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Article

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GENERAL & APPLIED ECONOMICS | RESEARCH ARTICLE

On the robust drivers of public debt in Africa: Fresh evidence from Bayesian model averaging approach

Madow Nagou¹, Nimonka Bayale^{2*} and Brigitte Kanga Kouassi³

Abstract: While economic theory suggests a wide range of potential drivers of public debt, there is little consensus regarding the most relevant ones. This paper analyzes the determinants of the public debt in Africa. This is done by adopting a Bayesian Model Averaging (BMA) approach applied to data of 51 African countries, spanning the period 1990–2018. Our results suggest that, among the set of twenty-seven (27) regressors considered, those reflecting international financial and institutional conditions as well as internal economic prospects tend to receive high posterior inclusion probabilities. Then, the study explores the effect of these regressors on public debt by employing the fixed effects (FE) and the system Generalized Method of Moments (GMM) estimators. The results reveal that, foreign aid, fiscal deficit, trade openness, military expenditure, interest and exchange rates, debt-service, domestic credit, government stability index, political regime type and socio-economic crises are the main and robust drivers of public debt accumulation in African countries. These findings are robust to changes in the model specification, the inclusion of socio-economic crises and regional heterogeneities.

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PUBLIC INTEREST STATEMENT

This study applied two complementary approaches to analyze the robust determinants of the public debt in Africa: (i) the Bayesian Model Averaging method which is based Markov chain Monte Carlo sampling and (ii) an econometric approach. The sample is made up of 51 African countries and covered the period 1990–2018. Findings reveal that, foreign aid, fiscal deficit, trade openness, military expenditure, interest and exchange rates, debt-service, domestic credit, government stability index, political regime type and socio-economic crises are the main and robust drivers of public debt accumulation in African countries.

Subjects: Development Policy; Economics and Development; Economics, Finance, Business & Industry; Economics; Finance; Social Sciences Development Studies

Keywords: Bayesian model averaging; panel data modelling; public debt; Africa

JEL classification: C11; C23; F34; N27

1. Introduction

Since the onset of the debt crises in the early 1970s and 1980s, which affected most developing and transition economies, there has been an upsurge in the empirical analysis of the determinants of public debt (International Monetary Fund (IMF), 2019; World Bank Group, 2019; Economic Commission for Africa (ECA), 2019; Easterly, 2002). Indeed, the economic literature has identified several factors both external and internal that can influence public debt (Atta-Mensah & Ibrahim, 2020; Bayale et al., 2020; Calderón & Zeufack, 2020; Chiminya & Nicolaidou, 2015; Fatás et al., 2019; Forslund et al., 2011; Sadik-Zada & Gatto, 2019). Externally, adverse global developments such as global financial crises, oil price shocks, high-interest rates, recessions in industrial and developed countries and weak commodity prices are identified to be the main drivers of public debt accumulation (African Development Bank, 2018; Atta-Mensah & Ibrahim, 2020; Chiminya & Nicolaidou, 2015; Easterly, 2002; Fatás et al., 2019). For instance, the shocks of the global financial crisis and the 2014 terms-of-trade shock have contributed to swelling-up the debt of many African countries. Even some social crises (global health crisis) such as COVID-19 could be part of drivers of public debt accumulation in developing countries (IMF, 2020; World Bank Group, 2019). On the domestic front, macroeconomic policies have been blamed such as fiscal irresponsibility, exchange rate misalignment, policies that deter saving and the institutional framework are often cited as debt determinants (Bayale, 2020a; Calderón & Zeufack, 2020; International Monetary Fund (IMF), 2019; World Bank Group, 2019).

Beyond studies cited above, Bayale et al. (2020), Fatás et al. (2019), Bohn and Veiga (2019) and Alesina and Passalacqua (2016) have found that, even if factors mentioned can explain some of the increases in public debt in recent decades, they cannot account for all of the observed changes. The political factors (for instance, electoral cycles and political regime type) may also generate different incentives to borrow. They are a major cause of overborrowing, though budgetary institutions and fiscal rules can play a role in mitigating governments' tendencies to overborrow. Most of these studies mentioned have applied a wide array of estimation methods on large sample sizes and various periods. This implies that, although it is important to unveil the main causes of public debt, there is no clear consensus on the real drivers of public debt in the literature. For instance, Zdravković (2019), Ksantini (2016), and Karazijiené (2015) provided an overview and critical discussion of the early evidence about the sources of the debt accumulation, reaching no conclusive results.

A theoretical foundation for the hypothesis that economic grievances generate public debt, based on the rational-choice theory and without dismissing non-economic factors, can be found in the papers of Fatás et al. (2019), Aybarç (2019), Alesina and Passalacqua (2016), and Bilan (2016). These authors suggest that the lack of empirical consensus on the causes of debt has to do with its heterogeneity and its link with the economy needs to be deeply investigated, especially in developing countries. This lack of consensus also emerges through the results of some studies that we can mention. For instance, when analyzing and explaining the trajectory of Africa's debt levels over the past decades, Atta-Mensah and Ibrahim (2020) have applied a statistical analysis and found that the interest rate-growth differential is the main drivers of overall debt dynamics in African economies. By focusing on the motives to borrow, Fatás et al. (2019) based on exploratory analysis and established that intertemporal tax-smoothing, fiscal stimulus and asset management can explain some of the increases in public debt in recent years. Coulibaly et al., (2019) indicate

that due to low domestic saving rates, African countries have had to resort to borrowing from a variety of sources, including international debt markets (Eurobond issuances), domestic markets, multilateral institutions, and Paris and non-Paris Club countries to support the growing needs for infrastructure and other economic programmes.

Sadik-Zada and Gatto (2019) investigated into the major drivers of the public debt growth in 184 countries. The authors applied panel data approach. Their findings have shown that, oil abundance, economic growth rate, the share of mineral rent in the total revenue and interest rate payments for foreign borrowings have statistically significant impact on the growth of the public debt, whereas defence spending, unemployment rate, and inflation rate do not have a statistically significant positive impact on the public debt rate. According to Chiminya and Nicolaidou (2015) who investigated into the determinants of external debt in Sub-Saharan Africa using pooled OLS and fixed effects, countries that received debt relief seem to accumulate less debt in comparison to those that did not receive debt relief. Their findings have also highlighted the importance of economic activity in reducing debt in the region. Economies that are more open to international trade reduce their debt burden. Forslund et al. (2011) analyzed the determinants of the composition of public debt in developing and emerging market countries. Authors have found a weak correlation between inflation and the composition of public debt. For Bayale et al. (2020), election events are positively correlated to public debt in African countries when fixed effects and GMM estimator are applied. Hence, it can be observed that, there is no consensus on the drivers of debt in the literature.

Motivated by the lack of consensus on the drivers of public debt, we contribute to the literature by introducing model uncertainty into this context through a Bayesian Model Averaging (BMA) approach. By proceeding in this way, we are able to simultaneously deal with model selection, estimation and inference. Besides the fact that, in most studies mentioned, the majority of the variables suggested in the literature are not taken into account, these previous studies have used haphazard approaches in analyzing the determinants of public debt; however, the Bayesian Model Averaging (BMA) approach improves on the earlier approaches by sequentially selecting key determinants based on posterior inclusion probabilities (PIP). This is a key methodological contribution of the study as researchers are often puzzled with the selection of variables for models. In a nutshell, BMA assigns a prior probability to a set of models and updates it according to the data. The posterior model probabilities are later averaged and used to construct PIPs for the candidate regressors (Sanso-Navarro and Vera-Cabello (2018)). Our aim is to investigate into the drivers of public debts in Africa using this sound methodological approach. Our empirical analysis controls the characteristics of our data on public debt in Africa by implementing the BMA in a panel data model framework. The first contribution of the paper is therefore linked to the methodological approach used. Second, we contribute to the existing literature by providing a more nuanced and in-depth detail on the debt determinants in Africa. Third, relying on the findings, this study proffers useful, relevant and practical recommendations for policy in Africa.

By applying BMA approach in panel data model framework, our analyses suggest that, official development assistance, trade openness, military expenditure, real interest and exchange rates, debt-service, domestic credit, government stability index, political regime type, budget balance, mobile cellular subscriptions and socio-economic crises recorded high PIPs. Furthermore, these findings are robust when the fixed effects (FE) and the system Generalized Method of Moments (GMM) estimators are applied. The remainder of this paper is organized as follows. Section 2 presents data sources and variables. In section 3, we present the empirical strategy adopted in this paper. We present results from our empirical analysis in section 4. Finally, Section 5 concludes, establishes policy recommendations and proposes avenues for future research.

2. Data sources and variables

In this paper, we follow Bayale et al. (2020), Fatás et al. (2019), Alesina and Passalacqua (2016), and Forslund et al. (2011), who identified broad theoretical families linking debt with socioeconomic, political and demographic factors of debt. In this regard, the International Monetary Fund (IMF), the World Bank, the Stockholm International Peace Research Institute (SIPRI), the National Elections Across Democracy and Autocracy (NELDA) and the International Country Risk Guide (ICRG) databases have been used. Thus, we then extracted data on public debt from the World Economic Outlook (WEO) of the IMF database. It contains selected macroeconomic data series such as budget balance, inflation, real effective exchange rate and real interest rate. It was reasonable to extract the data on this first group of variables from there because the IMF, whose mission is to ensure the stability of the international monetary system, has data closer to that of countries (national accounts) on these variables.

Due to the lack of data on some variables, our sample gathers 51 African countries and covers the period 1990–2018 (see Appendix Table A1). A description of the whole set of regressors considered in the baseline empirical analysis is tabulated in Appendix Table A2 above. The second dataset is the World Development Indicators (WDI) of the World Bank. Based on the literature review (see Bayale, 2020a; Bayale et al., 2020; Fatás et al., 2019; Forslund et al., 2011; Sadik-Zada & Gatto, 2019), we extracted some socioeconomic variables including GDP growth, real GDP per capita, gross-fixed investment, official development assistance, debt-service paid, money supply (M2), domestic credit provided by financial sector, trade (imports and exports), natural resources rents, mobile cellular subscriptions (per 1000 people), population growth, and school enrollment. Regarding data on military expenditure and arms imports, it is provided by the SIPRI database.

A last group of variables are reflecting institutional and political conditions. These variables include socioeconomic conditions, corruption and government stability (from the ICRG data), and elections events (from the NELDA) provided by Hyde and Marinov (2019). These are considered in this study because institutional factors as well as electoral cycles (political factors) may also generate different incentives to borrow (see Bayale et al., 2020; Fatás et al., 2019; Bohn & Veiga, 2019; Alesina & Passalacqua, 2016; Forslund et al., 2011).

3. Methodology

3.1. Bayesian Model Averaging (BMA)

In this study, we follow Zeugner and Feldkircher (2015) who offers a new version of the implementation packages of the panel BMA. This approach addresses model uncertainty in a canonical regression problem. As specified in equation (1), suppose a linear model structure, with y being the dependent variable (public debt), α_γ a constant, β_γ the coefficients, and ε a normal (*iid*) error term with variance σ^2 :

$$y = \alpha_\gamma + X_\gamma \beta_\gamma + \varepsilon, \quad \varepsilon \sim N(0; \sigma^2 I) \quad (1)$$

A problem arises when there are many potential explanatory variables in a matrix X : which variables $X_\gamma \in \{X\}$ should be then included in the model? And how important are they? In fact, the direct approach to do inference on a single linear model that includes all variables is inefficient or even infeasible with a limited number of observations (Bayale, 2020b; Forte et al., 2018; Moral-Benito, 2015). The BMA tackles the problem by estimating models for all possible combinations of $\{X\}$ and constructing a weighted average over all of them. If X contains K potential variables, this means estimating 2^K variable combinations and thus 2^K models (Raftery et al., 2017; Zeugner &

Feldkircher, 2015). The model weights for this averaging stem from posterior model probabilities that arise from Bayes' theorem:

$$p(M_\gamma|y, X) = \frac{p(y|M_\gamma, X)p(M_\gamma)}{p(y|X)} = \frac{p(y|M_\gamma, X)p(M_\gamma)}{\sum_{s=1}^{2^K} p(y|M_s, X)p(M_s)} \quad (2)$$

where $p(y|X)$ denotes the integrated likelihood which is constant over all models and is thus simply a multiplicative term (Bayale, 2020a; Okafor & Piesse, 2017; Zeugner & Feldkircher, 2015). Therefore, the posterior model probability (PMP) is proportional to the integrated likelihood $p(y|M_\gamma, X)$, which reflects the probability of the data given model M_γ . The marginal likelihood of model M_γ is multiplied by its prior model probability $p(M_\gamma)$ indicating how probable the researcher thinks model M_γ is before looking at the data (Forte et al., 2018; Moral-Benito, 2015). The difference between $p(y|X)$ and $p(y|M_\gamma, X)$ is that integration is once over the model space ($p(y|X)$) and once for a given model over the parameter space $p(y|M_\gamma, X)$. By re-normalization of the product from above one can infer the PMPs and thus the model weighted posterior distribution for any statistic θ :

$$p(\theta|y, X) = \sum_{\gamma=1}^{2^K} p(\theta|M_\gamma, y, X) \frac{p(M_\gamma|y, X)p(M_\gamma)}{\sum_{s=1}^{2^K} p(M_s|y, X)p(M_s)} \quad (3)$$

The model prior $p(M_\gamma)$ has to be elicited by the researcher and should reflect prior beliefs. A popular choice is to set a uniform prior probability for each model $p(M_\gamma) \propto 1$ to represent the lack of prior knowledge. The specific expressions for the marginal likelihoods $p(M_\gamma|y, X)$ and the posterior distributions $p(\theta|M_\gamma, y, X)$ depend on the chosen estimation framework. The literature standard is to use a *Bayesian regression* linear model with a specific prior structure in which each individual model M_γ suppose a normal error structure (Bayale, 2020b; Okafor & Piesse, 2017; Sanso-Navarro & Vera-Cabello, 2018; Zeugner & Feldkircher, 2015). In this study, we applied the panel BMA approach in the linear regression framework to bring out conclusions regarding the significance of particular potential regressors with the use of either an averaged t statistic or a Bayesian posterior probability for each variable. The reader interested in their further derivation as well as the derivation of BMA formulas might refer to one of the papers which incorporate this technique (see Fragoso et al., 2018; Moral-Benito, 2015). There also exist numerous other papers, which make use of it in different fields (see Bayale, 2020b; Sanso-Navarro & Vera-Cabello, 2018).

3.2. Panel data model specification

Beyond BMA regressions, we followed the panel data approach used in the majority of recent studies (Bayale, 2020c; Bayale et al., 2020; Calderón & Zeufack, 2020; Chiminya & Nicolaidou, 2015; Fatás et al., 2019; Forslund et al., 2011; Sadik-Zada & Gatto, 2019), focusing on the relationship between various factors and public debt. Hence, let Y represent an observation and X represent a $p \times 1$ vector of covariates that we aim to investigate the degree of association to Y through the linear panel data model specified as follows:

$$Y = \gamma X + \epsilon, \quad (4)$$

where γ is a $1 \times p$ parameter vector of fixed effects, ϵ is a random effect and X a vector of explanatory variables (potential drivers of public debt). Explanatory variables will be those selected by the BMA approach. After selecting the variables, it is therefore obvious that, the X of equation 4 will be less or equal to the X_γ of equation 1 ($X \leq X_\gamma$). A more adequate specification of equation 4 will be given in the next section after applying the appropriate statistical and economic tests.

Table 1. Bayesian model averaging results (Baseline)

	PIP	Post Mean	Post SD	Cond.Pos.Sign	Idx
aid	1.0000	0.2061	0.0283	1.0000	1
open	1.0000	0.1297	0.0254	1.0000	2
debt_ser	1.0000	0.1422	0.0262	1.0000	3
miexp	1.0000	0.1922	0.0300	1.0000	17
int_r	1.0000	-0.2128	0.0303	0.0000	18
gov_index	1.0000	0.1586	0.0257	1.0000	19
pol_sys	1.0000	-0.1621	0.0295	0.0000	22
cred_fin	1.0000	0.3023	0.0263	1.0000	27
bud_bal	0.9834	-0.0896	0.0268	0.0000	10
mobil_1000	0.6976	-0.0556	0.0432	0.0000	26
exch_cpi	0.5998	-0.0422	0.0395	0.0000	9
corr_index	0.5003	-0.0296	0.0393	0.0000	21
arm_imp	0.3909	0.0247	0.0348	1.0000	11
hipc	0.2188	-0.0136	0.0287	0.0000	23
imp_cov	0.1760	0.0092	0.0225	1.0000	16
infl	0.0813	0.0035	0.0136	1.0000	13
rgdpc	0.0641	0.0034	0.0147	1.0000	15
gdpg	0.0569	-0.0021	0.0103	0.0000	7
soc_index	0.0446	-0.0017	0.0100	0.0157	20
gfinv	0.0408	-0.0013	0.0084	0.0000	8
nat_ress	0.0256	0.0007	0.0060	1.0000	24
assem	0.0249	0.0006	0.0053	1.0000	6
hk_2	0.0175	0.0003	0.0043	1.0000	25
i_ctry	0.0168	0.0002	0.0041	0.9806	28
m2	0.0162	-0.0002	0.0036	0.0000	12
presid	0.0151	0.0002	0.0033	1.0000	4
pop_r	0.0137	-0.0001	0.0032	0.0857	14
legis	0.0123	-0.0000	0.0026	0.0000	5
Mean no. regressors		12.1822	Model space 2^K		2.7e+08
No. models visited		34,303	No. Obs.		1,479

PIP denotes the posterior inclusion probability of each variable. Mean and SD are the posterior mean and standard deviation of each coefficient from model averaging, respectively. Cond.Pos.Sign, the conditional posterior probability inclusion, sign certainty and Idx denotes the index of the variables.

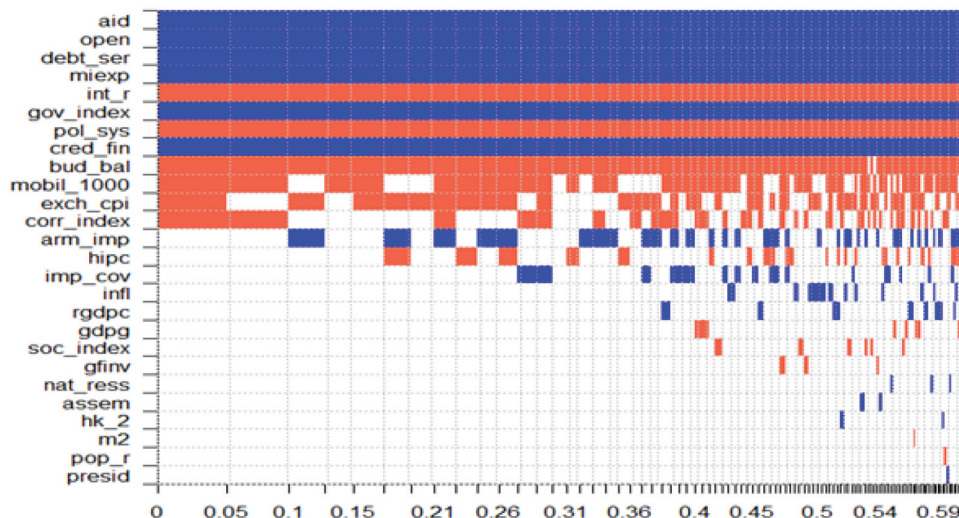
4. Results and discussion

4.1. BMA results

In line with the aim of this paper, [Table 1](#) shows the results obtained from the BMA approach. Indeed, the upper part of the table shows the variable names and their corresponding statistics while the lower part of the Table presents model size and model priors such as the number of observations (1,479), the number of models visited (34,303) and the posterior expected model size, which is equal to 12.18 in our case. In [Table 1](#), the first three (03) columns report, for each variable, the PIP, the mean and standard deviation of estimated coefficients when African public debt is

Figure 1. Cumulative model probabilities (baseline).

Figure 1 is the image plot: Blue color corresponds to a positive coefficient, red to a negative coefficient, and white to non-inclusion of the respective variable. The horizontal axis is scaled by the models' posterior model probabilities.



considered. These latter figures can be interpreted, respectively, as a BMA point estimation and standard error (Bayale, 2020b; Frago et al., 2018).

It can be observed that, official development assistance, trade openness, debt-service paid, military expenditure, real interest rate, government stability index, political regime type and the domestic credit provided by financial sector are priority variables that are included in the models visited ($PIPs = 100\%$). A part from this first group of variables, high PIPs are also observed for budget balance, mobile cellular subscriptions (infrastructure indicator), real effective exchange rate and corruption index ($PIPs \geq 50\%$). To expand the model, arm imports, HIPC and import cover can also be considered ($PIPs \geq 10\%$). When we look at the posterior mean of each coefficient of the identified variables from model averaging, we can comment that, real interest rate, political regime type, budget balance, mobile cellular subscriptions, real effective exchange rate are regressors with high PIPs and a negative influence on public debt in Africa. Moreover, corruption index, highly indebted poor countries initiative, GDP growth, socioeconomic conditions index, gross fixed investment, money supply, population growth and legislative elections have a negative influence on public debt, but with very lower PIPs. In contrary, official development assistance, trade openness, debt-service paid, military expenditure, credit provided by financial sector, arms imports, inflation, natural resources rent and presidential elections are increasing public debt in Africa.

A visual summary of the results described above is presented in Figure 1. It shows the cumulative baseline model probabilities. Each graph ranks, vertically, the potential determinants of public debt according to their PIPs. Furthermore, selected models are ordered, horizontally, taking into account their posterior probability, which is proportional to the column width. A colored rectangle reflects that the variable is included in the model and indicates the sign of its estimated influence (blue when positive and red when negative). For each specification, official development assistance, military expenditure and real interest rate are consistently included in all selected models. Other variables that display high PIPs are trade openness, debt-service paid, government stability index, political regime type, domestic credit provided by financial sector, budget balance, mobile cellular subscriptions, real effective exchange rate and corruption index. Precisely, the best model will include these variables with 5% posterior model probability whereas, the second group

of variables that includes arm imports, HIPC and import cover ($10\% < PIP < 50\%$), could be used in the extended model with 31% posterior model probability.

4.2. Panel data regression analysis

The estimates tabulated in Table 1 cannot be interpreted in the usual regression model partial derivative sense. Therefore, in this subsection, we provide direct impact estimates that describe how changes in the selected explanatory variables affect the level public debt in African countries. Hence, based on the results of the BMA approach, we specify the following empirical equation (5) deriving from equation (4) as ¹ follows:

$$DEBT_{i,t} = \gamma_0 + \gamma_i X_{i,t} + \varepsilon_{i,t}, \quad (5)$$

where $DEBT_{i,t}$ is the dependent variable in this model (public debt), measured as the total debt owed by government to domestic residents, foreign nationals and multilateral institutions such as the IMF, expressed as a percentage of GDP; and the composite error term $\varepsilon_{i,t} = v_i + \eta_{i,t}$. γ_i represents the coefficients of the selected drivers. The vector $X_{i,t}$ contains a list of control variables which are obtained based on BMA approach and the standard literature. These include budget balance as a percentage of GDP, real interest rate, trade openness, government stability, corruption index and political system (Agbloyor, 2019; Bayale et al., 2020; Bohn & Veiga, 2019; Chiminya & Nicolaidou, 2015; Forslund et al., 2011); aid, debt service, credit to financial sector and exchange rate (Gomez-Gonzalez, 2019; Sadik-Zada & Gatto, 2019); military expenditure, arm imports, imports cover, mobile cellular subscriptions, and the highly indebted poor countries initiative (Bayale, 2020a, 2020b; Chiminya & Nicolaidou, 2015; Sadik-Zada & Gatto, 2019). We expect a positive relationship between budget balance, aid, real interest rate, military expenditure, arm imports, respectively, and public debt (Bayale et al., 2020; Bohn & Veiga, 2019). Contrariwise, we expect a negative relationship between trade openness, imports cover, real interest rate, debt service, government stability, corruption index (Gomez-Gonzalez, 2019; Forslund et al., 2011). Furthermore, a negative relationship between highly indebted poor countries initiative, political system and public debt is expected (Chiminya & Nicolaidou, 2015).

With regard to the empirical strategy, it is imperative to note that, the empirical results based on the estimation of equation (5) would be consistent across two types of estimation procedures. Hence, we first employ a fixed effects model to address unit heterogeneity (Wooldridge, 2019, 2016), given the expected country-specific differences in the time-series cross-sectional data. Moreover, the results of a Hausman test also favour a fixed effect over a random effects specification, rejecting the null hypothesis $\chi^2_{(15)} = 51.369$, corresponding to a probability of 0.001. This implies that, the fixed effects estimates are consistent (Appendix Table A3). However, a potential problem with the fixed effects specification is that, this approach does not take into account for potential bias of endogeneity. This problem paramount in panel data where the time T is quite small. In social science data sets like ours with a $T \geq 20$, scholars have found that the potential bias from using a fixed effects estimator in these regressions is likely to be quite small (Bayale et al., 2020; Kaplan & Thomsson, 2017). We therefore resolve these problems by relying on the dynamic panel Generalized Method of Moments (GMM) estimation approach (Arellano & Bond, 1991; Rodman, 2009) where we can estimate equation (5) by using the first difference or system GMM after introduction of the lag of the public debt. Since v_i may be correlated with other regressors, we can first difference to eliminate the country-specific effect. However, this approach has very poor finite properties both in terms of bias and precision, especially when the explanatory variables are persistent over time as their lagged values tend to be weak instruments and predictors of endogenous changes (Blundell & Bond, 1998). In that case, the appropriate technique capable of yielding consistent and unbiased estimates is the system GMM which rests on the

combination of the system regression in differences with the regression in levels (Arellano & Bover, 1995; Blundell & Bond, 1998). In that process, two tests will be important: the serial correlation test which examines the null hypothesis that the error term is serially uncorrelated and the Hansen-Sargan's test examines the exogeneity of the instruments used in estimation process (Bayale et al., 2020).

4.3. Panel data estimates

The descriptive statistics are tabulated in Appendix Table A4 below. It can be observed that, the mean of public debt is about 67.34% of GDP over the sample period. This amount suggests that, debt has been an important source of development finance for African countries. Debt service is important because it represents 34.58% of GDP. The budget deficit represents on average more than 3.62% of GDP. This reflects a financing need that external resources such as debt and foreign aid (9.80% of GDP) would help to meet. On average, African countries have imported 9.647 thousand of arms per year, and the military expenditure recorded 1.12% of their GDP. Regarding trade openness, real interest rate, mobile cellular subscriptions and real effective exchange rate; these variables have recorded a mean about 41.05%, 2.09%, 252.83 per 1000 people and 397.12, respectively. The domestic credit provided by financial sector in Africa recorded 25.89% of GDP. This implies that, the credit affected to economies seems to be low. With regard to institutional variables, government stability recorded a mean of 7.6 of 12, whereas corruption recorded a mean of 2.69 of 6. These scores suggest high risk of government stability and corruption in Africa. Almost all of the standard deviations show low deviations, indicating that, the data points tend to be close to the mean. The values of skewness and kurtosis indicate that, almost all variables are normally distributed because they are closer to 0 and 3, respectively. The correlation results are exhibited in Appendix Table A5. These correlations show a positive association between public debt and official development assistance and trade openness, respectively. In addition, it can be observed a positive association between public debt and military expenditure in Africa. Contrariwise, there is a negative correlation between real interest rate, budget balance and mobile cellular subscriptions, respectively and debt. Real effective exchange rate, corruption index and the highly indebted poor countries initiative are also negatively correlated to public debt, whereas government stability index have a positive association with the public debt. Furthermore, the correlation matrix results indicate that, variables have, overall, low values. This implies that, all these variables can be maintained in the same empirical model without risk of creating a bias in the econometric results.

In Table 2, we present our results using both fixed effects and system GMM estimators. Two equations are estimated. The first equation is where the level public debt is explained by variables that recorded high level of PIPs ($PIPs \geq 50\%$). The second equation takes back the first one by adding variables with $10\% \leq PIP < 50\%$. These variables include arms imports, the highly indebted poor countries initiative and import cover in terms of months. The findings are robust irrespective of the estimation technique. Indeed, according to the reported results, almost all explanatory variables significant. This is like that because they were efficiently selected by the BMA approach. Official development assistance, trade openness, debt-service paid and military expenditure have a positive and significant effect on public debt in Africa. Hence, depending on the component of foreign aid, it contributing to debt accumulation in Africa. For instance, when analyzing the relation between foreign aid and fiscal resources mobilization in WAEMU countries, Bayale (2020c) find that, more than 43% of the total aid are loans. These kinds of loans can generate debt in countries. The results suggest that, more open economies are likely to have high debt levels compared with those who are less open to trade, as the coefficient of that variable is positive and significant (Bayale et al., 2020; Sadik-Zada & Gatto, 2019). This is consistent with Forslund et al. (2011) who found the effect of openness to be positively related to external debt in a group of middle-income countries.

Table 2. Baseline results: Fixed Effects (FE) and system GMM estimates

debt	Fixed Effects		System GMM	
cons	10.675*	12.199***	7.908***	9.182***
	(0.095)	(0.003)	(0.000)	(0.001)
debt_1	-	-	0.827***	0.827***
	-	-	(0.000)	(0.000)
aid	0.761***	0.745***	0.084***	0.052*
	(0.000)	(0.000)	(0.000)	(0.089)
open	0.043***	0.044***	0.102***	0.126***
	(0.004)	(0.000)	(0.000)	(0.000)
debt_ser	0.383***	0.394***	0.283***	0.252***
	(0.000)	(0.000)	(0.000)	(0.000)
miexp	4.883***	4.927***	-0.492***	-0.804***
	(0.000)	(0.000)	(0.002)	(0.117)
int_r	-3.355***	-3.216**	-0.804***	-0.654**
	(0.000)	(0.011)	(0.000)	(0.014)
gov_index	0.399***	0.983***	0.525***	0.689***
	(0.000)	(0.000)	(0.000)	(0.000)
pol_sys	-5.512***	-3.919***	-1.261***	-1.019***
	(0.000)	(0.006)	(0.000)	(0.000)
cred_fin	0.513***	0.533***	0.175***	0.177***
	(0.000)	(0.000)	(0.000)	(0.000)
bud_bal	-0.193***	-0.205***	-0.498***	-0.055***
	(0.000)	(0.000)	(0.000)	(0.000)
mobil_1000	-0.088**	-0.1134***	-0.029***	-0.042***
	(0.012)	(0.002)	(0.000)	(0.000)
exch_cpi	-0.006***	-0.007***	-0.004***	-0.001***
	(0.004)	(0.002)	(0.000)	(0.001)
corr_index	-1.518**	-1.209***	-1.407**	-1.093***
	(0.029)	(0.000)	(0.036)	(0.000)
arm_imp	-	0.047*	-	0.106***
	-	(0.081)	-	(0.000)
hipc	-	-4.254**	-	-3.624**
	-	(0.027)	-	(0.045)
imp_cov	-	0.214	-	0.192*
	-	(0.108)	-	(0.083)
Adjusted—R2	0.539	0.574	-	-
Prob. Fisher	(0.000)	(0.000)	-	-
Observation	1326	1326	1326	1326
Nb. of countries	51	51	51	51
Nb. of instruments	-	-	38	41
AR (1)/AR (2)	-	-	(0.000)/(0.328)	(0.000)/(0.299)
Hansen test	-	-	(0.184)	(0.175)

*, ** and *** respectively denote significance at 10%, 5% and 1%.

Table 3. Bayesian model averaging results (robustness check)

	PIP	Post Mean	Post SD	Cond.Pos.Sign	Idx
aid	1.0000	0.2058	0.0283	1.0000	1
open	1.0000	0.1281	0.0256	1.0000	2
debt_ser	1.0000	0.1424	0.0262	1.0000	3
miexp	1.0000	0.1933	0.0301	1.0000	23
int_r	1.0000	-0.2123	0.0302	0.0000	24
gov_index	1.0000	0.1582	0.0257	1.0000	25
pol_sys	1.0000	-0.1618	0.0294	0.0000	28
cred_fin	1.0000	0.3028	0.0262	1.0000	33
bud_bal	0.9881	-0.0902	0.0262	0.0000	16
mobil_1000	0.6597	-0.0521	0.0436	0.0000	32
exch_cpi	0.6314	-0.0451	0.0397	0.0000	15
corr_index	0.5121	-0.0299	0.0397	0.0000	27
arm_imp	0.3944	0.0254	0.0352	1.0000	17
hipc	0.2499	-0.0167	0.0322	0.0000	29
imp_cov	0.1541	0.0081	0.0212	1.0000	22
crisis	0.1263	0.0069	0.0206	0.0000	4
infl	0.0679	0.0029	0.0126	1.0000	19
rgdpc	0.0484	0.0024	0.0127	1.0000	21
gdpg	0.0445	-0.0016	0.0091	0.0000	13
soc_index	0.0392	-0.0016	0.0100	0.0151	26
gfinv	0.0315	-0.0011	0.0074	0.0000	14
sout_africa	0.0281	-0.0009	0.0067	0.0000	8
cent_africa	0.0177	0.0004	0.0044	1.0000	5
assem	0.0175	0.0004	0.0045	1.0000	12
nat_ress	0.0175	0.0004	0.0049	1.0000	30
wst_africa	0.0166	-0.0004	0.0043	0.0000	9
hk_2	0.0123	0.0002	0.0036	1.0000	31
m2	0.0113	-0.0001	0.0030	0.0000	18
i_ctry	0.0110	0.0001	0.0033	0.9620	34
east_africa	0.0105	-0.0001	0.0029	0.0000	6
presid	0.0101	0.0001	0.0027	1.0000	10
nor_africa	0.0101	-0.0001	0.0028	0.0000	7
pop_r	0.0099	-0.0001	0.0028	0.0762	20
legis	0.0082	-0.0003	0.0021	0.0000	11
Mean no. regressors		12.5855	Model space 2^k		1.7e+10
No. models visited		32,654	No. Obs.		1,479

PIP denotes the posterior inclusion probability of each variable. Mean and SD are the posterior mean and standard deviation of each coefficient from model averaging, respectively. Cond.Pos.Sign, the conditional posterior probability inclusion, sign certainty and Idx denotes the index of the variables.

Regarding debt service, it appears clearly that, the more debt is important, countries will be paying more debt service. As such, its repayment defines debt sustainability. We also find that military expenditure has a positive and significant effect on public debt in Africa. This is consistent with Bayale's (2020b) conclusions. The author has found that, given the importance of peace and

security issues, Sahel countries tempt to borrow in order to tackle strongly terrorism and instability issues. Furthermore, our estimates are indicating that, the arms imports have a positive and significant impact on public debt. This is in line with the study of Abid and Sekrafi (2020), who investigates the impact of terrorism on public debt in African countries. Authors found that, the rise in terrorism and military expenditure lead to an increase in public debt in Africa.

Turning to the other control variables, Table 2 shows a negative and significant relationship between real interest rate and public debt. When analyzing the determinants of the composition of public debt in developing and emerging market countries, Forslund et al. (2011) have found similar results. Also, there is a negative and significant relationship between budget balance and public debt. As most of African States accumulate budget deficits, our results suggest that, African countries are obliged to borrow in order to finance their deficit. The result is then an accumulation of public debt (Bayale, 2020a; Bayale et al., 2020). With regard to institutional variables, the study employs ICRG's government stability and corruption indexes. We found a negative and significant relationship between government stability and debt. This means that, stable governances have the capacities to contract loans than instable governances. Furthermore, higher level of corruption can reduce countries possibilities to borrow. This suggest that, an uncorrupted government favors a better domestic resources mobilization as well as their better channel towards productive investments (Bayale et al., 2020). Finally, the highly indebted poor countries initiative initiated by Bretton Wood's institutions have significantly reduced African's public debt.

4.4. Robustness checks

To ensure the robustness of our results on the drivers of public debt in Africa, we look deeply at the economic literature to find potentially irregular factors that could affect the accumulation of debt in Africa. Therefore, according to the papers of Jordà et al. (2011), De Fiore and Uhlig (2015), and Wee et al. (2020), the international economic context such as financial or social (sanitary) crises are likely to be factors favouring the accumulation of debt in African countries. Hence, we add to our model one variable that can capture crises effect on debt. That variable was constructed as a dummy, with a value of 1 in crises years and 0 otherwise. We also consider regional dummies representing the five regions according to the United Nations Economic Commission for Africa (UNECA): North Africa, West Africa, Central Africa, East Africa and Southern Africa. This allow us to proxy for the possible presence of unobserved heterogeneity by region in our database. We then rerun econometric estimations by taking into account these dummy variables, first for the whole Africa, and second for regional blocs as mentioned above.

Table 3 and Figure 2 exhibit the robustness analysis results relying on the BMA approach, whereas Table 3 tabulates econometric results. Indeed, the introduction of socio-economic crises and regional dummies does not alter the main conclusions drawn about the regressors with a more robust and significant relationship with public debt. Almost all these new variables that have been introduced have recorded lower PIPs (less than 50%). Looking at their posterior coefficients, it can be observed that, crises have a positive influence on public debt in Africa. This means that, socio-economic crises are likely to increase Africa's debt (De Fiore & Uhlig, 2015; Wee et al., 2020). At the regional level, it can be observed that, belonging to Central Africa seems to increase the probability of indebtedness since its coefficient is positive. This is not the case for the four other Africa's regions. Overall, the high inclusion probabilities of variables that were observed in the baseline results do not change (Table 2). All these results are consistent with those presented by the visual summaries in Figures 2, where the variable "crisis" is colored in blue with 29% posterior model probability. Specially, the Figure (Figure 2) shows that, socio-economic crises have spurred public debt in African countries Table 4.

Table 4. Estimates for Africa and by region

Variables	Africa			Regional level analyses (using FE estimator)			
	FE	GMM	Central	East	North	Southern	West
cons	12.969* (0.071)	8.368** (0.047)	13.214* (0.078)	7.265* (0.081)	6.854* (0.090)	8.326** (0.040)	9.087* (0.068)
debt_1	-	0.824*** (0.000)	-	-	-	-	-
aid	0.754*** (0.000)	0.044** (0.048)	0.984*** (0.000)	0.877** (0.019)	0.963*** (0.041)	0.254** (0.024)	0.884*** (0.000)
open	0.041** (0.014)	0.113*** (0.000)	0.051** (0.017)	0.069*** (0.009)	0.072*** (0.007)	0.038*** (0.001)	0.069*** (0.004)
debt_ser	0.397*** (0.000)	0.242*** (0.000)	0.514*** (0.000)	0.374*** (0.000)	0.488*** (0.000)	0.497*** (0.000)	0.299*** (0.000)
miexp	1.974*** (0.000)	1.524** (0.019)	1.251*** (0.000)	1.542** (0.027)	1.365*** (0.000)	1.057** (0.018)	1.688*** (0.000)
int_r	-3.231 (0.000)	-2.838*** (0.001)	-3.058*** (0.000)	-2.981*** (0.003)	-2.635*** (0.000)	-3.047*** (0.001)	-2.994*** (0.000)
gov_index	1.903*** (0.000)	0.714*** (0.000)	0.894*** (0.000)	1.057*** (0.000)	1.254*** (0.000)	1.056*** (0.000)	0.993*** (0.000)
pol_sys	-3.847*** (0.007)	-1.134*** (0.000)	-3.215*** (0.000)	-2.558*** (0.000)	-2.367*** (0.000)	-3.006*** (0.000)	-2.771*** (0.000)
cred_fin	0.543*** (0.000)	0.174*** (0.000)	0.458*** (0.000)	0.556*** (0.000)	0.458*** (0.000)	0.684*** (0.000)	0.704*** (0.000)
bud_bal	-0.205*** (0.000)	-0.055*** (0.000)	-0.247*** (0.000)	-0.301*** (0.000)	-0.407*** (0.000)	-0.325*** (0.000)	-0.269*** (0.000)
mobil_1000	-0.088** (0.020)	-0.048** (0.011)	-0.098** (0.028)	-0.066** (0.041)	-0.059** (0.033)	-0.084** (0.036)	-0.954** (0.025)

(Continued)

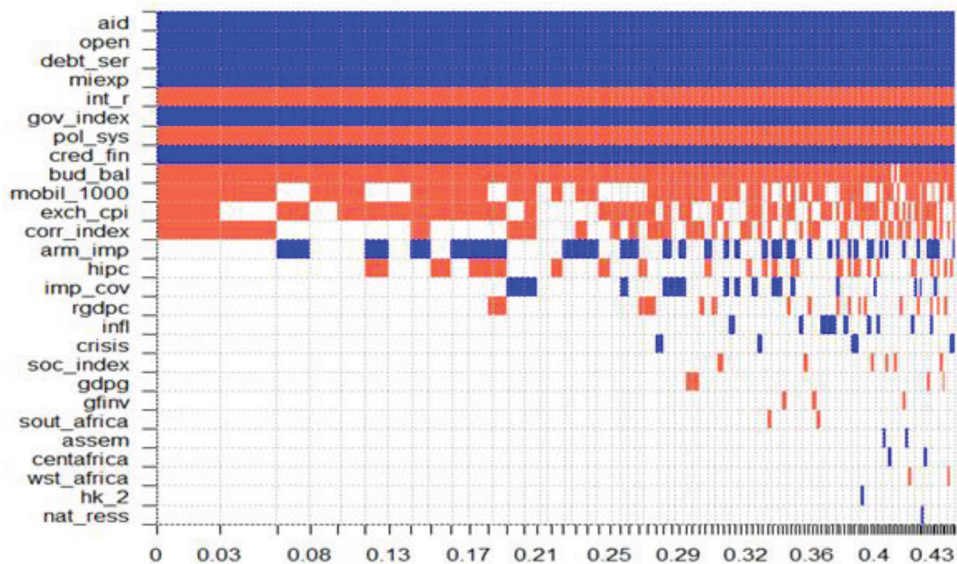
Table 4. (Continued)

Variables	Africa		Regional level analyses (using FE estimator)					
	FE	GMM	Central	East	North	Southern	West	
exch_cpi	-0.077*** (0.002)	-0.051*** (0.001)	-0.057*** (0.000)	-0.065*** (0.001)	-0.049*** (0.003)	-0.538*** (0.004)	-0.049*** (0.000)	
corr_index	-1.361*** (0.002)	-1.307*** (0.000)	-1.254*** (0.003)	-1.006*** (0.007)	-1.355*** (0.001)	-1.233*** (0.019)	-1.701*** (0.008)	
arm_imp	0.032** (0.040)	0.099*** (0.000)	0.068** (0.017)	0.038** (0.031)	0.052** (0.038)	0.036** (0.043)	0.046** (0.029)	
hipc	-4.696** (0.015)	-3.543* (0.069)	-4.356** (0.012)	-4.125** (0.023)	-3.984** (0.018)	-3.187** (0.017)	-4.695** (0.022)	
imp_cov	0.085** (0.025)	0.049** (0.013)	0.067** (0.011)	0.098** (0.036)	0.063** (0.093)	0.049** (0.028)	0.084** (0.015)	
crisis	2.827** (0.032)	2.139** (0.047)	2.654*** (0.000)	2.641*** (0.000)	2.749** (0.026)	2.599** (0.011)	2.996*** (0.003)	
Adjusted—R2	0.614	-	0.594	0.627	0.584	0.632	0.598	
AR (2)	-	(0.279)	-	-	-	-	-	
Hansen test	-	(0.384)	-	-	-	-	-	
Prob. Fisher	(0.000)	-	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Obs/Nb. of count	1326 (51)	1326 (51)	1326 (51)	1326 (51)	1326 (51)	1326 (51)	1326 (51)	

Note: *, **, and *** respectively denote significance at 10%, 5% and 1%.

Figure 2. Cumulative model probabilities (robustness check).

Figure 2 is the image plot: Blue color corresponds to a positive coefficient, red to a negative coefficient, and white to non-inclusion of the respective variable. The horizontal axis is scaled by the models' posterior model probabilities.



The same results can be observed when we compare regional level analyses to Africa's sample estimates tabulated in Table 3. The coefficients associated to crises are positive and significant everywhere. This is like that because, when crises occur, the governments are borrowing more than expected. For instance, this year 2020, several governments have borrowed or will borrow to face the COVID-19 pandemic consequences on their economies (IMF, 2020; World Bank, 2020). Finally, it can be seen that, the regional level estimates are consistent with those of the whole Africa, which are also strongly consistent with the results of the baseline model tabulated in Table 2.

5. Concluding remarks

This paper contributes to the empirical literature on the robust drivers of public debt in Africa by introducing model uncertainty to cover the period spanning from 1990 to 2018. With this aim, a Bayesian Model Averaging (BMA) has been implemented within a panel data model framework to select main potential factors that drive public debt accumulation in African countries. By applying this approach, we have been able to take into account the possible presence of unobserved heterogeneities in our sample's database. Also, regional dummies were taken into account. For, each variable of the model, the PIP, the mean and standard deviation coefficients are estimated. Likewise, cumulative model probabilities, size and index of models and posterior predictive density for public debt in Africa were presented and analyzed to check the consistency of the whole model. Furthermore, we employed fixed effects and system GMM estimators to provide direct impact estimates that describe how changes in the selected explanatory variables affect the level public debt in Africa.

The empirical findings support the fact that, official development assistance, trade openness, military expenditure, real interest rate, debt-service paid, domestic credit provided by financial sector, government stability index, political regime type, real effective exchange rate, budget balance and mobile cellular subscriptions are the main drivers of public debt accumulation in Africa. For this group of variables high PIPs are observed. These results are consistent with those obtained when econometric approaches (fixed effects and GMM) are applied. More importantly, findings hold regardless of the estimated equation and the estimation approach applied. In contrast, some socioeconomic and political factors such as GDP growth, gross fixed investment,

natural resources, money supply, population growth, inflation, human capital, corruption index, socioeconomic conditions index and types of elections events have recorded lower PIPs, showing that, these factors have little influence on public debt. Thus, their statistical impact is benign. Moreover, it should be also noted that, the taking into account of the socio-economic crises and regional heterogeneities does not change conclusions.

These results imply that, very profound economic, political and institutional reforms are critically required in managing and controlling the level of indebtedness for debt sustainability in Africa countries. They should enhance data coverage of debt and debt exposure. Countries therefore need to embark on better strategies for the management of their debt so as to borrow at lowest possible cost. It should be important for African countries to design and implement appropriate policies to increase private investment as large public debt chocks-off private investment. Efficiency in the classic tax collection, transparency and the use of local currency bond markets are possibilities that should not be overlooked. Furthermore, African countries need to work collectively to minimize governance failures, corruption and minimize the Illicit Financial Flows (IFFs). For instance, effectively combating IFFs would require policies at home as well as global cooperation on the taxation of multinational corporations. In addition, enforcement on taxation and better governance in natural resources would mobilize substantial resources to finance Africa's developmental needs. Likewise, sound fiscal policy coupled with real monetary policy would be important. A stable macroeconomic environment is a necessary ingredient for enhancing economic transformation process and growth. African governments should therefore strive to maintain macroeconomic stability. Hence, our future research could examine in greater depth how specific institutional frameworks, such as fiscal rules, inflation targeting or robust financial supervision and regulation could influence the public debt and its composition in some specific African economic and/or monetary zones. In doing this, threshold models could be applied. This will allow comparisons to be made at the regional level.

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Note

1. —It was possible to include a nonlinearity assumption in this specification. However, given the plethoric number of explanatory variables (15 variables) selected by the BMA approach and for the parsimony of the model, we simply specified a linear model. The relationship between debt and some specific variables could be studied in future research by applying threshold models for instance.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Declaration of interests

The authors also declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1. The list of countries included in the sample

The countries that have been included in the empirical analysis are Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cabo Verde, Central African Republic, Chad, Comoros, Dem. Rep. of Congo, Congo, Côte d'Ivoire, Djibouti, Egypt, Equatorial Guinea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, São Tomé and Príncipe, Senegal, Seychelles, Sierra Leone, South Africa, Sudan, Tanzania, Togo, Tunisia, Uganda, Zambia and Zimbabwe.

The study period is spanning from 1990 to 2018.

For robustness analysis, these countries have been grouped according to their geographic region following the United Nations Economic Commission for Africa (UNECA)'s list of economies (Central Africa, Eastern Africa, North Africa, Southern Africa and West Africa).

Table A2. Variable description and sources: potential drivers of public debt

N	Variable	Description	Source
1	debt	Public debt (% of GDP)	IMF data
2	bud_bal	Budget balance (% of GDP)	IMF data
3	infl	Inflation (%)	IMF data
4	exch_cpi	Real effective exchange rate (CPI-based)	IMF data
5	int_r	Real interest rate (%)	IMF data
6	hipc	Highly indebted poor countries initiative	IMF classification
7	gdpg	GDP growth (%)	World Bank data
8	gfinv	Gross fixed investment (% of GDP)	World Bank data
9	nat_ress	Natural resources rents (% of GDP)	World Bank data
10	m2	M2 (% of GDP)	World Bank data
11	pop_r	Population growth (%)	World Bank data
12	open	Trade openness (computed)	World Bank data
13	debt_ser	Debt-service paid/GDP	World Bank data
14	imp_cov	Import cover (months)	World Bank data
15	cred_fin	Domestic credit provided by financial sector (% of GDP)	World Bank data
16	aid	Official development assistance (% of GDP)	World Bank data
17	rgdpc	Real GDP per head (\$ at PPP)	World Bank data
18	hk_2	School enrollment, secondary (%)	World Bank data

(Continued)

Table A2. (Continued)

N	Variable	Description	Source
19	mobil_1000	Mobile cellular subscriptions (per 1000 people)	World Bank data
20	miexp	Military expenditure (% of GDP)	SIPRI data
21	arm_imp	Arms imports (SIPRI trend indicator values)	SIPRI data
22	presid	Presidential elections	NELDA database
23	legis	Legislative elections	NELDA database
24	assem	Constituent Assembly elections	NELDA database
25	pol_sys	Political regime type	NELDA database
26	soc_index	Socioeconomic Conditions index	ICRG data
27	gov_index	Government Stability index	ICRG data
28	corr_index	Corruption index	ICRG data

Note: Data sources are IMF, World Bank, SIPRI, NELDA and ICRG databases. The sample period covers the years from 1990 to 2018.

Table A3. Hausman test results

Test	Ho: difference in coefficients not systematic
Chi ² (15) =	$(b - B)'[(V_b - V_B)(b - B)]$
=	51.369
Prob > Chi ² =	(0.001)

Table A4. Descriptive statistics

	Observations	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
(1) debt	1326	57.345	40.662	547.727	0.488	53.756	0.093	19.893
(2) aid	1326	9.801	7.276	94.946	-0.251	10.553	-0.722	15.534
(3) open	1326	41.048	32.271	380.430	3.571	38.208	1.807	32.407
(4) debt_ser	1326	34.588	33.158	112.257	0.285	16.353	1.135	5.759
(5) miexp	1326	1.123	0.6710	31.587	0.000	1.648	1.377	148.399
(6) int_r	1326	2.096	1.393	31.608	0.000	2.039	0.449	37.223
(7) gov_index	1326	7.602	7.604	12.000	0.000	2.254	-0.450	2.852
(8) pol_sys	1326	0.567	0.500	1.000	0.000	1.406	0.044	2.529
(9) cred_fin	1326	25.891	18.098	144.281	-114.693	28.368	0.771	5.457
(10) bud_bal	1326	-3.625	-2.500	124.112	-662.416	28.029	-1.869	379.397
(11) mobil_1000	1326	252.834	34.548	1758.726	0.000	37.298	1.614	4.891
(12) exch_cpi	1326	397.12	94.763	8,003.745	0.000	780.382	1.990	35.823
(13) corr_index	1326	2.690	2.500	6.000	0.000	1.239	0.412	2.814
(14) arm_imp	1326	9.647	7.822	103.208	0.221	8.687	1.512	28.016
(15) hipc	1326	0.617	0.500	1.000	0.000	1.069	0.187	2.450
(16) imp_cov	1326	5.901	3.667	163.847	0.006	12.033	0.288	90.137

Table A5. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	1.000															
(2)	0.259	1.000														
(3)	0.057	0.167	1.000													
(4)	0.173	0.222	-0.130	1.000												
(5)	0.188	0.242	0.004	0.186	1.000											
(6)	-0.106	-0.083	0.013	0.192	0.508	1.000										
(7)	0.052	0.158	-0.144	-0.172	-0.063	0.014	1.000									
(8)	-0.099	0.015	0.041	-0.112	0.090	0.132	0.123	1.000								
(9)	0.270	-0.095	0.069	-0.014	0.134	0.072	0.051	0.241	1.000							
(10)	-0.157	-0.174	-0.005	-0.050	-0.007	0.046	0.057	-0.025	-0.081	1.000						
(11)	-0.160	-0.277	0.067	-0.216	-0.127	0.093	0.102	0.089	0.120	0.024	1.000					
(12)	-0.042	0.081	-0.086	-0.032	-0.109	-0.176	0.100	-0.199	-0.160	-0.008	0.008	1.000				
(13)	-0.062	0.072	0.187	-0.035	0.046	0.044	-0.126	0.293	0.083	0.012	-0.152	-0.102	1.000			
(14)	0.105	0.201	-0.091	0.057	-0.016	-0.134	-0.048	0.081	-0.016	-0.049	-0.166	0.080	-0.051	1.000		
(15)	-0.104	-0.081	0.029	-0.059	0.014	0.091	-0.043	0.374	0.135	-0.129	0.029	-0.163	0.439	0.048	1.000	
(16)	0.077	-0.082	-0.041	-0.069	-0.078	0.061	0.120	0.044	-0.223	0.039	0.074	-0.023	-0.012	-0.121	-0.061	1.000



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