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This paper examines the productivity of government expenditure. It adopts a Barro-type production function to chart out a growth model that accounts for the productivity of government spending and also adopts Wagner's hypothesis to account for endogeneity resulting from fiscal expansion. The model is estimated via the Bayesian technique using the data on Nigeria. The result shows that government expenditure was unproductive in Nigeria and that this conclusion is independent of the macroeconomic environment. Neither is it dependent on the external circumstances. The paper concludes that there is need for urgent budgetary evaluation and close monitoring of the government budget in Nigeria.

JEL classification: C11;H5
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1. Introduction

That government spending can influence the level of economic activity is the major hypothesis underlying the Barro-type production function. Barro (1990) and Barro and Sala-i-Martin (1992) gave a theoretical treatment of this view, which has become a standard in analyzing the connection between productivity of government expenditure and the level of economic activity. The literature in this direction has since proliferated. Yet an independent but related literature on the importance of Wagner's hypothesis has developed, and some studies have confirmed its relevance. The hypothesis shows how the level of economic activity can influence the level of government spending, perhaps with some delayed effect. Too, some level of endogeneity is being shown to exist through bi-directional causality tests between the level of economic activity and the level of government spending. Olomola (2004) establishes the validity of this hypothesis for Nigeria. He also establishes the bi-directional causal relation. The main messages are that Wagner's hypothesis has implications for how government spending impacts on the level of economic activity and that these implications have to be factored in to adequately understand the connections and the level of relationship between government spending and its productivity and the level of economic activity. Fortunately, inherent in Wagner's hypothesis is the dynamics that is very useful in coming up with a growth model in which the connections can be better understood. In structure, the model charted out is similar to that of Mankiw et al (1992).

The present paper proposes a Bayesian approach to estimating the model. The reason is simple: Our model is best estimated in structural form and the Bayesian econometrics provides the tools to do just that. The model is estimated on the Nigerian data. It is decisively found that government spending is unconditionally and relatively unproductive in Nigeria. A good guess why this is the case might well be the ingrained corruption in the political economy of the country.

The plan of this paper is as follows. Section 2 reviews the literature, while section 3 details the framework and model specification. In section 4 the methodological issues are undertaken. Also in the same section, data sources and definitions are provided. Section 5 analyzes the estimation results and findings. Concluding remarks are given in section 6.

2. Literature

A number of studies have empirically examined the productivity of government spending for various countries and cross-sections of countries. They include panel studies such as Landau (1983), Kormendi and Meguire (1985), Grier and Tullock (1989), Alexander (1990), Devarajan et al (1993), Kneller et al (1998) and Tanninen (1999); cross-sectional studies such as Landau (1986), Ram (1986), Romer (1990), Barro (1991), Chan and Gustafson (1991), Easterly and Rebello (1993), Lin (1994), Devarajan et al (1996) and Folster and Henrekson (2001); and time series such as Dunne and Nikolaidou (1999). More recently, authors have begun to exploit the utility of new techniques. Cooray (2009) uses an extended neoclassical production function to incorporate two dimensions of the government - the size and the quality dimensions and estimates the model on a cross section of 71 economies. The results show that both the size and quality of the government are important for economic growth. Chiung-Ju (2006), using the bounds test based on unrestricted error correction model and annual time series from 1979 to 2002, tests Wagner's hypothesis for China and Taiwan. He estimates the long-run relationship between government expenditures and output and finds that there exists no long-run relationship between these variables. Also using Granger non-causality test he finds that the Wagner law does not hold for China and Taiwan. Schaltegger and Torgler (2007) study the case of Switzerland from 1981 to 2001 and find that there exists negative relationship between government size and economic growth. Their results also confirm a negative relationship between current expenditure and economic growth. Ghosh and Gregoriou (2008) analyze panel data for 15 developing countries for 28 years. Using GMM techniques, they show that current spending positively impacts on growth. Capital spending on the other hand impacts negatively on growth. In the same vein, Afonso and Gonzalez-Alegre (2008) empirically examine relationship the composition of the expenditure and revenue and economic growth for a sample of 27 EU members from 1971 to 2006. The results from their study show that even among the EU members there are differences in the relationship between government spending and growth. Afonso et al (2005) carry out a consolidation process analysis on Central and Eastern Europe countries from 1991 to 2003 and find that the higher the share of expenditure reduction relative to an improvement in the budget balances the higher is the probability of fiscal consolidation success.

Few points must be noted about these studies. The first is that there is no unanimous verdict on the productivity of government spending even though unproductive spending generally impacts negatively on growth while productive spending impacts positively. The second is that there is no consensus on the significance of these results. The third is that neither the panel nor the cross-section studies are helpful in furthering our understanding of the relationship between government spending and growth. The fourth is that these studies have generally relied on the classical approach. The message is that more time series studies are still needed for country-specific results and that hopefully the Bayesian approach will give more robust results. To the best of my knowledge, Bayesian evidence on the relationship is still rare.

3. Theoretical framework and model specification

There is no unifying result with respect to how government expenditure may impact on the growth potential. Not even the taxonomy of government expenditure as productive and unproductive could secure the consensus among the scholars. If government expenditure were productive, the production function would follow the Barro-type specification. In this case, the aggregate production function will depend on government expenditure inter alia. Thus, by assuming that the resources are combined according to the Cobb-Douglas production function, we have that:

$$y_t = Ak_t^{\alpha} g_t^{\beta} \tag{1}$$

where $z_t \equiv \dfrac{Z_t}{L_t}$ is a per capita term and L_t is the aggregate labour. Given that government expenditure is financed contemporaneously with distortionary taxes we then specify a linear relationship between the government spending and the level of real output, or:

$$g_t = \tau_t y_t \tag{2}$$

The process of substituting Equation (2) in Equation (1) and then simplifying yields

$$y_t = Ak_t^{\gamma_1} \tau_t^{\gamma_2} \tag{3}$$

where $\gamma_1 \equiv \dfrac{\alpha}{1-\beta}$ and $\gamma_2 \equiv \dfrac{\beta}{1-\beta}$. Wagner's hypothesis states that government spending endogenously expands in response to economic activity. This is defined as:

$$G_t = \xi_t Y_{t-1} \tag{4}$$

where $\xi_t > 0$ is the time-varying proportionality factor, hereafter called "Wagner's spending ratio". Together with the identity $L_{t+1} \equiv (1+n)L_t$ and Equation (2), Wagner's hypothesis implies that the steady-state tax rate is:

$$\tau^* = \frac{\xi}{1+n} \tag{5}$$

The Solow fundamental equation also implies that the steady-state capital per head is given by:

$$k^* = \left(\frac{s\tau^{*\gamma_2}}{(n+\delta)}\right)^{\frac{1}{1-\gamma_1}} = \left(\frac{s\xi^{\gamma_2}}{(n+\delta)(1+n)^{\gamma_2}}\right)^{\frac{1}{1-\gamma_1}} \tag{6}$$

where the second equality follows from substituting out τ^*. Thus utilizing Equations (5) and (6) in Equation (3), we have:

$$y^* = A\left(\frac{s\xi^{\gamma_2}}{(n+\delta)(1+n)^{\gamma_2}}\right)^{\frac{\gamma_1}{1-\gamma_1}} \left(\frac{\xi}{1+n}\right)^{\gamma_2} \tag{7}$$

If government spending is not productive (i.e. if $\beta = 0$ or if $\gamma_2 = 0$ and $\gamma_1 = \alpha$), then the preceding reduces to the standard steady-state output per capita discussed in Mankiw et al (1992):

$$y^* = A\left(\frac{s}{(n+\delta)}\right)^{\frac{\alpha}{1-\alpha}} \tag{8}$$

The above shows that productive spending entails Wagner's spending ratio, ξ, and gross population growth , $1+n$, and that Equation (7) nests Equation (8) under the restrictions just given. Let the technology evolve as

$$A_t = (1+\gamma_0)^t A_0 \exp(\zeta_t)$$

where γ_0 is the growth rate of technology and $\zeta_t \sim N(0,\sigma^2)$. Then

$$\ln A_t = t \cdot \ln(1+\gamma_0) + \ln A_0 + \zeta_t \cong \gamma_0 t + \zeta_t \tag{9}$$

with the approximation following from normalizing A_0 to unit and using $\gamma_0 \cong \ln(1+\gamma_0)$. By taking the logarithm of Equation (7), using Equation (9) and rearranging, our estimating model becomes:[1]

$$\ln y_t = \gamma_0 t + \frac{\gamma_1}{1-\gamma_1}\ln s_t - \frac{\gamma_1}{1-\gamma_1}\ln(n_t+\delta) + \frac{\gamma_2}{1-\gamma_1}\ln\xi_t - \frac{\gamma_2}{1-\gamma_1}n_t + \zeta_t \qquad (10)$$

where $n_t \cong \ln(1+n_t)$. Equation (10) constitutes the baseline model that we shall analyze shortly.

4. Methodological issues

4.1 Motivation for the choice of technique

It is possible to estimate the above model in reduced form, using the classical approach although doing so does not afford us the opportunity of identifying the model parameter γ_2, except its value is recovered indirectly by comparing the two reduced coefficients. But there are costs to be paid for doing this. One, no idea of standard error of the recovered estimated coefficient will be offered. Two, it will be very difficult if not impossible to accommodate the implications of our model. In this particular study, the two concerns are of practical importance, since γ_2 is central to the productivity of government spending in this model and lack of information about the extent of error in the regression blurs the exposition.

For the Bayesian approach, however, the identification problem is easily overcome provided that we are prepared to make some probabilistic assumptions about the model parameters (Ciccarelli and Rebucci, 2003). This probabilistic view can be expressed by means of priors for the model, the process that at the same time allows us to accommodate the theoretical implications of the model under consideration. Since the Bayesian approach places the entire distribution before the researcher, not only the standard error but also any statistic of interest can be computed. Thus, we choose the Bayesian approach.

By choosing the Bayesian approach, we also avail ourselves other advantages of the method. In particular, the classical estimates are derived based on asymptotic distribution theory whereas Bayesian method is based on exact distribution. Thus, while the former lacks power in small sample and often gives incorrect estimates, the latter is capable of producing better results even under small sample. In addition, identification of structural parameters is more meaningfully undertaken using the Bayesian approach (Lancaster, 2007).

4.2 Method of estimation: Bayesian technique

Let our full sample model be generically represented by

$$\mathbf{y} = \Psi(\mathbf{X},\boldsymbol{\gamma}) + \boldsymbol{\zeta} \qquad \boldsymbol{\zeta} \sim N(\mathbf{0}, \sigma^2\mathbf{I}_T) \qquad (11)$$

where $\Psi : \mathbf{R}^{kT} \times \mathbf{C} \to \mathbf{R}^T$ is any (non)linear function, $\mathbf{C} = \{\boldsymbol{\gamma} : \boldsymbol{\gamma}_L < \boldsymbol{\gamma} < \boldsymbol{\gamma}_U\}$ defines the feasibility constraints implied by the model for the parameter space, $\boldsymbol{\gamma} = [\gamma_0, \gamma_1, \gamma_2]'$ is vector of parameters, and $\boldsymbol{\gamma}_L$ and $\boldsymbol{\gamma}_U$ respectively denote the lower and upper values for $\boldsymbol{\gamma}$. Note that the parameter vector $\boldsymbol{\gamma}$ is a nonlinear function of the model's deep parameters. We are interested in specifying the posterior distribution. The posterior density is derived as a product of the likelihood function and the prior density. The likelihood function

[1] Reintroducing time subscript into the steady-state equation is innocuous since the steady state is actually some time either now or in the future.

summarizes the data information while the prior density summarizes the belief, knowledge and expert opinion of the researcher. It is also possible to use theoretical implications to guide in model estimation. Technically, the prior density is useful because it imbues the likelihood function with curvature, which helps to speed up the optimization process. In other words, the prior density prevents the occurrence of corner solutions and/or local optimum.

From Equation (11), the Gaussian likelihood function is then specified by

$$p(\mathbf{y} \mid \boldsymbol{\gamma}, \sigma, \mathbf{X}) = (2\pi)^{-T/2} (\sigma^2)^{-T/2} \exp\left\{ -\frac{1}{2\sigma^2} (\mathbf{y} - \Psi(\mathbf{X}, \boldsymbol{\gamma}))'(\mathbf{y} - \Psi(\mathbf{X}, \boldsymbol{\gamma})) \right\} \tag{12}$$

The prior densities are chosen so that the constraints implied by our model are satisfied. Specifically, we assume a truncated multivariate normal prior density for $\boldsymbol{\gamma}$, that is,

$$\boldsymbol{\gamma} \sim N(\overline{\boldsymbol{\gamma}}, \overline{\mathbf{V}}) \text{ subject to } \boldsymbol{\gamma} \in \mathbf{C} \tag{13}$$

More explicitly the above is given by

$$\rho(\boldsymbol{\gamma}) = (2\pi)^{-k/2} \left| \overline{\mathbf{V}} \right|^{-k/2} \int_{\mathbf{C}} \exp\left\{ -\frac{1}{2} (\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}})' \overline{\mathbf{V}}^{-1} (\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}}) \right\} d\boldsymbol{\gamma} \tag{14}$$

For σ the prior density is gamma:

$$\rho(\sigma) = \frac{\kappa^{\bar{\nu}}}{\Gamma(\bar{\nu})} (\sigma^2)^{-(\bar{\nu}+1)} \exp\left(-\frac{\kappa}{\sigma^2} \right) \tag{15}$$

Under the implied constraints, our model is not amenable to the Gibbs sampling because the posterior distribution in Equation (14) is not standard. Under this circumstance, the Gibbs sampling strategy will only work with some refinement, which can be implemented through the random-walk Metropolis-Hastings (MH) sampling strategy. The MH is a Monte Carlo Markov Chain (MCMC) often used to sample from an otherwise complex multidimensional integrand, when the distributional form of the model is not known or not standard. The MCMC methods construct the Markov chains for the parameters of interest such that their stationary distributions are the posterior distributions on which interest often centers. The resulting complication can be appreciated by looking at the posterior distribution that emerges for our model. The posterior distribution kernel from Equations (12), (14) and (15) is given by

$$\begin{aligned} p(\boldsymbol{\gamma}, \sigma \mid \mathbf{y}, \mathbf{X}) \propto\ & (\sigma^2)^{-T/2} \exp\left\{ -\frac{1}{2\sigma^2} (\mathbf{y} - \Psi(\mathbf{X}, \boldsymbol{\gamma}))'(\mathbf{y} - \Psi(\mathbf{X}, \boldsymbol{\gamma})) \right\} \cdot \\ & (\sigma^2)^{-(\bar{\nu}+1)} \exp\left(-\frac{\bar{\kappa}}{\sigma^2} \right) \cdot \\ & \int_{\mathbf{C}} \exp\left\{ -\frac{1}{2} (\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}})' \overline{\mathbf{V}}^{-1} (\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}}) \right\} d\boldsymbol{\gamma} \end{aligned}$$

The posterior distribution for σ conditional on $\boldsymbol{\gamma}$ is thus gamma:

$$p(\sigma \mid \boldsymbol{\gamma}, \mathbf{y}, \mathbf{X}) \propto (\sigma^2)^{(-T-2\bar{\nu}-2)/2} \exp\left\{ -\frac{\bar{\kappa}}{\sigma^2} - \frac{1}{2\sigma^2} (\mathbf{y} - \Psi(\mathbf{X}, \boldsymbol{\gamma}))'(\mathbf{y} - \Psi(\mathbf{X}, \boldsymbol{\gamma})) \right\} \tag{16}$$

However, the posterior distribution for $\boldsymbol{\gamma}$ conditional on σ is not standard, and this nonstandard form is as a result of the feasibility constraints $\mathbf{C} = \{\boldsymbol{\gamma} : \boldsymbol{\gamma}_{\mathbf{L}} < \boldsymbol{\gamma} < \boldsymbol{\gamma}_{\mathbf{U}}\}$:

$$p(\boldsymbol{\gamma} \mid \sigma, \mathbf{y}, \mathbf{X}) \propto \exp\left\{-\frac{1}{2\sigma^2}(\mathbf{y}-\Psi(\mathbf{X},\boldsymbol{\gamma}))'(\mathbf{y}-\Psi(\mathbf{X},\boldsymbol{\gamma}))\right\}\cdot$$

$$\int_C \exp\left\{-\frac{1}{2}(\boldsymbol{\gamma}-\overline{\boldsymbol{\gamma}})'\overline{\mathbf{V}}^{-1}(\boldsymbol{\gamma}-\overline{\boldsymbol{\gamma}})\right\}d\boldsymbol{\gamma} \tag{17}$$

$$= \int_C \exp\left\{-\frac{1}{2\sigma^2}(\mathbf{y}-\Psi(\mathbf{X},\boldsymbol{\gamma}))'(\mathbf{y}-\Psi(\mathbf{X},\boldsymbol{\gamma}))-\frac{1}{2}(\boldsymbol{\gamma}-\overline{\boldsymbol{\gamma}})'\overline{\mathbf{V}}^{-1}(\boldsymbol{\gamma}-\overline{\boldsymbol{\gamma}})\right\}d\boldsymbol{\gamma}$$

To sample from the distribution we will employ the Metropolis-within-Gibbs approach. This approach builds the MH sampler in the otherwise Gibbs sampler. The MH part is designed to handle the nonstandard distribution for $\boldsymbol{\gamma}$. In using the approach, Equation (17) is used as the target density.

4.3 Prior and hyperparameter values

In choosing the prior densities and values for our model, we are led by the dictates of our model and the support for each of the parameters. In particular, we observe that the underlying parameters in our model are those introduced through the production function, that is, α and β. Thus, given the calibrated values for parameters α and β, it is easy to compute the prior values for γ_1 and γ_2. Specifically, we set $\alpha = (0.10, 0.30)$ and $\beta = (0.05, 0.25)$. The implied ranges of values for these parameters are in the last two rows of Table 1 below. For γ_0 which measures the growth rate of technology also shared by income, we choose -0.030 and 0.050 as the lower and upper values respectively. This is because Nigeria has rarely breached the upper value, while on occasions the economy has experienced slow-downs in growth. Based on these values, we estimate our model.

Another issue worth discussing is the choice of hyperparameter values. In our model there are four of such parameters namely $\overline{\boldsymbol{\gamma}}, \overline{\kappa}, \overline{\nu}$ and $\overline{\mathbf{V}}$. By construction they are the parameters of the prior densities. Their values are important in initiating the algorithm. As there is no hard and fast rule concerning the choice of values for hyperparameters, sensitivity analysis is advisedly carried out for various values of hyperparameters. The results not reported show that the estimates are robust to those values of hyperparameters.

Table 1: Prior values

Parameters	Lower values	Upper values
γ_0	-0.030	0.050
γ_1	0.105	0.400
γ_2	0.053	0.333

4.4 Model comparison

We consider the hypothesis that the government spending is not productive. This amounts to verifying the null hypothesis, $\gamma_2 = 0$ or $\beta = 0$, against the alternative, $\gamma_2 \neq 0$. One way to compare models in the Bayesian econometrics is through the Bayes factor. The Bayes factor is the ratio of the prior probabilities of the data under different models (Lancaster, 2007). In this case the Bayes factor in favour of model M_1 is given by:

$$BF = \frac{L(X \mid M_1)}{L(X \mid M_2)} \tag{18}$$

where

$$L(X|M_m)=\int L(X|\boldsymbol{\gamma}_m, M_m)p(\boldsymbol{\gamma}_m|M_m)d\boldsymbol{\gamma}_m \tag{19}$$

is the marginal likelihood and $\boldsymbol{\gamma}_m$ is the parameter vector under model M_m. Following Geweke (2005: p259) we approximate this quantity using the density ratio likelihood approximation technique:

$$[L(X|M_m)]^{-1}=\frac{1}{D}\sum_{d=1}^{D}\frac{f_\omega(\boldsymbol{\gamma}_m^{(d)})}{L(X|\boldsymbol{\gamma}_m^{(d)},M_m)p(\boldsymbol{\gamma}_m^{(d)}|M_m)} \tag{20}$$

where D is number of samples drawn from the posterior distribution for study after the burn-ins have been discarded. The quantity $f_\omega(\boldsymbol{\gamma}_m^{(d)})$ for realization d from the posterior distribution for M_m is the multivariate normal distribution truncated to the highest density region. This quantity is given by

$$f_\omega(\boldsymbol{\gamma}_m^{(d)})=(1-\omega)^{-1}(2\pi)^{-n/2}\left|\Sigma_m^{(d)}\right|^{-1/2}\exp[-(\boldsymbol{\gamma}_m^{(d)}-\overline{\boldsymbol{\gamma}}_m)'\Sigma_m^{-1}(\boldsymbol{\gamma}_m^{(d)}-\overline{\boldsymbol{\gamma}}_m)]\mathbf{1}(\boldsymbol{\gamma}_m^{(d)}\in\boldsymbol{\Gamma}_m) \tag{21}$$

where

$$\overline{\boldsymbol{\gamma}}_m=\frac{1}{D}\sum_{d=1}^{D}\boldsymbol{\gamma}_m^{(d)} \text{ and } \Sigma_m=\frac{1}{D}\sum_{d=1}^{D}(\boldsymbol{\gamma}_m^{(d)}-\overline{\boldsymbol{\gamma}}_m)(\boldsymbol{\gamma}_m^{(d)}-\overline{\boldsymbol{\gamma}}_m)'$$

and

$$\boldsymbol{\Gamma}_m=\left\{\boldsymbol{\gamma}_m^{(d)}:(\boldsymbol{\gamma}_m^{(d)}-\boldsymbol{\gamma}_m)'\Sigma_m^{-1}(\boldsymbol{\gamma}_m^{(d)}-\boldsymbol{\gamma}_m)\le\chi_\omega^2(n)\right\}$$

is the support of $f_\omega(\boldsymbol{\gamma}_m^{(d)})$ and $\mathbf{1}(\boldsymbol{\gamma}_m^{(d)}\in\boldsymbol{\Gamma}_m)$ is an indicator function taking the value of 1 if the expression $(\boldsymbol{\gamma}_m^{(d)}\in\boldsymbol{\Gamma}_m)$ is true and value of 0 otherwise. Kass and Raftery (1995) give the ranges of values in Table 2 for the strength of the Bayes factor in favour of a particular.

Table 2: Bayes factor table of decision

Range	Decision
$0\le\log(BF)<0.5$	Poor evidence
$0.5\le\log(BF)<1$	Substantial evidence
$1\le\log(BF)<2$	Strong evidence
$\log(BF)>2$	Decisive evidence

4.5 Data

Annual data are obtained from the World Development Indicators (CD-ROM, 2007) on all the variables. Wagner's spending ratio from Wagner's hypothesis [Equation (4)] is given by:

$$\xi_t=\frac{G_t}{Y_{t-1}} \tag{22}$$

We calibrate the rate of capital depreciation in the economy as $\delta=0.15$. This value is more than the value ordinarily used in the literature but acceptable for Nigeria in that most firms use very obsolete equipment with little or no maintenance. Openness is measured as the ratio of the sum of exports and imports to GDP, and financial depth as the ratio of M2 to GDP. Aid flow is measured as a percentage of GDP.

5. Empirical results

5.1 Model evaluation

Before we analyze the issues involved in this study, we first evaluate the models and assess the acceptability of the results. A total of 1,000,000 draws were sampled. The Markov chains are often notorious with autocorrelation, which can make the results very unreliable.

Thus, we thinned the Markov chains. Due to thinning, only one-tenth of them were retained. Thinning the Markov chains has the potential for abating the autocorrelation problem between drawings. We are comfortable with this result because autocorrelation disappears eventually. In fact, only in the case of γ_2 that it takes a while before autocorrelation finally disappears. The question of how many draws should retained for analysis was settled through the test of convergence. Specifically, we carried out a convergence test suggested by Bauwens et al (1999), which is based on the standardized running means of the marginal posteriors:

$$CS = \left(\frac{1}{d} \sum_{i=1}^{d} \gamma_i - \mu_\gamma \right) / \sigma_\gamma \qquad \text{with } d = 1, \ldots, D \tag{23}$$

According to this formula, any converging Markov chain will eventually gravitate towards the zero line. This was the case for all the parameters in all the models considered. Consequently we retained the last 30,000 draws for analysis.

Four models are considered in this paper. The simplest model, Model I, excludes government spending from the analysis. Thus, in this model no account is taken of the Wagner spending ratio. The only difference between Model I and Model II is that Model II takes into account the influence of Wagner's spending ratio. When these models are compared through the Bayes factor, the importance of Wagner's spending ratio is immediately obvious. The remaining two models, Models III and IV, are extended versions of Models I and II respectively, where we conditioned on some macro variables. The control variables included are measure of openness, financial depth and foreign aid. The inclusion of these variables is based totally on their availability for the period of the study.

Table 3 reports the comparative Bayes factors for these models. The table is read as follows: Each row gives the evidence in favour of the corresponding model and against the alternative model recorded in any of the columns. Of course, a model should have no evidence against itself. Thus the entries on the principal diagonal are 0's. For example, the Bayes factor in favour of Model II and against Model I -14.42 while the Bayes factor in favour of Model III and against Model II is 29.90. With reference to Table 2, it is observed that there is decisive evidence in favour of Model III, while Model IV performs better than the remaining two. In what follows we focus on Model II, Model III and Model IV.

Table 3: Bayes factor (in log)

Models:	Model I	Model II	Model III	Model IV
Model I	0			
Model II	-14.42	0		
Model III	15.48	29.90	0	
Model IV	4.93	19.35	10.54	0

5.2 Result analysis

The two basic models, Models I and II, are first presented. Table 4 reports the posterior results of these models. Referring to Table 4, we found that there is decisive evidence in favour of Model II, suggesting that government spending is not quite productive in Nigeria. Note that the growth rate and income elasticity of capital per head are higher in Model I than in Model II. Thus, this result tells us that the existence of government makes little difference even in the absence of other control variables beyond those implied by our model. The implied income elasticity of government spending in this case is 0.064, meaning that one per cent increase in government spending per capita elicits only 0.064 per cent increase in output per capita. Indeed, this value can hardly impact on the economy. The posterior distributions for Model I and Model II are given in Figures 1 and 2 below long with the chain's behaviour for each of the parameters.

Insert Figure 1 here

Insert Figure 2 here

Table 4: Posterior mean values

Parameters	Model I		Model II	
	Mean	95% HPD	Mean	95%HPD
γ_0	0.0431	[0.0262,0.0498]	0.0406	[0.0319,0.0483]
γ_1	0.1971	[0.1071,0.2920]	0.1360	[0.1063,0.2064]
γ_2			0.0677	[0.0535,0.1040]
log (Marg. Likelihd)		-62.1050		-76.6204

Table 5 reports the posterior results for Models III and IV. In this case, the importance of government spending is reversed from what it we obtained above between Models I and II. Specifically, Model III fits the data better than Model IV. Going by the value of the Bayes factor in Table 3, we found that evidence decisively supports Model III, where government has been excluded from the regression. Also, as is confirmed by the Bayes factors in Table 3, Model III fits better than both Models I and II. The posterior distributions for Model III and Model IV are given in Figures 3 and 4 below long with the chain's behaviour for each of the parameters.

Table 5: Posterior mean values

Parameters	Model III		Model IV	
	Mean	95% HPD	Mean	95%HPD
γ_0	0.0113	[0.0035,0.0199]	0.0134	[0.0061,0.0217]
γ_1	0.1434	[0.1023,0.2311]	0.1391	[0.1066,0.2109]
γ_2			0.0725	[0.0538,0.1151]
γ_3	-0.1519	[-0.1978,-0.0487]	-0.1628	[-0.1984,-0.0809]
γ_4	-0.1695	[-0.1987,-0.1029]	-0.1758	[-0.1991,-0.1206]
γ_5	-0.1371	[-0.1917,-0.0636]	-0.1593	[-0.1970,-0.0953]
log (Marg. Likelihd)		-46.6300		-56.6920

Insert Figure 3 here
Insert Figure 4 here

6. Concluding remarks

The model analyzed in this paper holds that Wagner's hypothesis is implicative for the productivity of government spending. We therefore use the model to empirically examine the Nigerian data, for which it is found in an independent work of Olomola (2004) that there are endogenous bi-directional causal relations between government spending and economic activity. The evidence suggests that the government spending is unconditionally and relatively unproductive for Nigeria. In other words, if government spending is not productive, it is hardly as a result of the macroeconomic environment and policies. In particular, this conclusion holds whether or not the country is open, has sound financial system, or enjoys flows of foreign aid.

Perhaps, this conclusion should not be surprising given a huge fiscal waste in the economy. For example, for many years government has been spending on education, but high and rising unemployment rate in the country has considerably severed the positive feedbacks of human capital. This is coupled with poor service delivery in the public sector and lack of transparency among the political office holders. The current high and rising remunerations and benefits for these minority political office holders have also dangerously positioned the economy. All these constitute fiscal waste.

But then, corruption too is an issue in the Nigerian political economy. We think that the "ten percent" syndrome has indeed depressed the economy. Government needs to urgently evaluate its spending pattern and the way budgetary plans are carried out at the ministry level. It is the case that many ministries just got the allocation for which they have no projects. The 2008 budget was revealing in this case as many ministries only returned their allocations at the end of that fiscal year. Worse than that, those allocations would ordinarily have ended up in private accounts in the previous years. It is in this sense that the due process and project monitoring should be encouraged.

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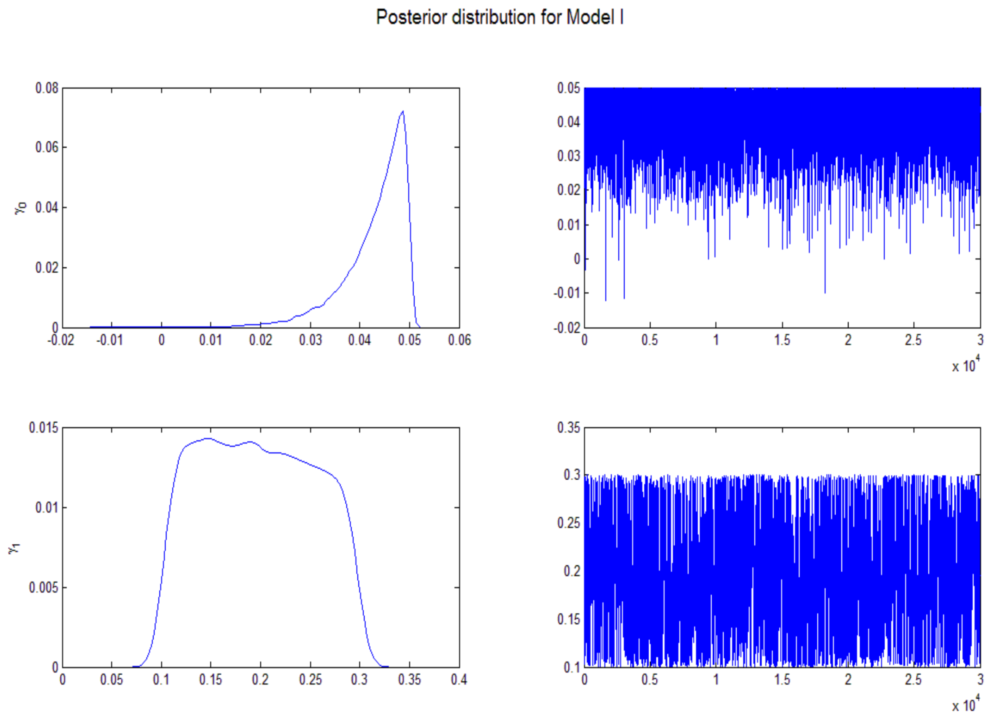
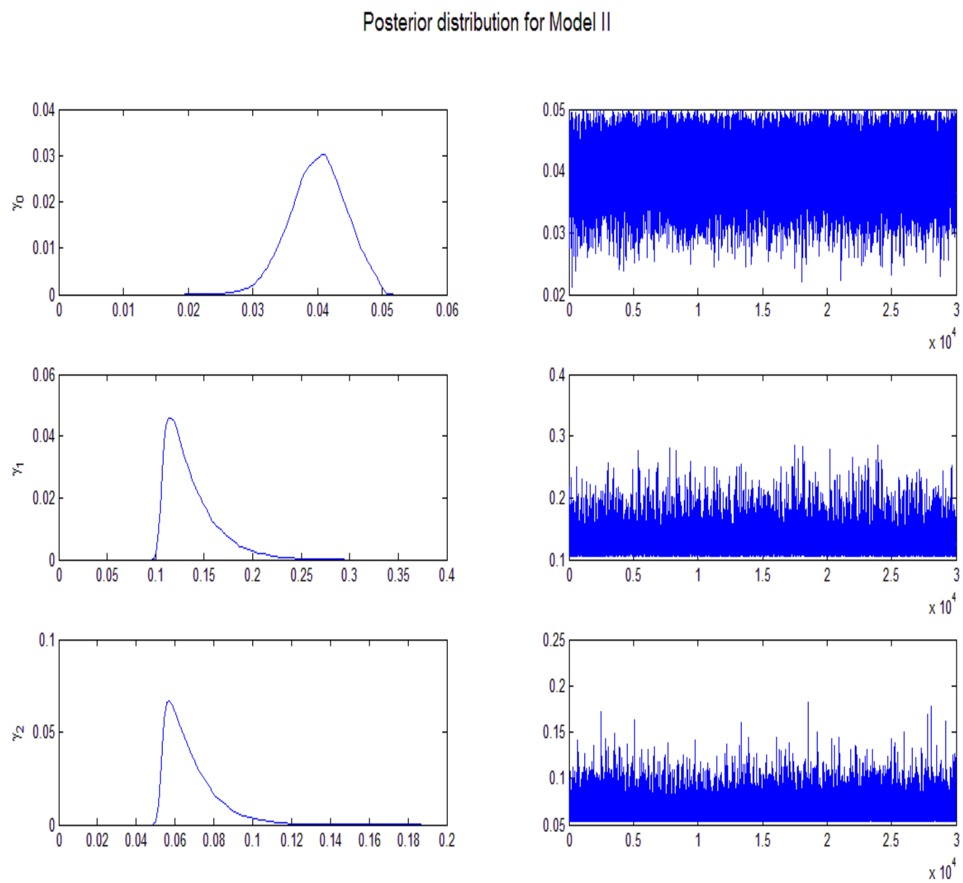
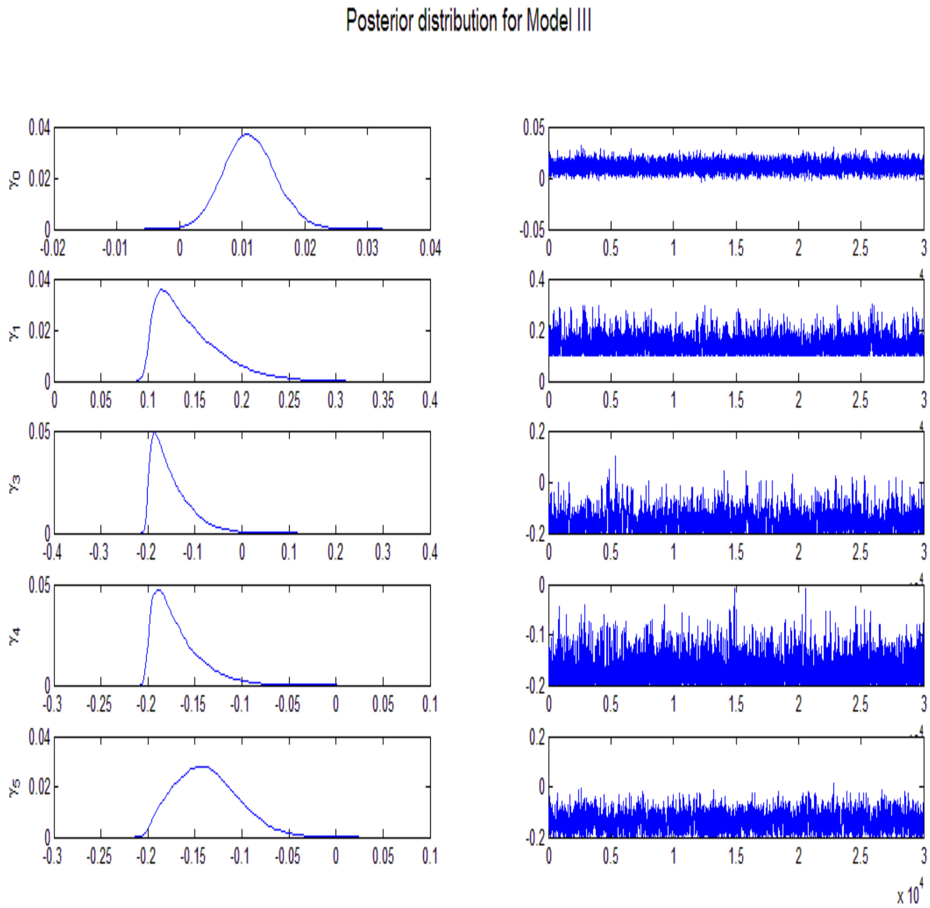

Posterior distribution for Model I
γ_0
0.08
0.06
0.04
0.02
0
-0.02 -0.01 0 0.01 0.02 0.03 0.04 0.05 0.06
0.05
0.04
0.03
0.02
0.01
0
-0.01
-0.02
0 0.5 1 1.5 2 2.5 3
x 10^4
γ_1
0.015
0.01
0.005
0
0 0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4
0.35
0.3
0.25
0.2
0.15
0.1
0 0.5 1 1.5 2 2.5 3
x 10^4



Posterior distribution for Model II
γ_0
γ_1
γ_2
x 10^4


Posterior distribution for Model III
γ_0
γ_1
γ_3
γ_4
γ_5
x 10^4

Posterior distribution for Model IV