DEPARTMENT OF ECONOMICS WORKING PAPER SERIES

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Working Paper 2006-01
http://www.bus.lsu.edu/economics/papers/pap06_01.pdf

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December 2005

Abstract

We investigate the role of initial conditions at colonial independence on economic growth in Africa in the post-independence period using Bayesian Model Averaging (BMA). A key innovation in our estimation methodology is that we incorporate parameter heterogeneity in model averaging as well as try to mitigate the endogeneity problem present in growth regressions. In order to ensure that differences in the growth determinants between Africa and the world are not driven by experiences of an alternative group of countries, we also control for the presence of OECD countries and former European colonies in the global sample. We find that the impact of different initial conditions on growth in Africa is strikingly different from the world. We argue that these initial conditions reflect the state of development at the close of the colonial era and are therefore inherently related with the legacy of colonialism.

JEL Classification: O40, O47.

Keywords: Africa, initial conditions, colonialism, model uncertainty, Bayesian Model Averaging (BMA), parameter heterogeneity, endogeneity.

*We thank two anonymous referees and especially the editor, Daron Acemoglu for very valuable comments. We aslo thank Gernot Doppelhofer, Steven Durlauf, Theo Eicher, Oded Galor, Paul Johnson, Eduardo Ley, Adrian Raftery, Dick Starz and participants in many universities and conferences in which this paper was presented for useful discussions and suggestions. We are also grateful to Carmen Fernàndez, Eduardo Ley and Mark Steel for making available to us their *Fortran* program, Xavier Sala-i-Martin, Gernont Doppelhofer and Ronald Miller for their *GAUSS* program and Adrian Raftery for his *R-BMA* programs.

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1 Introduction

This paper seeks to investigate the role of initial conditions and colonialism on post-colonial economic growth in Africa.[1] Although Africa's colonial relationship with Europe lasted a relatively short period (mostly from the 1880s to the 1960s), the historic record seems to suggest that colonialism should nonetheless be expected to exert enormous influence on Africa's post-colonial economic performance, although there is little consensus on whether that role is positive or negative. On the one hand, scholars of the modernization persuasion emphasize the positive development impulses that came from the colonizers. In general, they hold the view that colonialism promoted the integration of colonies into the world economy, channelled foreign capital and fostered the modernization of colonies that otherwise would not have occurred. On the other hand, the "drain of wealth" thesis argues that colonialism contributed to post-colonial underdevelopment by reducing indigenous physical capital accumulation through direct exploitation (whether through forced taxation, forced labor or enslavement) and the transfer of colonial surplus to metropolitan countries. Consequently, as hypothesized by Acemoglu, Johnson and Robinson (2001), extractive colonial institutions were established whose legacies have endured in the post-colonial era and are used by a new class of indigenous elites. Coupled with distorted educational policies which aimed at serving the needs of the metropolitan countries, colonialism may be responsible for generating societies with dysfunctional institutions, rent-seeking elites and ethnic conflict which have been the hallmarks of Africa's recent past.

This potential role of colonialism notwithstanding, in much of the economics literature the role of colonialism on cross country post-colonial economic growth has not been studied in earnest. In fact, following Barro's (1991) finding that a dummy for Africa exerts a significant and negative effect on average growth rates in per capita GDP, there has been a proliferation of studies that seek to document and understand why Africa's economic performance has been markedly worse than that of other regions (see, e.g. Easterly and Levine, 1997; Sachs and Warner, 1997; Rodrik, 1998; Temple, 1998; Collier and Gunning, 1999; Block, 2001; Acemoglu, Johnson and Robinson, 2003; Artadi and Sala-i-Martin, 2003; Masanjala and Papageorgiou, 2005; Paap, Franses and van Dijk, 2005; and Tsangarides, 2005). Possible sources of Africa's dismal performance have ranged from Africa's geographical and ecological peculiarity (see, e.g. Bloom and Sachs, 1998) to the institutional legacy of geography through colonialism (see, e.g. Acemoglu, Johnson and Robinson, 2001; 2002), the role of capital accumulation and adjustment (see, e.g. Berthelemy and Soderling, 2001), ethnic diversity (see, e.g. Easterly and Levine, 1997) or political instability (see, e.g. Bates, 2000). Yet, while these studies have managed to impose some structure on our understanding of Africa's poor economic performance, in the economic literature, there is a dearth of studies that explicitly analyze the impact of colonialism and conditions at independence on Africa's post colonial economic performance.[2]

In addition, most studies that have sought to specifically analyze Africa seem to suffer, to various degrees, from three problems that have plagued much of the growth literature: model uncertainty, endogeneity of regressors and parameter heterogeneity. The issue of model uncertainty is problematic on two significant levels. The first and commonest case is that of theory uncertainty. There are a number of competing theories which try to explain Africa's dismal performance the most prominent of which are the geography hypothesis, the institutions hypothesis and the integration/policy hypothesis. Second, is the uncertainty

[1] Throughout the paper when we refer to Africa we mean sub-Saharan Africa.

[2] A notable exception being Bertocchi and Canova (2002) who attempt to identify channels through which colonialism may have impacted post-colonial growth.

inherent in model selection. Even amongst scholars that subscribe to the same school of thought, there is little consensus regarding which regressors to include in growth regressions.[3] The issue of endogeneity of regressors arises in growth regressions because most studies that purport to explain long-run growth do so using explanatory variables that are not only jointly determined, but rather than explain the process of economic growth they also seem to be affected by it. Endogeneity is even more troubling because growth regressions are not amenable to standard econometric remedies due of lack of viable instruments. On the other hand, the issue of parameter heterogeneity arises in studies that use a representative single equation cross-country growth regression. In essence such studies not only assume a common production function across all countries, but also that the marginal impact of regressors on long-run growth is the same across the globe.[4] While a number of recent studies have addressed model uncertainty using Bayesian Model Averaging (BMA) and some incorporated parameter heterogeneity in BMA, none of these studies has tackled all three problems at the same time.[5]

In this paper we are investigating whether colonialism has a lasting legacy on post-colonial economic growth in Africa by addressing all three econometric issues. We address the issue of model uncertainty using Bayesian Model Averaging (BMA). We incorporate parameter heterogeneity in BMA by considering a growth models with Africa interaction dummies. To control for potential endogeneity of growth determinants, we only use regressors that were mostly predetermined in 1960s (with the exception of primary exports which were calculated in 1970). In that regard this paper seeks to understand the role of initial conditions at colonial independence on economic growth in Africa in the post-independence period. In order to ensure that differences in the growth determinants between Africa and the world are not driven by experiences of a small group of wealthy countries, we also control for the presence of OECD countries in the global sample. In addition, to see if Africa's growth experience is unique, we control for the presence of former European colonies in the global sample.

2 Estimation

2.1 The data

Table 1 reports descriptive statistics for the 32 variables that will be used as regressors in our analysis, distinguished by region. As alluded to above, to reduce the endogeneity problem we focus on "exogenous" variables that are determined in 1960 or thereabouts, thus leaving all of the political- and investment-related and openness-related variables that refer to the intervening period out.[6] The global dataset comprises 93 countries of which there are 69 former European colonies, 69 non-OECD countries and 30 sub-Sahara African countries. Of the 32 variables 28 are from Sala-i-Martin (1997), while malaria prevalence and the fraction of land area in tropical location is from Sachs and Warner (1997). In addition, we created two dummies: one for OECD countries and another for former European colonies. Whereas the regressors represent conditions at

[3] For example, initial tests of the geography hypothesis, used absolute latitude and tropical location as proxies. However, recently Sachs suggests that Malaria prevalence is the more meaningful proxy.

[4] For extensive discussions on these econometric problems see Temple (1999), and Durlauf, Johnson and Temple (forthcoming).

[5] Fernández, Ley and Steel (2001a,b) and Sala-i-Martin, Doppelhofer and Miller (2004) address model uncertainty while Brock and Durlauf (2001), Brock, Durlauf and West (2003) and Masanjala and Papageorgiou (2005) incorporate parameter heterogeneity in model uncertainty. In preliminary work Durlauf and Doppelhofer try to incorporate instrumental variable techniques in BMA to deal with the endogeneity problem.

[6] We are grateful to the editor, Daron Acemoglu, for his suggestions on this strategy.

Table 1: Descriptives statistics of regressors

	Regressor	Global		Africa		non-OECD		Colonies	
		Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
	Initial level of development								
1	ln GDP per capita, 1960	7.361	(0.91)	6.526	(0.51)	6.991	(0.67)	7.160	(0.80)
2	Fraction of mining, 1960	0.052	(0.08)	0.074	(0.11)	0.064	(0.93)	0.063	(0.09)
3	Primary exports, 1970	0.713	(0.28)	0.875	(0.16)	0.821	(0.21)	0.809	(0.20)
4	Primary school enrolment, 1960	0.708	(0.30)	0.429	(0.26)	0.616	(0.30)	0.661	(0.29)
5	Life expectancy, 1960	53.34	(12.2)	41.18	(4.27)	48.21	(9.35)	50.00	(10.7)
6	Secondary school enrollment, 1960	0.210	(0.22)	0.029	(0.03)	0.117	(0.12)	0.148	(0.17)
7	High education enrollment, 1960	0.036	(0.05)	0.000	(0.00)	0.018	(0.03)	0.029	(0.05)
8	Urbanization, 1960	0.356	(0.25)	0.131	(0.09)	0.279	(0.22)	0.312	(0.24)
9	Labor force, 1960	7698	(2199)	2853	(3379)	6080	(2340)	6908	(2473)
	Geographical variables								
10	Area	874.2	(1828)	604.9	(628)	685.4	(1187)	1050	(2079)
11	Absolute latitude	23.41	(18.7)	10.09	(7.78)	15.97	(11.2)	17.44	(12.6)
12	Malaria prevalence, 1960	0.359	(0.44)	0.880	(0.26)	0.484	(0.44)	0.445	(0.45)
13	Tropical location	0.563	(0.47)	0.919	(0.25)	0.746	(0.41)	0.709	(0.42)
14	Landlocked	0.172	(0.38)	0.400	(0.49)	0.203	(0.40)	0.174	(0.38)
	Regional Variables								
15	sub-Saharan Africa	0.323	(0.47)	1.000	(0.00)	0.435	(0.50)	0.406	(0.49)
16	Latin America	0.215	(0.41)	0.000	(0.00)	0.275	(0.45)	0.289	(0.45)
17	East Asian	0.097	(0.30)	0.000	(0.00)	0.101	(0.30)	0.073	(0.26)
18	OECD	0.258	(0.44)	0.000	(0.00)	0.000	(0.00)	0.072	(0.26)
	Colonial Variables								
19	Former Colony	0.742	(0.44)	0.933	(0.25)	0.913	(0.28)	1.000	(0.00)
20	British Colony	0.344	(0.48)	0.500	(0.50)	0.391	(0.49)	0.461	(0.50)
21	French Colony	0.172	(0.38)	0.333	(0.47)	0.232	(0.42)	0.232	(0.42)
22	Spanish Colony	0.161	(0.37)	0.000	(0.00)	0.203	(0.40)	0.217	(0.41)
	Ethnolinguistic Diversity								
23	Ethnolinguistic fractionalization	0.407	(0.30)	0.648	(0.26)	0.471	(0.30)	0.445	(0.30)
24	Fraction European language	0.319	(0.41)	0.021	(0.26)	0.328	(0.41)	0.331	(0.40)
25	Fraction speaking English	0.080	(0.24)	0.006	(0.03)	0.034	(0.16)	0.093	(0.26)
	Religious variables								
26	Fraction Buddhist	0.043	(0.16)	0.000	(0.00)	0.044	(0.16)	0.025	(0.11)
27	Fraction Catholic	0.356	(0.37)	0.206	(0.17)	0.336	(0.36)	0.378	(0.36)
28	Fraction Confucian	0.015	(0.07)	0.000	(0.00)	0.011	(0.05)	0.007	(0.04)
29	Fraction Hindu	0.026	(0.13)	0.000	(0.00)	0.036	(0.15)	0.023	(0.11)
30	Fraction Jewish	0.009	(0.08)	0.000	(0.00)	0.012	(010)	0.013	(0.10)
31	Fraction Muslim	0.212	(0.35)	0.296	(0.32)	0.271	(0.37)	0.247	(0.36)
32	Fraction Protestant	0.168	(0.23)	0.175	(0.14)	0.111	(0.14)	0.138	(0.16)

Notes: The values above are the means and standard deviations (in parentheses) of the 32 variables for the four samples considered in our analysis.

independence, post-colonial economic performance is measured as the average growth rate in GDP over the 1960-1992 period.[7] We classify these 32 predetermined variables in six categories: variables capturing the initial level of development at national independence, geographical variables, religious variables, measures of ethnolinguistic diversity, colonial dummies and regional dummies. Table 1 also compares the mean values of our variables for Africa with the global sample and samples of the non-OECD countries and former colonies.

Two significant patterns seem to stand out. First, at independence the colonialist bequeathed less developed economies to Africans than they did to colonies in other regions.[8] Notice that if we take Africa out of the global sample, then 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 enrolment was only 41% compared to 89% 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% of exports in the rest of the world, in Africa they accounted for 88% of the exports. More importantly Africa started with a very low level of human development. In Africa only 2% of the population aged 25 years and over had any secondary education in contrast to a range of 11% of the corresponding population in all developing countries to 21% globally. Similarly, whereas some 2-4% of the adult population in other regions had some tertiary education, in Africa virtually nobody had any tertiary education.

Second, it appears that Africa's geographical endowments and the associated ecology are not only significantly different but they also put Africa at an economic disadvantage. Relative to countries on other regions, African countries may be less able to benefit from scale economies because they are smaller in area. Moreover, since African countries are more tightly wrapped around the equator, it is not surprising that 92% of sub-Sahara Africa's land area lies between the tropics of Cancer and Capricorn and malaria is endemic in 88% of the countries. In addition, exports from many African countries may be internationally uncompetitive due to high transportation costs. In Africa, 40% of the countries have no direct access to the sea in contrast to about 20% of countries in other regions. Moreover, whereas only 19% of Africa's population lives within 100 kilometers of the cost, in the US and Europe, the comparable fractions are 67% and 89%, respectively.

2.2 Econometric Methodology

To address the issue of model uncertainty, we use Bayesian Model Averaging (BMA) with the proper regressor priors suggested by Fernàndez, Ley and Steel (2001a,b) as our benchmark methodology. Subsequently, we examine the robustness of our results to the regressor unit information prior implied by the Bayesian Information Criterion (BIC) approximation following Raftery, Madigan and Hoeting (1997). We also compare our results to those obtained using the prior model distribution used in the Bayesian Averaging of Classical Estimates (BACE) approach developed by Sala-i-Martin, Doppelhofer and Miller (2004).[9]

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

[7] Tables A1 and A2 in Appendix A list the countries and the definitions of variables used in this paper, respectively.

[8] This may actually reflect the fact that Africa had a shorter stint with colonialism (just 70 years) than other regions.

[9] All of the programs used in this paper (*Fortran* for FLS-BMA, *GAUSS* for BACE and *R* for BIC-BMA) accompanied with the relevant datasets are available by the authors upon request.

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.

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 $\beta_j \in \Re^{k_j}$ $(0 \leq k_j \leq k)$ groups regression coefficients corresponding to the submatrix Z_j, $\sigma \in \Re_+$ is a scale parameter, and ε is a random error term that follows an n-dimensional normal distribution with zero mean and identity covariance matrix. Exclusion of a regressor in a particular model implies that the corresponding element of β is zero. 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. It is important to note that to allow for parameter heterogeneity in model averaging we allow for subsample dummy interactions in the set of k variables. That is now k includes the original set of regressors plus subsample dummy interactions.[10]

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

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

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

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

[10] In a previous paper (Masanjala and Papageorgiou, 2005) we compared the regressor and model performance between the global sample and an Africa subsample. However, legitimate concerns were raised regarding the inference made when globally important variables became insignificant in the Africa sample and vice-versa. Since the Africa sample was smaller, the question that needed to be addressed was to what extent were the results driven by lack of variability in the Africa sample? 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 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 subsample there are two possibilities: either Africa looks different - due to lack of variability in regressors in the restricted subsample (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 $\mathcal{G}$. To obviate this ambiguity, we define $I(\mathcal{A})$ to be an indicator variable which equals 1 if $i \in \mathcal{A}$ and 0 otherwise. Therefore in our framework, equation (1) takes the form $y_i = \alpha + \alpha_{\mathcal{A}} I_{\mathcal{A}} + x_i\beta + x_i I_{\mathcal{A}}\beta_{\mathcal{A}} + Z_i\gamma + \varepsilon_i$, where $i \in \mathcal{G}$. We thank an anonymous referee who noted the lack of a natural metric for comparing results from the subsamples. We are also thank Eduardo Ley for pointing out to us how the lack of variability might impact inference and for recommending the subsequent remedy.

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.

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. First, due to the lack of prior knowledge about parameters in Africa, we use an improper non-informative prior (standard in the literature) 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

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

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 using as g-prior, $g = 1/max\{n, k^2\}$.[11] In this case the $(k - k_j)$ components of β which do not appear in M_j are set to zero. 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:

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

Since we lack of knowledge on model probability distribution, we assume a uniform distribution and that regressors are independent of each other, so that the prior probability of each model is $p_j = 2^{-k}$ and the prior probability of including any regressor equals $p_j = 1/2$.[12]

To implement this model within the BMA framework for the global sample with Africa interaction dummies, we considered $k^{GA} = 54$ regressors (32 regressors and 22 interaction dummies) and $n^G = 93$ observations so that Z^G is a 93×54 design matrix. Further robustness analyses of these baseline results included consideration of the global sample without OECD countries ($k^{GN} = 54$ and $n^{GN} = 63$) and a global sample comprising former colonies ($k^{GC} = 52$ and $n^{GC} = 63$) interaction dummies.

Although we use the model presented in equations (1)-(4) with a uniform prior on model probabilities, 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).[13] For the set of models visited by the chain, posterior probabilities will be computed by normalization of equation

[11] Fernàndez, Ley and Steel (2001b, pp. 394-396) consider nine alternative g-priors. They conclude, based on their empirical results on posterior model choice and predictive performance in the context of their extensive simulation study, the g-prior $g = 1/max\{n, k^2\}$ is a "safe" choice.

[12] Although the general practice for choosing prior model probabilities is to assume a uniform distribution that implies that the prior probability that a given variable appears in the true model is $p = 1/2$, Sala-i-Martin, Doppelhofer and Miller (2004) argue that the lower probability of about $p = 1/4$ is a more appropriate choice in growth regressions. In addition, assuming that $p = 1/2$ 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.

[13] In robustness analyses of our baseline FLS-BMA methodology to the BACE and BIC-BMA methodologies we use alternative samplers to MC^3. For more discussions on the "coinflip" sampler used in BACE see Sala-i-Martin, Doppelhofer and Miller (2004, pp. 818-819), and `bicreg` used in BIC-BMA see Hoeting, Madigan, Raftery and Volinsky (1999, pp. 181-182).

(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 denotes that the model has reached its equilibrium distribution.

3 Results

Table 2 presents posterior probabilities of regressors from the model where regressors have been interacted with the African dummy. A number of important implications seem to stand out. The Global column shows that when one considers cross-country growth regressions in a global context, then the most significant regressors should include initial GDP, which measures the convergence effect, life expectancy and whether the country is located in East Asia. However, the results also show that the global model may be inappropriate when explaining determinants of growth in Africa. For instance, of the ten regressors with highest posterior probability, six variables are only significant in explaining African growth but not global growth. Whereas tropical location has a posterior probability of 100% in Africa, in the global context tropical location has a posterior probability of just 3.5%. Similarly, the prevalence of malaria has a posterior probability of 78.9% in Africa in contrast to 12.8% in the global setting. Results also suggest that besides the tropical location and Malaria prevalence, cross country differences in growth in Africa are better explained by the fraction of mining in GDP, whether the country is landlocked, the country's land area and, more importantly, colonial influence. Yet these variable are not individually significant in the global context.

The results also suggest that the impact of initial conditions and colonial legacy even differ between Africa and other developing countries. Just like in the full global sample, when we control for the presence of OECD countries in the global sample, we find that cross-country growth among developing countries is largely explained by initial output, life expectancy and whether the country is located in East Asia. That African growth is peculiar is shown by the fact that the regressor with the highest posterior probability happens to be the fraction mining output to GDP in Africa. Notice that when interacted with Africa, mining has the highest posterior probability of 99.9% while it has a posterior probability of 13.6% when considered alone in the non-OECD subsample. In this sample there is also evidence that colonialism impacted post-colonial economic performance. With a significant number of former Spanish and French colonies in this sample, the colonial legacy is captured by the fraction of the population that professes the Catholic faith (61.9%) and the fraction of the population that speaks a European language (52.3%). However, the results also suggest that Africa differs from the non-OECD countries in a slightly different way than it differed from the global sample.

Similar implications can be drawn from the sample of former colonies. Just like in the sample of developing countries, cross-country variation in growth rates among former colonies is most influenced by initial GDP, life expectancy, the fraction of the population that's Confucian and the fraction Muslim. Similarly, just like in the non-OECD sample, the results show that the fraction of mining output in GDP in Africa has the highest explanatory probability at 99.8%.

We have also tested the robustness of these results to alternative model averaging methodologies, namely BACE (based on Sala-i-Martin, Doppelhofer and Miller, 2004) and BIC-BMA (based on Raftery, Madigan and Hoeting, 1997). Results and a discussion of the implications of these alternative methodologies are presented in Appendix B. In summary, just like results from the interaction model suggest, irrespective of

Table 2: Regressor posterior probabilities in interaction models using FLS-BMA

	Regressor	**A*Global**	**A*non-OECD**	**A*Colonies**
1	ln GDP per capita, 1960	100	95.4	97.6
2	Life expectancy, 1960	100	90.2	97.6
3	A*Tropical location	100	41.1	22.5
4	East Asian	93.9	69.6	25.3
5	Fraction Muslim	83.5	19.8	61.9
6	A*Malaria prevalence, 1960s	78.9	12.0	11.2
7	A*Mining, 1960	76.1	99.9	99.8
8	A*Landlocked	72.2	3.1	7.6
9	A*Land area	62.8	20.3	28.0
10	A*Colony	54.6	27.2	1.4
11	A*European language	51.4	3.0	9.3
12	Primary export	49.9	3.0	7.7
13	A*Fraction speaking English	47.1	0.5	0.7
14	OECD	45.3	n/a	5.4
15	A*Primary exports, 1970	43.1	33.5	18.9
16	Fraction European language	24.4	52.3	14.4
17	Fraction Confucian	21.7	32.9	74.6
18	Malaria prevalence, 1960s	12.8	2.0	1.1
19	A*Laborforce, 1960s	10.6	7.8	18.8
20	Latin America	7.5	9.3	20.3
21	Fraction Catholic	7.2	61.9	8.7
22	Landlocked	7.1	2.0	21.5
23	Mining, 1960	4.9	13.6	1.48
24	Primary school enrolment, 1960	4.4	5.4	1.3
25	Fraction Protestant	3.8	5.7	1.4
26	Tropical location	3.5	0.8	2.1
27	A*Primary school enrollment, 1960	3.2	1.0	0.6
28	A*GDP60	2.8	0.4	1.8
29	sub-Saharan Africa	2.7	2.0	n/a
30	Fraction Buddhist	2.0	4.5	0.3
31	A*Life expectancy, 1960	1.5	0.4	1.1
32	A*fraction Muslim	1.4	0.6	1.1
33	A*Urbanization rate	1.1	1.0	0.6
34	Secondary school enrollment, 1960	1.1	2.0	0.4
35	A*British colony	1.1	2.0	1.0
36	Fraction Hindu	1.0	0.4	0.2
37	A*Ethnoliguistic fractionalization	1.0	0.6	0.8
38	Former colony	0.9	0.6	n/a
39	A*Secondaryschool enrollment, 1960	0.9	0.3	0.6
40	Spanish colony	0.7	0.8	1.3
41	Land area	0.6	0.2	1.6
42	Absolute latitude	0.5	3.4	0.4
43	A*Catholic	0.5	1.0	3.9
44	Urbanization rate	0.3	0.2	0.3
45	French colony	0.3	0.2	0.8
46	British Colony	0.3	0.6	1.6
47	A*French colony	0.3	0.4	0.4
48	High education enrolment 1960	0.2	1.5	0.5
49	A*Fraction Protestant	0.2	0.6	0.3
50	Ethnolinguistic fractionalization	0.2	0.3	0.7
51	A*Absolute latitude	0.2	0.2	0.4
52	Fraction Jewish	0.1	0.3	0.2
53	Fraction English speaking	0.1	0.2	0.5
54	Laborforce	0.1	0.3	0.3

the model averaging methodology, there is evidence that colonialism and initial conditions have impacted Africa differently from either the world, the rest of the developing world and even other former colonies. That is, whereas there is some uniformity regarding regressors with highest posterior probabilities across the other regions, African results are not comparable.[14]

3.1 Discussion

Results given in Table 2 above and Tables B1 and B2 in Appendix B clearly show that factors governing growth in Africa are significantly differently from the rest of world. In general, the results revealed that initial conditions at independence have exerted a lasting impact on post-independence growth in all regions including Africa. Yet while the channels through which this happened are quite consistent for the rest of the world, they are peculiar and unique for Africa. To begin with, when we account for the uncertainty inherent in model selection we find that the variables that best explain African growth are different from those that explains global growth. Similarly, when we account for parameter heterogeneity, the results suggest that the differences in growth determinants between Africa and the rest of the world are neither driven by presence of developed countries in the global sample nor by the mere fact that African countries are mostly former colonies. Therefore, we hypothesize that these differential impacts are largely because of the interplay between Africa's geography and colonialism.

From our BMA results, it is unequivocally apparent that more than any other region, geographical and ecological variables are more important in explaining Africa's post-independence economic growth. There are several avenues through which geography can affect colonial development in Africa. For example, the geography hypothesis postulates that geographical and ecological variables shape economic development directly, by influencing productivity, and indirectly, by influencing the choice of political and economic institutions (see, e.g. Gallup, Sachs and Mellinger, 1998).[15] Alternatively, one can argue, following Acemoglu Johnson and Robinson (2001) hypothesis, that Africa's geography has impacted its post-colonial growth directly through institutions. As these authors note, 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.

The Acemoglu-Johnson-Robinson hypothesis is especially plausible in light of our BMA results as the most important regressors in explaining Africa's growth is the fraction of mining in GDP followed by tropical location and malaria prevalence. Given the high regressor posterior probability associated with malaria, we take the "germ" view of institutions, and argue that the dominance of the mining in GDP may actually reflect

[14] We also tested whether these results hold if we re-estimate the regressor posterior probabilities without an African interaction dummy. In other words, we have also implemented the BMA framework (without interaction dummies) for the global, Africa, non-OECD and former colony samples. For the global sample we considered $k^G = 32$ regressors and $n^G = 93$ observations so that Z^G is a 93×32 design matrix. 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. Therefore, in the Africa subsample we have $k^A = 22$ regressors and $n^A = 30$ observations (sub-Saharan Africa countries) so that Z^A is a 30×22 design matrix. For the non-OECD subsample we have $k^N = 31$ and $n^N = 69$ and the former colony subsample $k^C = 31$ and $n^C = 69$. The fact that $k^N = k^C$ and $n^N = n^C$ is a coincidence. The sample results are qualitatively similar to our benchmark interaction dummy global results with Africa regressors flagged out to be important being very different from the world, non-OECD and former colony samples. In order to redeem space, the posterior regressor probabilities derived using FLS-BMA (benchmark), BACE and BIC-BMA, and a discussion of their implications are available by the authors upon request.

[15] In addition, according to Sowell (1998) geography may play a significant role in making cultural interaction more difficult between Africa and the rest of the world and within Africa. This lack of interaction is evident from the fact that whereas 33% of populations in other former colonies speak a European language in Africa it is only 3%.

the legacy of extractive colonial institutions. 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 in GDP. Since 92% of sub-Saharan Africa lies in the tropics and in 88% of the area malaria is endemic, it seems natural for Africa's geography to breed extractive colonial institutions, one of whose manifestation being the fraction of mining in GDP. As such, we argue that dominance of mining is more reflective of the persistence of institutions that promote conditions favorable for rent-seeking than mere geography.

Whereas the germ theory of institutions is about the *nature* of colonialism we also hypothesize that African geography also impacted economic growth through colonialism in another way - the *timing* and *duration* of colonialism. As alluded to earlier, whereas other regions have been under colonialism for at least 300 years, Africa has been formerly colonized for about 70 years.[16] With the exception of South Africa, European settlers came to Africa late, extracted as much as they could and left early. Therefore, at independence Africa's general level of development was significantly lower than the level of development in other regions.

While we acknowledge that initial conditions on independence have an impact on post-independence economic growth, we still do not know if this impacted Africa negatively or positively. In other words, since colonialism happened we have no counterfactual for what Africa's economic performance would have been had Africa not been colonized. Similarly, we do not know if economic performance would be better had African countries remained colonies to date. Yet we know that in areas where geography was favorable, colonies that developed did better than those with poor geography. It also seems that in regions with comparable climatological factors, the level of economic development was positively correlated with the *period* under colonialism.

4 Conclusion

This paper sought to investigate the role of initial conditions and colonialism on post-colonial economic growth in Africa. Since the majority of African countries got their political independence between 1957 and 1966, we took initial conditions predetermined in the 1960s as reflective of the state of development at the close of colonial era, and the impact of variables capturing those initial conditions on post-colonial economic performance as reflecting the legacy of colonialism. In addition, we also attempted to address some common pitfalls that attend to cross-country growth regressions especially problems of model uncertainty, endogeneity of regressors and parameter heterogeneity. To this end we dealt with model uncertainty by using Bayesian Model Averaging (BMA). The issue of endogeneity of regressors was simultaneously dealt with when we chose initial conditions that were predetermined in 1960. Finally, we used an interaction model within the BMA framework to allow for parameter heterogeneity while also estimating the posterior probabilities for different regions.

Our main finding is that initial conditions at colonial independence has exerted a significant impact on Africa's post-colonial economic performance. This has been doubly magnified by Africa's geography. While not arguing for geographical determinism, we have demonstrated that Africa's peculiar geography

[16] Although Portuguese and Arab traders had traded with Africa for centuries, formal colonialism began around 1880, after the "Scramble for Africa" at the Berlin conference organized by Otto Von Bismarch in 1884.

and ecological environment, impacted the nature, timing and duration of colonial relationships with European countries. Consequently, the impact of initial conditions and colonialism on post-colonial economic performance in Africa are different from that in other regions.

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Appendix A

Table A1: List of countries in four samples

	Country	Goobal	Africa	non-OECD	Colony		Country	Goobal	Africa	non-OECD	Colony
1	Algeria	✓	x	✓	✓	48	Argentina	✓	x	✓	✓
2	Benin	✓	✓	✓	✓	49	Brazil	✓	x	✓	✓
3	Botswana	✓	✓	✓	✓	50	Chile	✓	x	✓	✓
4	Burundi	✓	✓	✓	✓	51	Colombia	✓	x	✓	✓
5	Cameroon	✓	✓	✓	✓	52	Ecuador	✓	x	✓	✓
6	CAR.	✓	✓	✓	✓	53	Paraguay	✓	x	✓	✓
7	Congo	✓	✓	✓	✓	54	Peru	✓	x	✓	✓
8	Egypt	✓	x	✓	✓	55	Uruguay	✓	x	✓	✓
9	Ethiopia	✓	✓	✓	x	56	Venezuela	✓	x	✓	✓
10	Gabon	✓	✓	✓	✓	57	Hong Kong	✓	x	✓	✓
11	Gambia	✓	✓	✓	✓	58	India	✓	x	✓	✓
12	Ghana	✓	✓	✓	✓	59	Iran	✓	x	✓	x
13	Kenya	✓	✓	✓	✓	60	Iraq	✓	x	✓	✓
14	Lesotho	✓	✓	✓	✓	61	Israel	✓	x	✓	✓
15	Liberia	✓	✓	✓	x	62	Japan	✓	x	✓	x
16	Madagascar	✓	✓	✓	✓	63	Jordan	✓	x	✓	✓
17	Malawi	✓	✓	✓	✓	64	S. Korea	✓	x	✓	x
18	Mali	✓	✓	✓	✓	65	Malaysia	✓	x	✓	✓
19	Morocco	✓	x	✓	✓	66	Nepal	✓	x	✓	x
20	Niger	✓	✓	✓	✓	67	Pakistan	✓	x	✓	✓
21	Nigeria	✓	✓	✓	✓	68	Philippines	✓	x	✓	✓
22	Rwanda	✓	✓	✓	✓	69	Singapore	✓	x	✓	✓
23	Senegal	✓	✓	✓	✓	70	Sri Lanka	✓	x	✓	✓
24	Sierra Leone	✓	✓	✓	✓	71	Syria	✓	x	✓	✓
25	Somalia	✓	✓	✓	✓	72	Taiwan	✓	x	✓	x
26	South Africa	✓	✓	✓	✓	73	Thailand	✓	x	✓	x
27	Sudan	✓	✓	✓	✓	74	Austria	✓	x	x	x
28	Tanzania	✓	✓	✓	✓	75	Belgium	✓	x	x	x
29	Togo	✓	✓	✓	✓	76	Denmark	✓	x	x	x
30	Tunisia	✓	x	✓	✓	77	Finland	✓	x	x	x
31	Uganda	✓	✓	✓	✓	78	France	✓	x	x	x
32	Zaire	✓	✓	✓	✓	79	Germany	✓	x	x	x
33	Zambia	✓	✓	✓	✓	80	Greece	✓	x	x	x
34	Zimbabwe	✓	✓	✓	✓	81	Ireland	✓	x	x	x
35	Canada	✓	x	x	✓	82	Italy	✓	x	x	x
36	Costa Rica	✓	x	✓	✓	83	Netherlands	✓	x	x	x
37	Dom. Rep.	✓	x	✓	✓	84	Norway	✓	x	x	x
38	El Salvador	✓	x	✓	✓	85	Portugal	✓	x	x	x
39	Guatemala	✓	x	✓	✓	86	Spain	✓	x	x	x
40	Haiti	✓	x	✓	✓	87	Sweden	✓	x	x	x
41	Honduras	✓	x	✓	✓	88	Switzerland	✓	x	x	x
42	Jamaica	✓	x	✓	✓	89	Turkey	✓	x	x	x
43	Mexico	✓	x	x	✓	90	UK	✓	x	x	x
44	Nicaragua	✓	x	✓	✓	91	Australia	✓	x	x	✓
45	Panama	✓	x	✓	✓	92	N. Zealand	✓	x	x	✓
46	Trin. & Tob	✓	x	✓	✓	93	Papua NG	✓	x	✓	✓
47	United States	✓	x	x	✓	Note: ✓ =in sample; x = not in sample					

Table A2: Definitions of variables

Mnemonic	Regressor
	Initial level of development
GDP60	ln GDP per capita in 1960
Mining60	Fraction of mining in GDP in 1960
PRIEXP70	Percentage of primary commodities in exports in 1970
P60	Percentage of pop. above 25 with primary schooling in 1960
LIFE60	Life expectancy in 1960
S60	Percentage of pop. above 25 completed secondary schooling in 1960
H60	Percentage of pop. above 25 with tertiary education in 1960
URB60	Fraction of urban based population in 1960
LAB60	Size of labor force in 1960
	Geographical variables
Area	Land area
ABSLAT	Distance from the equator
MALA66	Malaria prevalence in 1960s
TROPICVAR	Fraction of land area in located in tropics
LANDLOC	Dummy = 1 if country has no sea ports
	Regional variables
SSA	Dummy = 1 if country is in sub-Saharan Africa
LAAM	Dummy = 1 if country is in Latin America
EAST	Dummy = 1 if country is in South-East Asia
OECD	Dummy = 1 if country belongs to OECD
	Colonial variables
COLONY	Dummy = 1 if country is a former colony
BRITISH	Dummy = 1 if country is former British colony
FRENCH	Dummy = 1 if country is a former French colony
SPANISH	Dummy = 1 if country is a former Spanish colony
	Ethnolinguistic diversity
FRAC	Prob. two randomly selected people belong to different ethnic groups
OTHER	Fraction speaking European language
ENGLISH	Fraction speaking English
	Religious variables
BUDDHA	Fraction Buddhist
CATH	Fraction Catholic
CONFUC	Fraction Confucian
HINDU	Fraction Hindu
JEW	Fraction Jewish
MUSLIM	Fraction Muslim
PROT	Fraction Protestant

Appendix B

Robustness analysis using BACE and BIC-BMA

In what follows we present results based on the interaction-dummy models using two alternative model averaging procedures found in the literature. More precisely, we examine robustness of our results from FLS-BMA to BACE introduced by Sala-i-Martin, Doppelhofer and Miller (2004), and BIC-BMA developed by Raftery (1995). This exercise is motivated from existing literature (see, e.g. Discussion and Rejoinder sections of Hoeting, Madigan, Raftery and Volinsky, 1999) suggesting that choice of (both within model and model) priors may significantly affect outcomes.

Although there are various differences between FLS-BMA and BACE, the following two stand out (for extensive discussions indicating the differences between the two approaches see Sala-i-Martin, Doppelhofer and Miller (2004, p. 815): First, whereas the former approach does not control for model size (always implying a preferred model size of $\bar{k} = k/2$), the later does. In the spirit of Sala-i-Martin, Doppelhofer and Miller's arguments for setting the preferred model size to $\bar{k} = 7$, we set ours to $\bar{k} = 15$ to control for the fact that we allow for dummy interactions. We have also examined the robustness of our results with $\bar{k} = 7$ and results remain qualitatively similar. Second, FLS-BMA use proper regressor priors, developed in Fernàndez Ley and Steel (2001b), whereas BACE uses an improper (or diffuse) regressor prior.

Table B1 presents comparable results to our baseline FLS-BMA results presented in Table 2 in the main text using BACE. The main finding from this exercise is that our results are quite robust using BACE as our model averaging approach with the different regressor and model priors. For example, comparing results of the Global-Africa interaction dummy model from the two methodologies (column 3 in Table 2 and Table B1) shows that eleven out of the top twelve regressors (with posterior probability greater than 50%) found to be effective for growth in FLS-BMA, continue to be the most effective in BACE (with posterior probability greater than 27.8% using Sala-i-Martin, Doppelhofer and Miller's cut-off point $\bar{k}/k(= 15/54)$). In general, these results extend to considering the non-OECD-Africa interaction dummy model (column 4 in Table 2 and Table B1) and the Colony-Africa interaction dummy model (column 5 in Table 2 and Table B1).

There are important difference between FLS-BMA and BIC-BMA (for extensive discussions see, e.g. Fernàndez Ley and Steel, 2001b; and Hoeting, Madigan, Raftery and Volinsky, 1999). For example in terms of sampling, FLS-BMA uses a Markov chain Monte Carlo model composition MC^3 sampler, (see, Madigan and York, 1995), whereas BIC-BMA uses Occam's window (see, Madigan and Raftery, 1994). However, the key difference between FLS-BMA and BIC-BMA is based on the choice of within-model (regressor) priors used. As mentioned above, the former approach uses proper priors whereas the later approach uses the Bayesian Information Criterion (BIC) that implies the diffused unit information prior.

Results from using BIC-BMA are presented in Table B2. Although there are more difference between FLS-BMA and BIC-BMA than between FLS-BMA and BACE, and although BIC-BMA results seem to be assigning a lot more weight on the "best" models and effective regressors and little or no weight in the rest of the regressors, our qualitative results hold quite robust. As done previously, comparing results of the Global-Africa interaction dummy model from the two methodologies (column 3 in Table 2 and Table B2) shows that ten out of the top twelve regressors (with posterior probability greater than 50%) found to be effective for growth in FLS-BMA, continue to be effective in BIC-BMA.

This exercise suggests that our main results are robust to alternative regressor and model priors as used in BACE and BIC-BMA. It is worth mentioning that in addition to the regressor posterior probabilities we were also able to obtain and compare the best models using the three alternative model averaging methodologies. The best models obtained under the three approaches were quite different with BIC-BMA finding the "best" models (with the highest R^2). We have also obtained and compared the posterior means and standard deviations of coefficient estimates for all variables considered. In general, these estimates were quite robust across the three approaches. To save space we do not report these results but are available by the authors upon request.

Table B1: Regressor posterior probabilities in interaction models using BACE

	Regressor	A*Global	A*non-OECD	A*Colonies
1	ln GDP per capita, 1960	100	97.9	99.2
2	Life expectancy, 1960	100	98.1	99.6
3	A*Tropical location	29.3	43.6	31.4
4	East Asian	95.9	85.8	40.1
5	Fraction Muslim	80.6	31.9	51.5
6	A*Malaria prevalence, 1960s	20.2	27.0	21.3
7	A*Mining, 1960	100	100	100
8	A*Landlocked	34.1	20.4	26.2
9	A*Land area	83.8	70.5	78.2
10	A*Colony	50.5	55.5	19.2
11	A*European language	65.5	32.4	56.8
12	Primary export, 1970	29.6	15.8	32.4
13	A*Fraction speaking English	6.9	7.6	7.6
14	OECD	82.2	n/a	42.8
15	A*Primary export, 1970	67.2	49.4	41.7
16	Fraction European language	64.2	76.8	53.1
17	Fraction Confucian	43.2	22.1	57.8
18	Malaria prevalence, 1960s	12.8	8.5	7.3
19	A*Laborforce, 1960s	12.8	14.8	22.6
20	Latin America	12.0	14.6	38.1
21	Fraction Catholic	18.4	60.7	15.6
22	Landlocked	21.1	18.0	37.9
23	Mining, 1960	18.6	38.0	21.3
24	Primary school enrolment, 1960	7.4	11.4	13.8
25	Fraction Protestant	14.0	30.7	13.2
26	Tropical location	6.6	16.3	27.4
27	A*Primary school enrollment, 1960	20.5	26.6	22.4
28	A*GDP60	19.1	12.5	21.6
29	sub-Saharan Africa	15.5	12.6	n/a
30	Fraction Buddhist	9.8	8.0	6.9
31	A*Life expectancy, 1960	8.8	11.6	12.8
32	A*Fraction Muslim	18.7	26.5	38.3
33	A*Urbanization rate	21.9	24.9	16.1
34	Secondary school enrollment, 1960	6.1	19.4	22.8
35	A*British colony	9.4	18.0	9.5
36	Fraction Hindu	17.1	13.2	7.6
37	A*Ethnolinguistic fractionalization	5.3	8.4	6.4
38	Former colony	9.1	10.1	n/a
39	A*Secondary school enrollment, 1960	8.7	8.1	8.0
40	Spanish colony	6.2	10.7	12.9
41	Land area	12.3	7.1	18.3
42	Absolute latitude	10.5	35.2	50.2
43	A*Catholic	6.6	8.1	15.6
44	Urbanization rate	4.7	8.8	7.8
45	French colony	4.9	7.1	6.1
46	British Colony	5.6	7.6	7.9
47	A*French colony	5.1	6.9	5.5
48	Higher education enrolment, 1960	6.4	26.3	6.2
49	A*Fraction Protestant	6.4	9.5	7.2
50	Ethnolingistic fractionalization	4.9	8.3	7.2
51	A*Absolute latitude	8.4	10.0	11.9
52	Fraction Jewish	4.8	6.5	6.1
53	Fraction English speaking	4.6	8.8	26.7
54	Laborforce	5.1	5.1	9.0

Table B2: Regressor posterior probabilities in interaction models using BIC-BMA

	Regressor	**A*Global**	**A*non-OECD**	**A*Colonies**
1	ln GDP per capita, 1960	100.0	100.0	100
2	Life expectancy, 1960	100.0	100.0	100
3	A*Tropical location	38.3	22.2	38.2
4	East Asian	100.0	99.5	25.5
5	Fraction Muslim	100.0	42.6	46.9
6	A*Malaria prevalence, 1960s	49.0	26.4	15.4
7	A*Mining, 1960	100.0	100.0	100
8	A*Landlocked	81.4	39.1	66.3
9	A*Land area	100.0	100	100
10	A*Colony	19.5	15.6	30
11	A*European language	69.8	75.1	99.7
12	Primary export, 1970	2.2	19.2	7.7
13	A*Fraction speaking English	0.4	0	0
14	OECD	100.0	n/a	99
15	A*Primary export, 1970	97.8	95.8	92.3
16	Fraction European language	98.8	99.5	73.2
17	Fraction Confucian	91.0	0.5	92
18	Malaria prevalence, 1960s	0	21.1	15.4
19	A*Laborforce, 1960s	0	0	5.1
20	Latin America	0	0.9	13.5
21	Fraction Catholic	0	8.0	0
22	Landlocked	16.6	50.9	n/a
23	Mining, 1960	40.5	91.4	3.2
24	Primary school enrolment, 1960	4.0	0.5	1
25	Fraction Protestant	0	5.0	3.3
26	Tropical location	3.2	62.2	50.4
27	A*Primary school enrolment, 1960	37.1	0	54.5
28	A*GDP60	44.6	12.2	24.2
29	sub-Saharan Africa	44.2	57.9	n/a
30	Fraction Buddhist	2.8	2.5	3.1
31	A*Life expectancy, 1960	4.4	13.0	0
32	A*Fraction Muslim	30.8	67.8	56.1
33	A*Urbanization rate	92.2	95.1	26.9
34	Secondary school enrollment, 1960	0	38.4	5
35	A*British colony	0	n/a	0
36	Fraction Hindu	92.5	40.4	4.8
37	A*Ethnoliguistic fractionalization	0	12.1	3.5
38	Former colony	0.8	10.8	n/a
39	A*Secondary school enrollment, 1960	n/a	0	0
40	Spanish colony	0.5	49.8	42.7
41	Land area	4.3	1.4	28.5
42	Absolute latitude	39.5	83.4	100
43	A*Catholic	0.5	3.4	0
44	Urbanization rate	0.2	0	31
45	French colony	0	0	0
46	British Colony	0	0	0
47	A*French colony	0	0	0
48	Higher education enrolment, 1960	3.4	85.6	0
49	A*Fraction Protestant	0	0	0
50	Ethnolinguistic fractionalization	n/a	13.0	3.8
51	A*Absolute latitude	n/a	n/a	0.3
52	Fraction Jewish	n/a	n/a	n/a
53	Fraction English speaking	n/a	n/a	n/a
54	Laborforce	n/a	n/a	n/a