2004; and Leon-Gonzalez and Montolio, 2003, respectively).[6] This paper is in the spirit of FLS, who use BMA to determine the posterior probability of including certain regressors in cross-country growth regressions. However, unlike FLS, we also report the model posterior probabilities to ascertain the combinations of regressors that have explanatory probability and need to be taken seriously.

3.1 Bayesian Model Averaging

Our model closely follows FLS. We consider n independent replications from a linear regression model where the dependent variable, per capita GDP growth in n countries grouped in vector y, is regressed on an intercept α and a number of explanatory variables chosen from a set of k variables in a design matrix Z of dimension n x k. Assume that $r(\iota_n : Z) = k+1$ where $r(\cdot)$ indicates the rank of a matrix and ι_n is an n-dimensional vector of ones. Further define β as the full k-dimensional vector of regression coefficients.

[5] Levine and Renelt (1992) include initial level of income, the investment rate, the secondary school enrollment rate and population growth rate. In contrast, Sala-i-Martin (1997) retained initial output, the investment rate and life expectancy and allowed for four additional variables.

[6] For further discussion on BMA and its potential uses see Draper (1995), Raftery, Madigan and Hoeting (1997) and Hoeting, Madigan, Raftery and Volinsky (1999). Fernàndez, Ley and Steel (2001b) explore properties of BMA applicable to economic analysis. For new developments on BMA see the "Bayesian Model Averaging Home Page" at `http://www.research.att.com/~volinsky/bma.html`.

Now suppose we have an $n \times k_j$ submatrix of variables in Z denoted by Z_j. Then denote by M_j the model with regressors grouped in Z_j, such that

$$y = \alpha \iota_n + Z_j \beta_j + \sigma \varepsilon, \tag{1}$$

where $B_j \in \Re^{k_j}$ $(0 \leq k_j \leq k)$ groups regression coefficients corresponding to the submatrix Z_j, $\sigma \in \Re_+$ is a scale parameter and ε is assumed to follow an n-dimensional normal distribution with zero mean and identity covariance matrix. In addition, exclusion of a regressor in a particular model implies that the corresponding element of β is zero. Notice that since we allow for any subset of variables in Z to appear in the model M_j, this gives rise to 2^k possible sampling models.

Given this setup, the notion of BMA implies that the posterior probability of any given parameter of interest which has common interpretation across models, say Δ, is the weighted posterior distribution of that quantity under each of the models, with weights given by the posterior model probabilities, so that

$$P_{\Delta|y} = \sum_{j=1}^{2^k} P_{\Delta|y,M_j} P(M_j|y). \tag{2}$$

That is, the marginal posterior probability of including a particular regressor is the weighted sum of the posterior probabilities of all models that contain the regressor. The posterior model probability is given by

$$P(M_j|y) = \frac{l_y(M_j)p_j}{\sum\limits_{h=1}^{2^k} l_y(M_h)p_h}, \tag{3}$$

where $l_y(M_j)$, is the marginal likelihood of model M_j given by

$$l_y(M_j) = \int p(y|\alpha, \beta_j, \sigma, M_j) p(\alpha, \sigma) p(\beta_j|\alpha, \sigma, M_j) d\alpha \, d\beta_j \, d\sigma, \tag{4}$$

where $p(y|\alpha, \beta_j, \sigma, M_j)$ is the sampling model corresponding to equation (1), and $p(\alpha, \sigma)$ and $p(\beta_j|\alpha, \sigma, M_j)$ are the priors defined below in equations (5) and (6), respectively.

The implementation of this framework is subject to three challenges. First, since the number of models to be estimated increases with the number of regressors at the rate of 2^k, the number of terms in equation (2) can be enormous, rendering the exhaustive summation infeasible. Second, the computation and evaluation of integrals implicit in equation (4) may be difficult because the integral may not exist in closed form. Third, the choice of the specification of the prior distributions over competing models remains a challenge. Below we briefly discuss how we have addressed these issues.[7]

3.2 Prior Distributions

To complete the sampling model, we need to specify a prior distribution for all models in the model space, and the models and parameters in M_j, namely α, β_j and σ. While the inclusion of prior information is a distinguishing feature of the Bayesian approach to inference, when prior knowledge about a parameter is vague or diffuse, then Bayesian analysis with non-informative prior is suitable (Judge et al., 1988). In this work, since prior knowledge about the parameters for Africa is lacking, incorporating prior information is neither feasible nor desirable, so we need a benchmark prior distribution that will have little influence on posterior inference. Following Fernàndez, Ley and Steel (2001a,b), we use an improper non-informative prior for the parameters that are common to all models and a g-prior structure for β_j which corresponds to the product of

$$p\left(\alpha, \sigma\right) \propto \sigma^{-1}, \tag{5}$$

and

$$p(\beta_j|\alpha, \sigma, M_j) = f_N^{k_j}\left(\beta_j|0, \sigma^2(gZ_j'Z_j)^{-1}\right), \tag{6}$$

where $f_N^q(w|m, V)$ denotes the density function of a q-dimensional normal distribution on w with mean m and covariance matrix V and $g = 1/max\{n, k^2\}$. In this case the $(k - k_j)$ components of β which do not appear in M_j are set exactly equal to zero. Notice that the distribution in equation (5) is the standard non-informative prior for location and scale parameters which is invariant to location and scale transformations.

In addition to the prior distribution of the subset M_j, due to uncertainty about choice of regressors, there is a need to specify the sampling and prior distribution over the space $\mathcal{M}$ of all 2^k possible models as follows:

$$P(M_j) = p_j, \quad j = 1, ..., 2^k, \quad \text{with } p_j > 0, \text{ and } \sum_{j=1}^{2^k} p_j = 1. \tag{7}$$

[7] High colinearity among certain variables is inevitable. Looking at Table 1 we can readily notice that, for example, political variables (Civil Liberties, Revolutions and Coups and Political Rights) are very highly correlated. One of the advantages of BMA is that it is capable of handling this colinearity by appropriately weighting the information added to a regression from two colinear variables. For more on this issue see FLS and Hoeting et al. (1999).

When substantive prior information on the model probability distribution is lacking, it is standard to assume a uniform distribution on the model space. Therefore, if we assume uniform distribution and that regressors are independent of each other, then the prior probability of each model is $p_j = 2^{-k}$ and the prior probability of including any regressor is $\mathfrak{p} = 1/2$.[8]

The issue of choosing the "right" prior regressor and prior model distributions is far from being settled. Many researchers use diffuse prior on the model specific coefficients. As discussed in Brock, Durlauf and West (2003), the advantage of this prior is that, when the errors are normal with known variance, the posterior value of the variable of interest Δ conditional on the data and model M_j, is OLS estimator $\hat{\Delta}_{M_j}$. The disadvantage of this prior is that Bayes factors are sensitive to the choice of prior distributions for the parameters within each model and, even asymptotically, the influence of this distribution does not vanish (see, e.g. Kass and Raftery, 1995). For this reason, new research is diverting focus on data-dependent proper priors as in Raftery et al. (1997) or on prior hyperparameters as in Fernàndez, Ley and Steel (2001b), and George and Foster (1997).

In terms of the choice for prior model probabilities, the general practice is to assume a uniform distribution that implies that the prior probability that a given variable appears in the true model is $\mathfrak{p} = 1/2$. But there is no consensus in this practice; i.e., Sala-i-Martin, Doppelhofer and Miller (2004) argue that the lower probability of about $\mathfrak{p} = 1/4$ is a more appropriate choice. The general practice of assuming that $\mathfrak{p} = 1/2$ implies that the probability that one variable appears in the model is independent of whether other variables appear. Brock, Durlauf and West (2003) argue against this assumption, especially used in economic growth applications, because some regressors are quite similar whereas some are very different. These authors propose a tree structure to organize model uncertainty for linear growth models.

Our choice of informative regressor priors developed by Fernàndez, Ley and Steel (2001b) is based on our small sample size which closely resembles that of FLS. However, we examine robustness of our results to defuse prior on the model specific coefficients and to prior model distribution used in the Bayesian Averaging of Classical Estimates (BACE) approach of Sala-i-Martin, Doppelhofer and Miller (2004). These results are reported in the Robustness section of the paper.

[8]According to Hoeting et al. (1999), when there is little prior information about the relative plausibility of the models considered, the assumption that all models are equally likely a priori is a reasonable "neutral" choice.

3.3 Implementation

In this paper we use a subset of $k = 25$ regressors from the Sala-i-Martin dataset which did not entail substantial loss of observations. We have available $n = 37$ observations (sub-Saharan Africa countries) for all these regressors so that Z will be a 37×25 design matrix corresponding to these variables, and we shall allow for any subset of these 25 regressors giving a total of 2^{25} possible models under consideration in $\mathcal{M}$. We use the Bayesian model presented in equations (1)-(4) with a uniform prior on model probabilities ($p_j = 2^{-k}$). In addition, since $n < k^2$, then for the g-prior we use $g = 1/k^2$ as in FLS (p. 568).

Given that the number of models under consideration increases with the number of regressors at the rate of 2^k, we will approximate the posterior distribution on the model space $\mathcal{M}$ by simulating a sample using a Markov chain Monte Carlo model composition sampler (MC^3) proposed by Madigan and York (1995). For the set of models visited by the chain, posterior probabilities will be computed by normalization of equation (7). As a diagnostic tool, a high positive correlation between posterior model probabilities based on empirical frequencies of visits in the chain and the exact marginal likelihoods will denote that the model has reached its equilibrium distribution.

In order to answer if Africa grows differently, we compare the results derived from the Africa-only sample with those obtained by FLS using a global sample of 72 countries. Notice that by concentrating on Africa, a number of variables relevant in a global context were excluded, either due to data unavailability or irrelevance of the variable to Africa. Variables that are dismissed due to data unavailability include rule of law, equipment and nonequipment investment (replaced by the share of aggregate investment in GDP), black market premium, standard deviation of black market premium, age, size of labor force, ratio of workers to population, higher education enrollment and the budget share of public education. Variables dismissed due to their irrelevance to the Africa sample are regional dummies for Sub-Sahara Africa, Latin America and Spanish colonial influence, the fraction of the population that is Confucian, Buddhist, Hindu and Jewish.

4 Estimation Results

The results reported are based on a run with one million recorded drawings after a burn-in of 100,000 discarded drawings. As a diagnostic, we note that the model performance is satisfactory, evidenced by the high correlation coefficient between visit frequencies and posterior probabilities of 0.991. In addition, due to our choice of the improper uninformative prior, the prior has little effect on posterior model probabilities. Although 32,996 models were visited, the prior probability for a single model is 0.14E-05 percent. When we estimate the model posterior probabilities, the total posterior mass is spread out with 5,010 models accounting for 90 percent of the posterior mass. However, the cumulative posterior probability of the best 132 models, those with posterior probabilities greater than 0.10 percent, is 44 percent of total posterior mass.

Since the posterior mass is spread out, this necessitated Bayesian Model Averaging. This methodology not only provides information on which combinations of regressors are more likely to occur, thereby avoiding models with collinear regressors, but also the Bayes factor obtained in equation (2) has a built-in mechanism to avoid overfitting. This improved the model performance because 3,043 models were now visited from which just 2,422 of them accounted for over 90 percent of the posterior model probability and the 142 models with posterior probability greater than 0.10 percent accounted for 50.27 percent of the posterior mass. Although the model ranking is identical, the posterior model probability rises when we averaged over the models. The model gives two sets of results: regressor and model posterior probabilities. We discuss these next.

4.1 Regressor Posterior Probabilities

The first exercise involves analyzing the importance of individual regressors by looking at the regressor's posterior probability. This is especially important for cross-country growth in two contexts. First, is the issue of model uncertainty. Based on solid statistical inference, BMA allows us to independently assess particular regressors thereby offering some guidance regarding variables which have high posterior probability and ought to be considered for inclusion in growth regressions. Second, if the assertion that factors governing growth in Africa and the rest of the world are the same is valid, then the posterior probabilities of individual regressors in the global sample should in principle be highly correlated with those in the Africa-only sample.

Table 2 compares the marginal importance of regressors derived from the BMA methodology on our Africa sample of 37 countries and the FLS global sample of 72 countries. In general, notice that except for *GDP per capita in 1960*, which measures the convergence effect, the posterior probabilities and the relative rank of all regressors are strikingly different in the two samples. For example, the posterior probability for the *Fraction of Mining in GDP* in the Africa sample is 0.944 whereas for the global sample is only 0.441. Perhaps more striking are the posterior probabilities assigned to *Primary Exports, 1970* (0.921 for the Africa sample and only 0.071 for the global sample) and *Primary School Enrollment, 1960* (0.719 compared to 0.184). In addition, posterior probabilities for *Outward Orientation* (0.546 and 0.021 for the Africa and global samples, respectively), *British Colony Dummy* (0.541 and 0.022), *Revolutions and Coups* (0.472 and 0.017) and *Life Expectancy, 1960* (0.416 and 0.946), are also remarkably different in the two samples. Indeed, the Spearman's rank correlation coefficient of the posterior probabilities of all 25 variables in the two samples is only 0.35.[9]

According to the BMA methodology the three "most important" variables explaining sub-Saharan Africa growth are (in descending order) initial output, fraction of mining and primary exports. In contrast, initial output, the fraction of the population that is Confucian, life expectancy and investment are the variables most important for global growth.[10] These results highlight the role of initial conditions on African growth. In the Africa-only sample, two of the three significant regressors reflect the initial level of economic development (*GDP per capita, 1960* and *Primary Exports, 1970*) while the third variable (*Fraction of Mining in GDP*), reflects both natural resource endowments and persistence of extractive institutions. Apart from the level of initial output, all variables with posterior probability above 0.90 in the global model, like life expectancy and investment, lose their probability of inclusion in the Africa sample.[11] Similarly, a number of variables that had low posterior probability in the global sample turn out to have relatively higher probability of inclusion in African growth regressions.

The implication of these results is that, prima facie, there is evidence that the marginal importance of regressors in the African and global growth regressions is different. First, the posterior

[9] We have also examined whether the results for the global sample in FLS are robust to inclusion or exclusion of sub-Saharan African observations. Table A3 in the appendix reports results from this exercise. Column 4 shows that the global results are somewhat sensitive to exclusion of African countries. In particular, when we exclude the 18 African countries from the original sample of 72 countries, initial output, the fraction Confucian and life expectancy remain significant. However, the posterior probability of equipment investment declines. More importantly, the posterior probability of the rule of law rises from 0.516 to 0.884. In other words, the presence of African countries dampness the role of rule of law to the rest of the world.

[10] There is no theoretical justification of what may be the appropriate threshold of posterior probability over which we should regard a regressor as "most important." Fernandez, Ley and Steel (2001b) call a regressor which obtains a posterior probability over 0.90 "highly effective." In our work we use 0.90 as our threshold because both in the Africa and global samples there is a significant jump in regressor with posterior probability below 0.90. For example note that in ranking the regressors in the Africa sample there is a jump from *Primary Exports, 1970* with posterior probability of 0.921 to *Primary School Enrollment, 1960* with posterior probability down to 0.719. Similarly, in the global sample there is a jump from *Investment* with probability of 0.942 to *Fraction Muslim* with probability 0.656.

[11] Note that a variable which was significant in the global sample (with posterior probability 0.995) but excluded in Africa sample due to irrelevance was the fraction of the population that is Confucian.

Table 2: Comparison of individual regressor BMA posterior probabilities

	Regressor	Africa Sample	Global Sample
1	ln GDP per capita, 1960	**0.993**	**1.000**
2	Fraction of Mining in GDP	**0.944**	0.441
3	Primary Exports, 1970	**0.921**	0.071
4	Primary School Enrollment, 1960	0.719	0.184
5	Investment	0.631	**0.942**
6	Years Economy Open	0.593	0.502
7	Fraction Protestant	0.553	0.461
8	Outward Orientation	0.546	0.021
9	British Colony Dummy	0.541	0.022
10	Revolutions and Coups	0.472	0.017
11	Fraction Muslim	0.469	0.656
12	Life Expectancy, 1960	0.416	**0.946**
13	Fraction Speaking English	0.415	0.047
14	Area (Scale Effect)	0.391	0.016
15	Ethnolinguistic Fractionalization	0.390	0.035
16	Economic Organization	0.334	0.478
17	Fraction Speaking Foreign Language	0.285	0.047
18	Population Growth	0.274	0.022
19	War Dummy	0.250	0.052
20	Political Rights	0.235	0.069
21	Absolute Latitude	0.233	0.024
22	French Colony Dummy	0.229	0.031
23	Exchange Rate Distortion	0.222	0.060
24	Fraction Catholic	0.219	0.110
25	Civil Liberties	0.216	0.100

Notes: The global sample includes the 72 countries used in FLS (pp.567-568). The Africa sample includes 37 countries (see Table A1 in the appendix). Using the global sample, FLS find that the Fraction Confucian variable yields the second highest posterior probability equal to 0.995. This variable is excluded from our estimation as there are no reported cases of Confucians in Africa.

probability of inclusion of the same regressor differs between African and global models. At the very least, the fact that globally important variables become insignificant in the African growth regression, and that some globally unimportant regressors become significant for Africa, argues against asserting that factors governing the growth process in Africa and the rest of the world are the same. Second, the relative importance of regressors differs between Africa and the rest of the world. In other words, even if the determinants of growth were the same, the variables' marginal impact on growth in Africa would be different from that in the rest of the world.

While this ranking of variables, based on their posterior probability, is informative about the relative importance of regressors, it can still be argued that model uncertainty is about the significance of particular regressors in the presence of other regressors. Therefore, we need to investigate the combinations of these regressors that best explain the observed patterns in growth of per capita output. We now turn to this issue.

4.2 Model Posterior Probabilities

Table 3 presents the best three models and the associated posterior probabilities in the Africa and global samples. Although the models reported for the African context have a maximum of five variables, the full set of models ranges between three and seven regressors. In contrast, in the global sample, models range from six to twelve regressors. These differences notwithstanding, it is worth noting that in both contexts the model sizes accord with Sala-i-Martin's (1997) and Sala-i-Martin, Doppelhofer and Miller (2004) conjecture that the desirable number of regressors in growth regressions is seven. The best model in the Africa sample has a posterior probability of 4.82 percent while the best model in the global context has posterior probability of 2.85 percent.

The evidence in Table 3 further underscores the fact that factors governing the process of economic growth in Africa are different from the rest of the world. Given our set of 25 regressors, only two variables emerge as of common importance in both the global and Africa-only samples, namely the level of output per capita in 1960 and the ratio of total investment to GDP. Otherwise, in the African context, the model with the single highest posterior explanatory probability is one that also includes the number of years the economy has been open and the share of primary commodities in exports. The union of the three best models adds the share of mining and revolution and coups as other regressors that are important in explaining Africa's growth tragedy. Even more noteworthy, is the fact that although the investment rate, the number of years the economy has been open

Table 3: BMA model posterior probabilities

Model	**Regressors**	**Post. Prob. (%)**
	Africa Sample	
Best	GDP60, YrsOpen, PrimExp70, Invest	4.82
Second-Best	GDP60, YrsOpen, Mining, PrimExp70, Invest	3.65
Third-Best	GDP60, YrsOpen, Rev/Coup, Mining	2.22
	Global Sample	
Best	GDP60, EcOrg, LifExp, Invest, SubSah, Confucious, Muslim, Protestant, RuleLaw	2.85
Second-Best	GDP60, EcOrg, LifExp, Invest, SubSah, Confucious, Muslim, RuleLaw	2.49
Third-Best	GDP60, LifExp, Invest, SubSah, YrsOpen, Confucious, Muslim, Mining	1.66

Notes: The table above presents the BMA posterior probabilities of the best three models using the Africa and global samples. For a brief description of the variables flagged as important in these models see Table A2 in the appendix.

and revolutions and coups do not have significantly high individual posterior probabilities, they are, nonetheless, flagged as important in explaining African growth in combination with the other regressors.

In contrast, the best model in the global sample comprises nine variables which include life expectancy, initial output, the type of economic organization, rates of investment, a sub-Saharan Africa dummy, the fractions of the population that are Confucian, Muslim and Protestant and the rule of law. A close look at variables flagged as globally important seems to suggest that results in the global cross-country regression may be unduly driven by the extraordinary growth experiences of the Asian tigers, the majority of whose population are Confucian. Therefore, for one to argue that determinants of growth in Africa and the rest of the world are the same, one has to justify how these religious variables impact African growth.

4.3 Growth Regressions

Given the preceding results, the next step in investigating whether Africa grows differently is to compare the performance of our models with those implied by the global sample. In this context, the hypothesis that Africa grows differently should be rejected if the regressors selected by the global model fit the data just as well as those selected by the African models or the associated coefficients are statistically significant. Table 4 reports results from six growth regressions from the three best models in the African and global samples.[12] The results unequivocally show that the models selected by the Africa sample are more superior to those selected by the global sample in the two important respects.

First, the models selected by the Africa sample fit the data better. The best and second-best models selected by BMA from the Africa sample explain about two-thirds of the cross-country variation in African growth, in contrast to the globally relevant models which explain only about one-third of the cross-country variation. Moreover, the coefficients in the regressions from the Africa models are generally quite stable across the three models.

Second, regressors included in models selected using the Africa sample have higher statistical significance than those selected using the global model. All variables identified using the Africa models have the expected sign and are significant at the 1 percent level. In contrast only three of the globally relevant regressors are statistically significant, albeit at lower levels of significance. In addition, the results also show that inclusion of extraneous or nuisance regressors in a growth regression negatively affects the statistical significance of other regressors. For instance, initial output and the share of investment in GDP which are significant at the 1 percent level in all the Africa models are only significant at the 10 percent level when combined with regressors implied by the global models.

In a nutshell, the results from the regressor and model posterior probability exercises and growth regressions suggest that the determinants of growth and mechanism through which they influence African growth are different from the rest of the world. Yet this raises even more interesting questions. Why are these determinants, or combinations thereof, more important in explaining African growth than global growth? Alternatively why do some globally relevant regressors lose their explanatory power in Africa? In addition, can our results contribute to the debate about the

[12] Due to data constraints imposed by global variables our Africa sample is reduced from 37 to 31 countries.

Table 4: Growth regression results from best three models using the Africa and global samples

Specification	**Best Model**		**Second Best Model**		**Third Best Model**	
	Africa	**Global**	**Africa**	**Global**	**Africa**	**Global**
Constant	11.803***	0.822	11.178***	0.814	5.833**	3.358
	(3.257)	(4.136)	(3.046)	(4.042)	(2.770)	(3.866)
YrsOpen	6.658***	—	5.401***	—	3.720***	4.347
	(1.919)		(1.879)		(1.181)	(2.855)
PrimExp70	−5.215***	—	−4.506***	—	—	—
	(−1.314)		(1.266)			
GDP60	−1.280***	−0.942	−1.274***	−0.942	−0.902**	−0.619
	(0.400)	(0.492)	(0.326)	(0.481)	(0.428)	(0.459)
Invest	0.127***	0.093*	0.096***	0.094*	—	0.102**
	(0.031)	(0.047)	(0.032)	(0.046)		(0.043)
Mining	—	—	3.826***	—	6.399**	4.030*
			(1.766)		(3.234)	(2.227)
Rev/Coup	—	—	—	—	−1.256	—
					(0.954)	
LifExp	—	0.075	—	0.077	—	0.007
		(0.074)		(0.071)		(0.070)
EcOrg	—	0.210	—	0.214	—	—
		(0.134)		(0.127)		
Muslim	—	0.094	—	0.023	—	−0.438
		(1.020)		(0.867)		(0.862)
Protestant	—	0.328	—	–	—	—
		(2.346)				
RuleLaw†	—	2.846**	—	2.825**	—	—
		(1.220)		(1.183)		
Adj. R^2	0.601	0.302	0.638	0.333	0.614	0.379
Obs.	31	31	31	31	31	31

Notes: The dependent variable is growth of per capita GDP (1960-1992). In the global regressions the Fraction Confucian and sub-Saharan Africa dummy variables were excluded. *** Significantly different from 0 at the 1% level. ** Significantly different from 0 at the 5% level. * Significantly different from 0 at the 10% level. Standard errors are in parentheses. White's heteroskedasticity correction was used. Due to the inclusion of additional variables in the global sample our sample is reduced from 37 to 32 countries. † In addition, the best and second best models from the global sample propose the Rule of Law as one relevant regressor. However, Rwanda has a missing value for this variable hence our sample is further reduced to 31 countries.

primacy of geography, institutions or policy which has dominated the recent literature on economic growth? Below, we address these issues in turn.

4.4 Most effective variables for Africa

The fact that mining has higher posterior probability in Africa than in the rest of the world should come as no surprise since nine of the world's 14 so-called mineral-based economies are in Africa. Notice that although mining has a positive effect on economic growth, the dominance of mining in GDP has been a double-edged blessing for Africa. Although Africa's all-time fastest growing economy, Botswana, is mostly dependent on exports of diamonds, for the most part, reliance on mining is more pertinent in explaining Africa's slow growth. Heavy reliance on mining has rendered many mineral-dependent economies vulnerable to variations in global demand. African star performers of the 60s and 70s, e.g. Zambia, experienced a reversal of fortune when technological innovations such as fibre-optics and wireless technology in the communication industry, led to substantial decline in the demand for copper. Whereas in 1980 Africa exported 1.3 million metric tons of copper, by 1993 copper exports had fallen to just 0.6 million metric tons. Similarly, Africa's iron exports declined from 28 million tons in 1980 to 18.9 million in 1993 (World Bank, 2000). Since mining is positively related to economic growth, as demand for mining output declined so did economic growth rates.

The fraction of primary commodities in exports is equally important in explaining Africa's slow growth. As expected, it has a negative effect on growth. While the abundance of natural resources is often cited as a redeeming feature of Africa's geography and a source of comparative advantage in natural resources exports (see, e.g. Collier and Gunning, 1999a,b; Landes, 1998), export concentration in primary commodities has also meant that African terms of trade remain ransomed to the capriciousness of international commodity prices. For the most part, African economies remain undiversified, relying for their foreign exchange earnings on a few primary commodities, usually the ones which have been the mainstay of the economy since colonial days. A case in point, although agricultural output accounts for 35 percent of GDP, agricultural commodities comprise over 80 percent of the export bundle for most countries (World Bank, 2000). At the opposite end, although manufacturing output accounts for 11 percent of Africa's GDP, the share of African manufacturing output in global output has averaged less than 1 percent (UNCTAD, 2002).

Even though the number of years an economy has been open does not yield high individual posterior probability, it is shown to be important for African growth in combination with other regressors.[13] This is because upon independence in the 1960s, most of Africa's nationalist governments closed themselves to international trade and instead engaged in import-substitution industrialization. To that end they created new monopolies which extended the role of the state in entrepreneurship. The main justification of state intervention in the market was a desire to promote industrialization and economic growth. It was argued that the interest of the private investor who dominated the colonial economy could scarcely be entirely harmonious with national needs of development (see, e.g. Ake, 1985). However, economic participation of state enterprises became distortionary to both internal and external balances. In most countries, the government created state marketing monopsonies that acted as intermediate traders between local farmers and international markets and undermined efficiency in product markets by abolishing competition and by imposing price and quantity controls. In this regard, the low number of years that African economies have been open should be seen as a proxy for periods with relatively higher inefficiency in factor and product markets. Nowhere was this inefficiency more evident than in the failure of the policy of *Ujamaa Uijijini* (Socialism and Rural Development), a cornerstone of Tanzania's *Arusha Declaration* of 1967 (see Ake, 1985).[14]

The results also suggest that the revolutions and coups variable is important, in combination with other regressors, for Africa. Political instability in the region south of the Sahara desert is an established and well-documented fact and therefore inclusion of this variable in our list of important regressors was highly expected. We were rather surprised that out of the five variables that proxy for political instability available in our sample of 25 variables (including ethnolinguistic fractionalization, political rights, war dummy, civil liberties) only revolutions and coups came out to have an important effect on African growth (note that it appears only in the third-best model and ranks only tenth in terms of individual regressor posterior probability.) We discuss the potential implications of this result subsequently. It is also important to note that the key neoclassical growth determinants, investment and initial output, highlighted by the pioneer work of Solow (1956) are shown to have a truly global effect as they appear to be important in both samples. This result supports the standard practice of using the neoclassical growth model as a universal spring board

[13] There is a long list of recent papers that highlight the importance of openness and trade in economic growth (see, e.g. Ventura, 1997; Frankel and Romer, 1999; Alcalà and Ciccone, 2004).

[14] The *Arusha Declaration*, which committed Tanzania to socialism, involved the consolidation of rural populations into bigger villages, called *Ujamaa* villages. By 1974, 20 percent of Tanzania's population lived in these villages. It also resulted a threefold increase in the number of parastatal enterprises from 43 in 1967 to 139 in 1974.

for empirical growth analysis.

Why do some regressors that have high posterior probability in the global sample lose their explanatory power in the Africa sample? The fraction of the population that is Confucian does not affect African growth because no one on the continent professes this religion, hence it was excluded in estimation of the posterior probability in the Africa sample and in the regressions. However, with regard to life expectancy in 1960 which has a very high posterior probability in the global sample, we conjecture that the combination of limited access to public education, poor public health institutions, low incomes and tropical climatological factors resulted in high morbidity and mortality in general, and high infant mortality in particular, which translated into low life expectancy at birth. However, owing to gains in public health made in the 60s and early 70s, the low life expectancy in 1960 did not have long term effect on growth.

Although our empirical analysis suggests that patterns of growth in Africa differed from the rest of the world during the period 1960-1992, it is not suggestive as to whether this is due to Africa being in a different stage of a global development path, or due to Africa being in an entirely different development path. The former possibility is consistent with Rostow's *The Stages of Economic Growth* (1960, pp. 4-16) in which he characterized the process of modern growth through a series of five stages.[15] In addition, this possibility is consistent with Galor and Weil's (1999, 2000) "unified theory of economic growth" in which development stages are the key to escape from the Malthusian demographic trap and to transit into sustained economic growth.[16] The latter possibility is consistent with the view that different groups (clubs) of countries are characterized by common features (like location, climate, institutions, policy) and move along potentially different development paths (see, e.g. Quah, 1996, 1997). Therefore to reiterate, our key result – that the BMA approach flags out different growth determinants for the Africa sample than the global sample – is consistent with both the "development stages" view and also the "development paths" view.

[15] The African growth experience during the 1960-1992 period may generally fall in the first Rostowian stage of economic development called "The Traditional Society."

[16] Unlike Rostow, Galor and Weil characterize economic growth as a transition between three distinct regimes: Malthusian, post-Malthusian and modern growth. Since technological progress and population growth in Africa are glacial by modern standards and income is roughly constant, most African countries easily qualify into the Malthusian regime.

4.5 Geography, Institutions and Policy

As alluded to in the introduction, three schools of thought have dominated the debate on the determinants of economic growth in Africa: the geography hypothesis, institutions hypothesis and policy/integration hypothesis. Whereas the geography hypothesis argues that geographical and ecological variables shape economic development directly, by influencing productivity, and indirectly, by influencing the choice of political and economic institutions (see Gallup, Sachs and Mellinger, 1998; Sachs, 2001) the institutional hypothesis argues that the role of geography in explaining cross-country variations in growth patterns of per capita income operates predominantly or exclusively through the choice of institutions (e.g. Acemoglu, Johnson and Robinson (2002)) and the integration/policy hypothesis emphasizes the role of macroeconomic policy and the degree of integration in international trade in affecting economic growth (e.g. Frankel and Romer (1999)). The question is, do our results shed any light on this debate?

The union of the best three models obtained by the BMA exercise suggests that six variables are important in explaining Africa's growth tragedy. The key variables are initial per capita output, the fraction of GDP in mining, the fraction of primary commodities in exports, years open, revolutions and coups, and investment. Out of these six key variables, the first three are also flagged as particularly important by the individual regressor posterior probability. A first look at these variables may indicate that they cannot discriminate among these hypotheses. For example, consistent with the neoclassical growth model and the vast majority of growth regressions in the literature, our approach reveals that initial income and investment are truly global determinant of economic growth. Beyond these two key neoclassical variables, the share of mining and primary exports variables can be argued as being favorable to the geography/endowment hypothesis. Their contribution to explaining slow growth can be described in the notion of resource curse, where although natural resources appear to be redeeming feature of Africa's geography, reliance on a narrow range of primary commodities has rendered Africa hostage to fluctuations of international terms of trade. In addition, the revolutions and coups variable can easily be associated with the institutional hypothesis. Finally, the openness variable can be linked to the policy/integration hypothesis, as a large body of recent work (summarized by the World Bank Development Report, 2000) argues that the degree of openness to international trade is predominantly a function of policy and good governance.

A closer look at the relevant variables identified by our analysis (beyond the neoclassical variables) maybe more informative for the alternative hypotheses debate. One can argue that the share of mining and primary exports – the two key variables flagged as important by both the individual regressor posterior probability and the model posterior probability – may actually reflect the legacy of extractive colonial institutions. As noted by Acemoglu, Johnson and Robinson (2001), where climatic conditions did not favor European settlement, Europeans established extractive colonies and created institutions that empowered the elite to extract minerals and valuable commodities. Since these extractive colonies had already created institutions for effectively extracting resources, the legacy of these institutions has endured after independence and are reflected in the share of mining and primary exports. As such reliance on mining and primary exports is more reflective of international division of labor and persistence of institutions that promote a climate for rent-seeking than mere geography.

We can go a step further and ask whether our analysis can discriminate between the effect of economic and political institutions on African growth. Our results seem to suggest that measures of economic institutions have relatively high single and joint posterior probability while indices of political institutions (with the exception of the revolutions and coups variable) have low posterior probability. These results accord with findings by Easterly and Levine (1997, 2003) and Acemoglu, Johnson and Robinson (2001). To the extent that the share of mining and primary export variables can be argued as inherently associated with institutions, our findings lend support to the institutional hypothesis. However, this support is tapered by the low posterior probability of political institutions and other variables that the growth literature uses to reflect institutional quality (e.g. ethnolinguistic diversity, political right and civil liberties; see Table 2). The latter result accords with Bates (2001), who notes the lack of correlation between ethnic diversity and activities that are disruptive to the attainment of economic growth. In addition, in line with Barro (1996, p. 24) "... the more general conclusion, is that advanced western countries would contribute more to the welfare of poor nations by exporting their economic systems ... rather than their political systems."[17]

There is also some evidence in favor of the policy/integration view as the openness variable is

[17] A first attempt to understand which institutions matter to economic growth is Acemoglu and Johnson (forthcoming). They show that "property rights institutions," which protect agents against expropriation by the government and powerful elites, have first-order effect on investment, financial development and long-run economic growth. In another interesting paper, Temple (1998) argues that the origins of slow growth in Africa may be traced to Africa's social arrangements.

included in the best three models identified by our analysis. The number of years the economy has been open, as constructed by Sachs and Warner (1997), measures the role of a country's economic policies and integration in the international economy, being an intersection of five variables related to international trade. We wonder whether economic institutions in Africa relate to the integration policies that are shown to have benefitted African growth. Whether integration policy is related to existing economic institutions is a testable hypothesis that is beyond the scope of the present paper but certainly warrants further investigation.

Taken as a whole, we interpret our results to suggest that even though geography and policy were important determinants of African growth, (economic) institutions had the most pronounced effect. However, as qualified previously, the implications of our results to the geography, institutions, or policy hypotheses debate can only be suggestive as their meaningful separation is not possible in the current analysis.

5 Robustness

Any attempt to empirically address the issue of model uncertainty must address some methodological queries which can call into question the validity and robustness of conclusions derived. Given the nature of data used in cross-country regressions, although we can not alleviate all possible methodological concerns, we can address some. Here we address two issues. The first is to what extent are our results an artifact of the technique employed? In other words, can the qualitative conclusions hold up to alternative techniques of addressing model uncertainty? Second, to what extent are the results driven by peculiarities of the particular sample?

To address the first concern we consider the robustness of our baseline results to an alternative model averaging methodology that considers alternative regressor and model priors to those developed by FLS. We re-estimate the global and African samples using Bayesian Averaging of Classical Estimates (BACE) developed by Sala-i-Martin, Doppelhofer and Miller (2004). To address the second issue, we consider an alternative regression model which allows for the interaction of an African dummy variable with the most effective variables obtained from our baseline results in the global sample.[18] This alternative regression model will help us determine whether the results we

[18] Following advice by Koop, we initially intended to interact all variables (not only the most effective) with the African dummy. However, this proved impracticable since the number of regressors would exceed the number of observations.

obtained are due to real effects or due to the potentially differential variability of global vs. African data series.

5.1 Bayesian Averaging of Classical Estimates (BACE)

Sala-i-Martin, Doppelhofer and Miller (2004) propose a variation to BMA that they call Bayesian Averaging of Classical Estimates (BACE). Methodologically BACE differs from the BMA approach presented above in three important ways. First, whereas we employ proper within-model prior a là FLS, BACE uses diffuse priors (Sala-i-Martin, Doppelhofer and Miller (pp. 816-818, 2004)).[19] Second, whereas we assume a uniform model prior distribution which implies that the prior probability that a given variable appears in the true model is $\mathfrak{p} = 1/2$, Sala-i-Martin, Doppelhofer and Miller (p. 818, 2004) argue that the lower probability of about $\mathfrak{p} = 1/4$ is a more appropriate choice. This alternative probability is chosen to assign more weight to models with fewer regressors, which according to these authors is more appropriate especially in growth regressions. Finally, BACE uses an alternative "stratifying sampler" rather than the more common MC^3 sampler that has been used extensively in the literature.[20] Our experimentation with both samplers revealed that a key advantage of the "stratifying" over the MC^3 sampler is that it can efficiently consider a much larger set of possible regressors.[21]

Table 5 reports regressor posterior probabilities for the Africa sample using BMA and BACE. Comparison of the two sets of results reveal that our baseline results are robust to using BACE. It was particularly striking to us that the six variables identified as the most effective from the union of the top three models using BMA also obtained the highest posterior probabilities using BACE. It is therefore confirmed by BACE that initial GDP, mining, primary exports, investment, years open, and revolutions and coups are the most effective variables in explaining Africa's growth experience. In a more general sense this robustness exercise reveals that the choice of priors (whether proper or diffuse) is not that important in our application.[22]

[19] Brock and Durlauf (2001) and Brock, Durlauf and West (2003), also use diffuse prior on the model specific coefficients.

[20] For the specifics on this sampler see Sala-i-Martin, Doppelhofer and Miller (pp. 818-819, 2004) and Doppelhofer's web link on BACE: `www.econ.cam.ac.uk/faculty/doppelhofer/research/BACE.html`.

[21] For example Sala-i-Martin, Doppelhofer and Miller (2004) considered 67 regressors using the "stratifying sampler." Our attempts to consider the same number of regressors using MC^3 were unsuccessful due to the prohibitive number of computations involved.

[22] Table A4 in the appendix reports results for the FLS sample of 72 countries and 41 regressors. Results obtained using BMA and BACE are strikingly similar.

Table 5: Comparison of regressor posterior probabilities using BMA and BACE (Africa-sample)

	Regressor	FLS-BMA	BACE
1	**ln GDP per capita, 1960**	**0.993**	**0.951**
2	**Fraction of Mining in GDP**	**0.944**	**0.774**
3	**Primary Exports, 1970**	**0.921**	**0.720**
4	**Primary School Enrollment, 1960**	**0.719**	0.264
5	**Investment**	**0.631**	**0.583**
6	**Years Economy Open**	**0.593**	**0.770**
7	Fraction Protestant	0.553	0.171
8	Outward Orientation	0.546	0.183
9	British Colony Dummy	0.541	0.234
10	**Revolutions and Coups**	0.472	**0.323**
11	Fraction Muslim	0.469	0.123
12	Life Expectancy, 1960	0.416	0.174
13	Fraction Speaking English	0.415	0.127
14	Area (Scale Effect)	0.391	0.159
15	Ethnolinguistic Fractionalization	0.390	0.270
16	Economic Organization	0.334	0.111
17	Fraction Speaking Foreign Language	0.285	0.098
18	Population Growth	0.274	0.161
19	War Dummy	0.250	0.129
20	Political Rights	0.235	0.124
21	Absolute Latitude	0.233	0.080
22	French Colony Dummy	0.229	0.088
23	Exchange Rate Distortion	0.222	0.076
24	Fraction Catholic	0.219	0.087
25	Civil Liberties	0.216	0.095

Notes: BACE regressor posterior probabilities are obtainted using prior model size $\bar{k} = 7$ as in the benchmark estimation of Sala-i-Martin, Doppelhofer and Miller (2004).

5.2 Model with Interaction Dummies

A legitimate concern can be raised regarding the inference that we make when globally important variables become insignificant in an Africa sample and vice-versa. Since the African sample is smaller, one can ask to what extent are the results driven by lack of variability in the Africa-only sample?[23] To illustrate the potential impact of restricting sample size, suppose $\mathcal{G}$ is a global dataset and $\mathcal{A} \in \mathcal{G}$ is a subset of Sub-Saharan African countries. Suppose we estimate two regressions, one using $\mathcal{G}$ and the other using $\mathcal{A}$. In general, for the coefficient of any regressor to be found statistically significant, two necessary conditions must be met: the observed regressor should display enough variability and be sufficiently orthogonal to other regressors. If a particular regressor lacks variation, its contribution to the explanatory variable will be absorbed by the constant term, while if it is collinear its contribution may be masked by coefficients of other regressors.

Consequently, if the regressor was important in the global regression and becomes insignificant in the African sub-sample there are two possibilities: either Africa looks different - due to lack of variability in regressors in the restricted sub-sample (although the data generating mechanism is the same), or Africa indeed grows differently and the data generating mechanism underlying $\mathcal{A}$ is given by a process that is different from that underlying $\mathcal{G}$. Our claim is that the latter is the case for Africa. To test whether the results are driven by lack of variability, let $\mathcal{I}_{\mathcal{A}}$ be an indicator variable which equals 1 if $i \in \mathcal{A}$ and 0 otherwise. We then estimate the following global regression:

$$y_i = \alpha + \alpha_{\mathcal{A}}\mathcal{I}_{\mathcal{A}} + x_i\beta + x_i\mathcal{I}_{\mathcal{A}}\beta_{\mathcal{A}} + \boldsymbol{Z}_i\gamma + \varepsilon_i, \quad \text{where } i \in \mathcal{G}. \tag{8}$$

Given this framework, we want to investigate whether the inclusion of the interaction regressors makes some variables that were only important in Africa globally important.

Posterior probabilities of regressors reported in the upper panel of Table 6 confirm that primary exports can be globally important when interacted with the sub-Sahara African dummy (SSA). With the exception of investment, the inclusion of SSA does not affect the posterior probability and ranking of the globally relevant variables like initial GDP and life expectancy.

It is important that we also look at the best models under the alternative specification given by equation (8). The lower panel of Table 6 reports the model posterior probabilities for the best three models in the global sample including SSA interaction dummy variables. The results show

[23] The following discussion is based on a comment by Eduardo Ley who served as a discussant of this paper in a session of the Econometric Society's 2005 North America Winter Meetings. We are grateful to him not only for pointing this potentially important issue but also for providing a viable solution to it which we present in this section.

Table 6: Regressor and model posterior probabilities in model with SSA interaction dummies

	Regressor	Africa Sample	Global Sample	SSA Dummy
1	ln GDP per capita in 1960	**0.993**	**1.000**	**1.000**
1b	SSA*GDP60	–	–	0.110
2	Fraction of Mining in GDP	**0.944**	0.441	0.073
2b	SSA*Mining	–	–	0.378
3	Primary Exports, 1970	**0.921**	0.071	0.026
3b	SSA*PRIEXP	–	–	**0.938**
4	Primary School Enrollment, 1960	0.719	0.184	0.014
4b	SSA*P60	–	–	0.097
5	Investment	0.631	**0.942**	0.336
5b	SSA*EQUIP.INV	–	–	0.579
6	Years Economy Open	0.593	0.502	0.786
7	Fraction Protestant	0.553	0.461	0.218
8	Outward Orientation	0.546	0.021	0.002
9	British Colony Dummy	0.541	0.022	0.005
10	Revolutions and Coups	0.472	0.017	0.007
11	Fraction Muslim	0.469	0.656	0.843
12	Life Expectancy, 1960	0.416	**0.946**	**0.999**
13	Fraction Speaking English	0.415	0.047	0.048
14	Area (Scale Effect)	0.391	0.016	0.007
15	Ethnolinguistic Fractionalization	0.390	0.035	0.070
16	Economic Organization	0.334	0.478	0.299
17	Fraction Speaking Foreign Language	0.285	0.047	0.027
18	Population Growth	0.274	0.022	0.008
19	War Dummy	0.250	0.052	0.003
20	Political Rights	0.235	0.069	0.003
21	Absolute Latitude	0.233	0.024	0.009
22	French Colony Dummy	0.229	0.031	0.007
23	Exchange Rate Distortion	0.222	0.060	0.008
24	Fraction Catholic	0.219	0.110	0.002
25	Civil Liberties	0.216	0.100	0.003

Model	Regressors	Post. Prob. (%)
	SSA*Global Sample	
Best	GDP60, YrsOpen, LifExp, Invest, Confucious, Muslim, **SSA*PRIEXP**, Rule of Law	1.99
Second-Best	GDP60, YrsOpen, LifExp, **SSA*Mining,** SubSah Confucious, Muslim, **SSA*PRIEXP**, Rule of Law	1.27
Third-Best	**SSA*P60**, GDP60, YrsOpen, LifExp, Invest, Confucious, Muslim, **SSA*PRIEXP**, Rule of Law	0.99

Notes: The upper panel presents the regressor posterior probabilities and the lower panel presents the best three models posterior probabilities in the global model with SSA interaction dummies.

that some variables that were important in the Africa-only sample now attain global importance. Consistent with our benchmark results, primary exports become globally important and enter in all of the best three models, while the share of mining in GDP enters the second best model and primary education in 1960 enters the third best model.

In general, this robustness exercise shows that although there are differences when one considers the alternative model with the sub-Sahara African interaction dummy variables, our key result that Africa's growth path depends on different determinants than the global growth path holds firm.

6 Conclusion

Motivated by the economic tragedy of sub-Sahara African countries in the last century, this paper asks a simple but powerful question: Does Africa grow differently from the rest of the world? We sought the answer to this question by examining whether determinants of economic growth (or combinations thereof) are the same in Africa as the rest of the world, using the Bayesian Model Averaging (BMA) methodology. In particular, we estimated the posterior probability of a large number of potential explanatory variables and cross-country regression models. Our results have shown that the determinants of growth in Africa are different from the rest of the world. In contrast to the global sample, African growth is heavily influenced by the share of mining in GDP and the share of primary commodities in exports.

Our results also have broader implications for the growth literature in three important respects: First, we have shown that the issue of model uncertainty is a very serious problem in growth regressions, not the least for the sub-Saharan Africa sample. Our exercise shows that model uncertainty is at least as serious a problem as endogeneity and parameter heterogeneity and therefore it can have important implications in reassessing the robustness of existing empirical growth findings. Second, our findings can provide guidance in constructing richer and more realistic growth models. Third, given these findings, the one-size-fits-all economic policies motivated by the vast majority of existing cross-country regressions are less likely to succeed in Africa and have to be re-evaluated taking into account country/region specific characteristics.

In our view, there are two areas of future research that may prove particularly fruitful. First, our analysis so far imposes strong homogeneity assumptions on the growth process of African countries. Assuming parameter homogeneity in our growth regressions is equivalent to assuming that all sub-Saharan Africa countries have identical production technologies. In a pioneer paper, Brock, Durlauf and West (2003) use a tree structure that considers parameter heterogeneity and model uncertainty sequentially, in order to facilitate policy evaluation under several forms of uncertainty. Future work that aims to merge the literatures on endogenous clustering (i.e., Durlauf and Johnson, 1995; and Hansen, 2000) with model averaging – hence considering parameter heterogeneity and model uncertainty *simultaneously* – is very promising. Second, our analysis, and to our knowledge all existing work on BMA, fails to consider the endogeneity problem that has plagued most growth regressions. In Masanjala and Papageorgiou (2005), we focus entirely on exogenous variables that are predetermined in 1960 or thereabouts, and thus leave all investment-, political- and openness-related variables that refer to the intervening period out. In work in progress, Durlauf and Doppelhofer try to incorporate instrumental variable techniques in BMA to deal with the endogeneity problem.

Since model averaging is still very new in econometric analysis and even more so in growth econometrics, there are several methodological issues that are debated including the model space, the choice of priors, and the efficiency and effectiveness of samplers used in averaging models.[24] Nonetheless, we believe that our approach along with those in Brock and Durlauf (2001), and Brock, Durlauf and West (2003) can provide a valuable alternative to existing efforts aiming to explain Africa's growth tragedy.

[24] A comprehensive summary of these issues exists in Hoeting et al. (pp. 401-415, 1999) and more recently in Durlauf, Johnson and Temple (pp. 74-85, 2005).

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Appendix

Table A1: List of countries in baseline Africa sample and key initial conditions

	Country	Growth	GDP60	LifExp60	PrimSch60
1	Angola	0.00	6.79	37.5	0.21
2	Benin	-0.01	7.02	38.9	0.27
3	Botswana	0.06	6.28	45.7	0.42
4	Burkina Faso	0.00	6.15	36.3	0.08
5	Burundi	0.00	6.38	41.8	0.18
6	Cameroon	0.01	6.55	43.4	0.65
7	Cent'l Afr. Rep.	-0.01	6.49	39.3	0.32
8	Chad	-0.02	6.50	34.9	0.17
9	Congo	0.02	6.97	47.3	0.78
10	Ethiopia	0.00	5.52	42.2	0.07
11	Gabon	0.02	7.49	40.9	1.00
12	Gambia	0.01	6.20	32.3	0.12
13	Ghana	0.00	6.77	45.2	0.38
14	Cote d'Ivoire	0.00	6.88	39.5	0.60
15	Kenya	0.01	6.46	45.0	0.47
16	Lesotho	0.04	5.66	47.7	0.83
17	Liberia	-0.01	6.55	41.5	0.31
18	Madagascar	-0.02	7.06	41.0	0.52
19	Malawi	0.01	5.91	37.9	0.67
20	Mali	0.00	6.20	35.9	0.10
21	Mauritania	0.00	6.75	35.3	0.08
22	Mauritius	0.02	7.94	59.4	0.98
23	Mozambique	-0.02	7.03	35.2	0.48
24	Niger	0.00	6.22	35.4	0.05
25	Nigeria	0.01	6.32	39.7	0.36
26	Rwanda	0.01	6.24	46.5	0.49
27	Senegal	0.00	6.92	39.6	0.27
28	Sierra Leone	0.01	6.94	31.5	0.23
29	Somalia	0.00	6.92	36.1	0.09
30	South Africa	0.01	7.65	49.2	0.89
31	Sudan	0.00	6.82	38.8	0.25
32	Tanzania	0.02	5.74	40.6	0.25
33	Togo	0.01	5.89	39.5	0.44
34	Uganda	-0.01	6.52	43.2	0.49
35	Zaire	-0.01	6.13	42.1	0.60
36	Zambia	-0.01	6.86	41.8	0.42
37	Zimbabwe	0.00	6.92	45.5	0.96
Mean		**0.00**	**6.58**	**40.9**	**0.42**
Std. Dev.		**0.016**	**0.531**	**5.339**	**0.278**

Notes: The 37 countries listed above constitute our baseline Africa sample. Columns 3-6 present rounded values of the average per capita GDP growth (1960-1992), initial per capita GDP (1960), initial life expectancy (1960), and initial primary schooling (1960), respectively.

Table A2: Variable definition and sources

Variable	Definition	Source
Growth	Average growth of GDP, 1985 international prices (1960-1992)	SH
GDP60	GDP per capita in 1960	SH
LifExp60	Life expectancy at birth in 1960	WB
PrimSch60	Average years of primary schooling in total population over 25 in 1960	BL
OutOrient	Index of outward orientation	Br
Area	Size of country's land area in millions of square kilometers	L
PopGrowth	Average growth of population (1960-1990)	SH
YrsOpen	Fraction of years economy open (1965-1990)	SW
Rule	Index for the rule of law	Bk
Rev/Coup	Average number of revolutions and coups per year (1960-1984)	Bk
War	Dummy for countries participated in at least one external war (1960-1985)	Bk
Rights	Index of political rights (ranges from 1-7 where 1 represents most freedom)	BL
CivilLib	Index of civil liberties (ranges from 1-7 where 1 represents most freedom)	BL
AbslLat	Measure of distance form the equator	BL
Frac	Prob. two randomly selected people are from different ethnolinguistic group	TH
PrimExp70	Share of exports of primary products in GDP in 1970	WB
RERD	Real exchange rate distortion	BL
British	Dummy if country is former British colony	BL
French	Dummy if country is former French colony	BL
Catholic	Fraction of population Catholic	Br
Confucian	Fraction of population Confucian	Br
Protestant	Fraction of population Protestant	Br
Muslim	Fraction of population Muslim	Br
Mining	Fraction of GDP in mining	HJ
EconOrg	Type of Economic Organization: measure of degree of capitalism	HJ
Other	Fraction speaking foreign language	Br
English	Fraction speaking English language	Br
Invest	Ratio of real domestic investment (public and private) to real GDP	SH

Notes: The dataset used in this study is available in its entirety from the authors upon request. Ba = Banks (1997), Br = Barro (1991), Bt = Bates (2001), BL = Barro and Lee (1993), HJ = Hall and Jones (1999), L = Lee (1993), SH = Summers and Heston (1991), SW = Sachs and Warner (1995), TH = Taylor and Hudson (1972), WB = World Bank (2000).

Table A3: Regressor posterior probabilities, FLS sample with/without Africa

	Regressor	FLS Sample	FLS Sample without Africa
1	ln GDP per capita, 1960	**1.000**	**0.920**
2	Fraction Confucian	**0.995**	**1.000**
3	Life Expectancy	**0.946**	**0.920**
4	Equipment Investment	**0.942**	0.248
5	Sub-Saharan dummy	0.757	—
6	Fraction Muslim	0.656	0.572
7	Rule of Law	0.516	**0.884**
8	Years Economy Open	0.502	0.542
9	Degree of capitalism	0.478	0.008
10	Fraction Protestant	0.461	0.590
11	Fraction of Mining in GDP	0.441	0.053
12	Non-Equipment investment	0.431	0.513
13	Latin American dummy	0.190	0.246
14	Primary School Enrollment, 1960	0.184	0.008
15	Fraction Buddhist	0.167	0.169
16	Black Market premuim	0.157	0.136
17	Fraction Catholic	0.110	0.215
18	Civil Liberties	0.100	0.010
19	Fraction Hindu	0.097	0.020
20	Primary Exports, 1970	0.071	0.006
21	Political Rights	0.069	0.026
22	Exchange Rate Distortion	0.060	0.010
23	Age	0.058	0.004
24	War Dummy	0.052	0.004
25	Size of Laborforce	0.047	0.002
26	Frac Speaking Foreign Language	0.047	0.013
27	Fraction Speaking English	0.047	0.014
28	Ethnolinguistic Fractionalization	0.035	0.051
29	Spanish Colonial dummy	0.034	0.005
30	SD black-market premium	0.031	0.165
31	French Colony Dummy	0.031	0.005
32	Absolute Latitude	0.024	0.008
33	Ratio of workers to population	0.024	0.011
34	Higher education enrollment	0.024	0.007
35	Population Growth	0.022	0.007
36	British Colony Dummy	0.022	0.003
37	Outward Orientation	0.021	0.046
38	Fraction Jewish	0.019	0.022
39	Revolutions and Coups	0.017	0.018
40	Public education share	0.016	0.019
41	Area (Scale Effect)	0.016	0.017

Notes: The sample without African countries includes 54 of the 72 countries used in FLS. For a description of the above 41 regressors see FLS (pp. 567-568).

Table A4: Regressor posterior probabilities BMA vs BACE

	Regressor	FLS-BMA	BACE
1	ln GDP per capita, 1960	**1.000**	**0.999**
2	Fraction Confucian	**0.995**	**0.991**
3	Life Expectancy	**0.946**	**0.934**
4	Equipment Investment	**0.942**	**0.924**
5	Sub-Saharan dummy	0.757	0.749
6	Fraction Muslim	0.656	0.643
7	Rule of Law	0.516	0.513
8	Years Economy Open	0.502	0.497
9	Degree of capitalism	0.478	0.484
10	Fraction Protestant	0.461	0.473
11	Fraction of Mining in GDP	0.441	0.471
12	Non-Equipment investment	0.431	0.453
13	Latin American dummy	0.190	0.218
14	Primary School Enrollment, 1960	0.184	0.206
15	Fraction Buddhist	0.167	0.202
16	Black Market premuim	0.157	0.191
17	Fraction Catholic	0.110	0.136
18	Civil Liberties	0.100	0.126
19	Fraction Hindu	0.097	0.136
20	Primary Exports, 1970	0.071	0.103
21	Political Rights	0.069	0.096
22	Exchange Rate Distortion	0.060	0.079
23	Age	0.058	0.085
24	War Dummy	0.052	0.075
25	Size of Laborforce	0.047	0.076
26	Frac Speaking Foreign Language	0.047	0.066
27	Fraction Speaking English	0.047	0.070
28	Ethnolinguistic Fractionalization	0.035	0.057
29	Spanish Colonial dummy	0.034	0.057
30	SD black-market premium	0.031	0.048
31	French Colony Dummy	0.031	0.057
32	Absolute Latitude	0.024	0.044
33	Ratio of workers to population	0.024	0.042
34	Higher education enrollment	0.024	0.044
35	Population Growth	0.022	0.039
36	British Colony Dummy	0.022	0.039
37	Outward Orientation	0.021	0.038
38	Fraction Jewish	0.019	0.036
39	Revolutions and Coups	0.017	0.030
40	Public education share	0.016	0.031
41	Area (Scale Effect)	0.016	0.031

Notes: The global-sample dataset is from FLS with 72 countries and 41 regressors. For a description of the above variables see FLS (pp. 567-568).