The Composition of KZN Public Expenditure and Provincial Economic Growth: A VAR and GMM Approach

Key Words: economic growth, composition of public expenditure, VAR, GMM

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ABSTRACT

The debate about the economic impact of government expenditure has over the last number of years flared up because of the global financial crisis and the associated sovereign debt crisis in Europe. There are those that avidly support “big” government and those that avidly support “small” government. Advocates of bigger government argue that government expenditure provides valuable "public goods" such as education and infrastructure. They also claim that increases in government spending can bolster economic growth by putting money into people's pockets.

Proponents of smaller government have the opposite view. They explain that higher spending undermines economic growth by transferring additional resources from the productive sector of the economy to government, which uses them less efficiently. They also warn that an expanding public sector complicates efforts to implement pro-growth policies - such as tax cuts.

These debates very seldom occur at a provincial government level which traditionally has been viewed as a social institution rather than an economic institution. But it is possible to argue that given the size of the provincial budgets, provincial government expenditure does in fact have some economic impact or effect. It can also be argued that the reason for the lack of interest in the question has been the lack of credible data. There has also been very little interest in provincial government expenditure per se since the national government expenditure debate per definition includes provincial government expenditure.

This paper evaluates the impact of the components of provincial government spending on economic performance in the province of KwaZulu-Natal. It discusses the theoretical arguments, reviews the international evidence, highlights the latest academic research and then focuses on the application of two econometric techniques to empirically test or evaluate the economic impact of the components of provincial government expenditure.

1. INTRODUCTION

The question whether or not government expansion causes economic growth has divided policy makers into two distinctive theoretical camps; as proponents of either big government or small government. Economic theory would suggest that on some occasions, lower levels of government spending would enhance economic growth while on other occasions, higher levels of government spending would be more desirable. From an empirical perspective, the evidence generated becomes more confusing as a number of studies favour one or the other approach.

A recent study by Bose, Haque and Osborn (2003) for example found the following:

> Firstly, the share of government capital expenditure in GDP is positively and significantly correlated with economic growth, but current expenditure is insignificant.
> Secondly, at the sectoral level, government investment and total expenditures in education are the only outlays that are significantly associated with growth once the budget constraint and omitted variables are taken into consideration.

A study by Loizides and Vamvoukas (2004) found, amongst others, that in their sample of countries, public expenditure Granger causes growth in national income either in the short or the long run. This was born out by the bivariate as well as the trivariate analysis. Their analysis generally rejects the hypothesis that public expansion has hampered economic growth in the sample of countries. Their argument is that the underlying growth rates impact of the public sector has been positive, which means that public spending fosters overall economic development.

Devarajan et al (1996) states that the significant increase in public expenditure as a percentage of gross domestic product (GDP) in developing countries has promoted a fair amount of research on the relationship between the size of government and economic growth. They note further that much less is known on how the composition of public expenditure affects a country’s growth rate. Several observers distinguish between “productive” and “unproductive” expenditures, and show how a country can improve its economic performance by changing the mix between the two.

In a recent study reviewing the empirical evidence of 93 economic journal articles about the impact of fiscal policy on economic growth, Nijkamp and Poot (2004) come to the conclusion that only for public expenditures on infrastructure and education a robust and positive impact on economic growth can be found. Cullison (1993) analyses the growth effects of the composition of public expenditures for the United States. According to Cullison's findings, government expenditure for education, active labour-market policies, justice and diverse benefits provided by the state boosted economic growth in the period from 1952 to 1991. Singh and Weber (1997), who analyse Swiss data from 1950 to 1994, come to the conclusion that only education but not public infrastructure is growth-enhancing. Singh and Weber (1997) exclude, however, the revenue side of the government budget. According to the conclusion drawn by Kocherlakota and Yi (1997), the result regarding public infrastructure of Singh and Weber (1997) could be due the fact that the growth effects of public infrastructure and taxation are exactly offsetting at the margin. Moreover, Singh and Weber (1997) find that healthcare expenditure is unfavourable to growth. Recently, Ramirez (2004) comes to the conclusion, using Mexican data for the period from 1955 to 1999, that public infrastructure, comprised of transport, communications, water and sewer systems, education and health care, positively affects growth. A study for Turkey in the period from 1963 to 1999 by Ismihan et al. (2005) ascertains a significant impact of public and public core investment on growth in the medium- but not in the long-term.

The recent revival of interest in the endogenous growth theory has also revived interest among researchers in verifying and understanding the linkages between fiscal policies and economic growth. Moreover, there seems to be a lack of time series studies analysing the effects of the composition of government expenditures on growth. This study aims to fill this gap. The primary objective of this study is to examine the growth effects of the composition of provincial public expenditure on the provincial economy.

2. CONCEPTUAL FRAMEWORK AND EMPIRICAL ECONOMETRIC MODEL

The conventional regression model to examine the growth effects of the composition of public expenditure on the economy can be expressed as follows:

$$\boldsymbol{Y}\mathbf{t} = \boldsymbol{\alpha}\mathbf{t} + \boldsymbol{\beta}\mathbf{1}\boldsymbol{X}\mathbf{1t} + \boldsymbol{\beta}\mathbf{2}\boldsymbol{X}\mathbf{2t} + \cdots . \boldsymbol{\beta}\mathbf{n}\boldsymbol{X}\mathbf{nt} + \boldsymbol{\varepsilon}\mathbf{t}$$

where Y_t = the real economic growth rate at time t, α = constant at time t, X_1, X_2 … X_n is the various components of government expenditure at time t and ε is the error term at time t. β_1, β_2 and β_n are the coefficients to be estimated.

The regression equation in matrix format can be expressed as follows;

$$\boldsymbol{Y}\mathbf{t} = \boldsymbol{\alpha}\mathbf{t} + \boldsymbol{\beta}'\mathbf{i}\boldsymbol{X}\boldsymbol{i}\mathbf{t} + \boldsymbol{\varepsilon}\mathbf{t} \qquad \mathbf{i} = \mathbf{1}, .., \mathbf{N}$$

where X_{it} is a vector of the various components of government expenditures.

Karagöl (2004) states that whilst the majority of studies used the conventional regression method, it may have several disadvantages. For example, it may not be able to account for the endogeneity problem of the independent variables. Most fiscal variables are also strongly correlated with each other so that multicollinearity results and makes it difficult to identify the impact of a single regressor on the dependent variable. Cheng and Lai (1997) further state that the conventional simultaneous equations technique or structural modelling procedure have been criticized as simply too restrictive, and the selection of endogenous and exogenous variables is far too arbitrary and judgmental.

Cheng and Lai (1997) argue, on the other hand, that in a Vector Autoregression Regression (VAR) system, all the variables in the model are endogenous and that each can be written as a linear function of its own lagged values and the lagged values of all other variables in the system. Additionally, one of the usages of VAR has been in testing for causality between two or more variables. Moreover, the results of testing for causality with a multivariate VAR model are much more reliable compared with the typical bivariate causality tests (Barnhart and Darrat, 1989). Furthermore, by adopting a multivariate model, it may avoid biased causality inferences due to the omission or exclusion of relevant variables (Lutkepohl, 1982). Karagöl (2004) and Ramey (2007) also support the argument of using a VAR model.

Yu et al (2009) choose a dynamic model with lagged dependent variables to assess the impact of the composition of government spending on economic growth in developing countries. They argue that it allows for sufficient information about the whole time period and individual heterogeneity in investigation of dynamic relationships and obtaining consistent parameter estimates. The generalized method of moments (GMM) estimator is used to estimate a production function based on a dynamic panel data model, taking both endogeneity and dynamic panel bias into consideration. Wang and Davis (2005) employ the Arellano-Bond two-step GMM method to address the endogeneity and model uncertainty problems.

2.1 Vector Auto Regression Approach

A VAR is an n-equation, n-variable linear model in which each variable is in turn explained by its own lagged values, plus current and past values of the remaining n-1 variables. This simple framework provides a systematic way to capture rich dynamics in multiple time series. The VAR model has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting. It often provides superior forecasts to those from univariate time series models and elaborate theory-based simultaneous equations models.

A natural starting place for multivariate models is to treat each variable symmetrically. In the two-variable case, we can let the time path of the y_t be affected by current and past realizations of the z_t sequence and let the time path of the Z_t sequence be affected by current and past realizations of the z_t sequence. Consider the simple bivariate system:

$$y_t = b_{10} - b_{12}z_t + \gamma_{11}y_{t-1} + \gamma_{12}z_{t-1} + \varepsilon_{yt}$$

$$z_t = b_{20} - b_{21}y_t + \gamma_{21}y_{t-1} + \gamma_{22}z_{t-1} + \varepsilon_{zt}$$

where it is assumed (i) that both y_t and z_t are stationary; (ii) ε_{yt} and ε_{zt} are white-noise disturbances with standard deviations of σ_y and σ_z, respectively; and (iii) ε_{yt} and ε_{zt} are uncorrelated.

The above two equations constitute a first-order VAR since the longest lag length is unity. The structure of the system incorporates feedback since y_t and z_t are allowed to affect each other. For example, $-b_{12}$ is the contemporaneous effect of a unit change of z_t on y_t and γ_{12} is the effect of a unit change in z_{t-l} on y_t. Note that the terms ε_{yt} and ε_{zt} are pure innovations (or shocks) in y_t and $z_{t,}$ respectively. Of course, if b_{21} is not equal to zero, ε_{yt} has an indirect contemporaneous effect on z_t, and if b_{12} is not equal to zero, ε_{zt} has an indirect contemporaneous effect on y_t.

The equations are not reduced form equations since y_t has a contemporaneous effect on z_t and z_t has a contemporaneous effect on $y_{t.}$ Fortunately, it is possible to transform the system of equations into a more usable form. Using matrix algebra, we can write the system in the compact form:

$$\boldsymbol{Bx}\mathrm{t} = \boldsymbol{\Gamma 0} + \boldsymbol{\Gamma 1x}\mathbf{t} - \mathbf{1} + \boldsymbol{\varepsilon}\mathbf{t}$$

where:

$$B = \begin{bmatrix} 1 & b12 \\ b21 & 1 \end{bmatrix}; x\mathrm{t} = \begin{bmatrix} \mathrm{yt} \\ z\mathrm{t} \end{bmatrix}; \ \Gamma 0 = \begin{bmatrix} b10 \\ b20 \end{bmatrix}$$

$$\Gamma 1 = \begin{bmatrix} \gamma 11 \ \gamma 12 \\ \mathrm{y}21 \ \gamma 22 \end{bmatrix}; and \ \varepsilon\mathrm{t} = \begin{bmatrix} \varepsilon\mathrm{yt} \\ \varepsilon\mathrm{zt} \end{bmatrix}$$

The above equation represents a VAR in primitive form. Premultiplication by B^{-1} allows us to obtain the VAR model in standard form:

$$X_t = A_0 + A_1 X_{t-1} + \varepsilon t$$

where:

$A_0 = B^{-1}\Gamma_o$; $A_1 = B^{-1}\Gamma_1$ and $\varepsilon_t = B^{-1}\varepsilon_1$

For notational purposes, we can define a_{i0} as element i of the vector A_0; a_{ij} as the element in row i and column j of the matrix A_1; and e_{it} as the element i of the vector e_t Using this new notation, we can rewrite the $Bx\mathrm{t}$ in the equivalent form:

$$y_t = a_{10} + a_{11}y_{t-1} + a_{12}z_{t-1} + e_{1t}$$
$$z_t = a_{20} + a_{21}y_{t-1} + a_{22}z_{t-1} + e_{2t}$$

Important properties of the model are its linearity and its flexibility, in the sense that one does not have to make many a priori restrictions to set it up, compared to other econometric models. The basic estimation procedure, least squares regression, is well understood, easy to apply and known to be quite robust to (near) (seasonal) unit root nonstationarities (Chan and Wei (1988)), which are now widely believed to be important characteristics of most macroeconomic time series. The superiority of least squares is also well established in the finite sample case (Tjestheim and Paulsen (1983), Hannan and McDougall (1988)).

Estimating a VAR involves choosing which variables to include in the system, and deciding on the number of lags. The results obtained can be sensitive to both of these choices. The number of lags is usually determined by statistical criteria and variable selection is generally informed by economic theory. These considerations highlight a few of the potential problems in estimating VARs. First, estimation problems increase as the number of variables and lags included in the system rises. More specifically, problems with degrees of freedom will occur if there are large numbers of parameters to be estimated. And the degree of correlation between the lagged variables is likely to reduce the precision of estimated coefficients. The application of economic theory to help determine which variables to include in the VAR is a type of restriction. This implies that VARs are not completely atheoretic. However, such concerns can be addressed by making the theory determining the choice of variables sufficiently general or uncontentious. Finally, it should be noted that if the restrictions imposed by more traditional macro econometric models are valid, the parameter estimates derived from such models are likely to be more precise than those derived from the VAR.

In addition to data description and forecasting, the VAR model can also be used for structural inference and policy analysis. In structural analysis, certain assumptions about the causal structure of the data under investigation are imposed, and the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized. These causal impacts are usually summarized with impulse response functions and forecast error variance decompositions.

2.2 Generalized Method of Moments Approach

Generalized Method of Moments (GMM) (Hansen, 2007) refers to a class of estimators which are constructed from exploiting the sample moment counterparts of population moment conditions (some-times known as orthogonality conditions) of the data generating model. GMM estimators have become widely used, for the following reasons:

- GMM estimators have large sample properties that are easy to characterize in ways that facilitate comparison. A family of such estimators can be studied a priori in ways that make asymptotic efficiency comparisons easy. The method also provides a natural way to construct tests which take account of both sampling and estimation error.
- In practice, researchers found it useful that GMM estimators can be constructed without specifying the full data generating process (which would be required to

write down the maximum likelihood estimator). This characteristic has been exploited in analyzing partially specified economic models, in studying potentially misspecified dynamic models designed to match target moments, and in constructing stochastic discount factor models that link asset pricing to sources of macroeconomic risk.

Wooldridge (2000) states that many commonly used estimators in econometrics, including ordinary least squares and instrumental variables, are derived most naturally using the method of moments. As a starting point, consider a population linear regression model:

$$\boldsymbol{y} = \boldsymbol{\beta}\mathbf{0} + \boldsymbol{\beta}\mathbf{1}\boldsymbol{X}\mathbf{1} + \boldsymbol{\beta}\mathbf{2}\boldsymbol{X}\mathbf{2t} + \cdots . \boldsymbol{\beta}\mathbf{k}\boldsymbol{X}\mathbf{k} + \boldsymbol{\mu}$$

where y is the dependent or response variable, the x_j are the covariates or explanatory variables, and μ is the unobserved error or disturbance. The goal is to estimate the k+1 regression parameters, β_j, given a random sample on (y, x_1, x_2, . . . , x_k). A common assumption in linear regression is that the population error has a mean of zero and that each x_j is uncorrelated with the error term, that is,

$$\mathrm{E}(\mu) = 0, \quad \mathrm{E}(x_j\,\mu) = 0, \quad , j = 1, \ldots, k.$$

For brevity, Wooldridge (2000) calls this the “zero correlation assumption”. This assumption implies that k+1 population moments involving the covariates and the error are identically zero. Wooldridge (2000) writes the error in terms of the observable variables and unknown parameters as $\mu = y - \beta_0 - \beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_k x_k$, and replaces the population moments with their sample counterparts, the moment conditions implied by the zero correlation assumption lead to the first-order conditions for the ordinary least squares estimator.

The zero correlation assumption is the weakest sense in which the covariates are exogenous in the population linear model. Under these, the ordinary least squares is the only sensible estimator of the βj. However, often a stronger exogeneity assumption is needed. Assuming that the error term has a zero mean conditional on the covariates,

$$E(\mu \mid x_1, x_{2,..,}x_k) = 0,$$

alternatives to ordinary least squares become available. Specifically, if the zero conditional mean assumption holds and $Var(\mu \mid x_1, x_{2,..,}x_k)$ depends on some of the covariates, it is possible to obtain method of moments estimators that have smaller asymptotic variances than the ordinary least squares estimator.

The starting point of GMM estimation, according to Wojcik and Rosiak-Lada (2007), is a theoretical relation that the parameters should satisfy. The idea is to choose the parameter estimates so that the theoretical relation is satisfied as closely as possible. The theoretical relation is replaced by its sample counterpart and the estimates are chosen to minimize the weighted distance between the theoretical and actual values. GMM is a robust estimator in that (unlike e.g. MLE) it does not require information of the exact distribution of an error term. In fact, many common estimators in econometrics can be considered as special cases of GMM (i.e. OLS). The theoretical relation that the parameters should satisfy are usually called ortgogonality (uncorrelated) conditions between some (possibly nonlinear) function of the parameters $f(\theta)$ and a set of instrumental variables z_t:

$$E(f(\theta)'Z) = 0,$$

where θ are the parameters to be estimated. The GMM estimator selects parameter estimates so that the sample correlations between the instruments and the function f are as close to zero as possible, as defined by the criterion function:

$$J(\theta) = (m(\theta))' Am(\theta),$$

where m(θ) = f(θ)'Z and A is a weighting matrix. Any symmetric positive definite matrix A will yield a consistent estimate. However, a necessary (but not sufficient) condition to obtain an asymptotically efficient estimate is to set A equal to the inverse of the covariance matrix of the sample moments m.

3. KZN PUBLIC EXPENDITURE AND GDP: TRENDS, SIZE, COMPOSITION, CHARACTERISTICS AND TRANSFORMATION

The table below indicates the size and behaviour of the provincial budget and GDP over the period in real terms (deflated by using the annual CPI). It is evident that provincial public expenditure increased at a much faster pace than the provincial economy.

Table 1: Size and Behaviour of the Provincial Budget and GDP in Real Terms

	KZN Public Expenditure R'000	KZN GDP R'000	KZN Public expenditure as a % of GDP
Total 2006-07	35 315 916	269 045 168	13.13
Total 2007-08	41 864 377	284 904 866	14.69
Total 2008-09	50 836 349	296 224 504	17.16
Total 2009-10	60 544 391	290 947 350	20.81
Total 2010-11	66 368 675	300 729 829	22.07
Total 2011-12	75 553 621	310 703 563	24.32
	Year-on-Year increase		
Year-on-Year 2006-07	6.03	5.53	-0.52
Year-on-Year 2007-08	13.51	5.89	4.84
Year-on-Year 2008-09	14.28	3.97	6.23
Year-on-Year 2009-10	9.02	-1.78	14.16
Year-on-Year 2010-11	2.92	3.36	2.75
Year-on-Year 2011-12	10.30	3.32	5.04

(KZN Provincial Treasury, Stats SA, Own calculations)

Provincial public expenditure can be disaggregated in five components (classifications) of expenditure, i.e.,

$$ProvPublicExp_t = (ExpCom_t, ExpGoodsServ_t, ExpTrans_t, ExpCapital_t, ExpInfra_t)$$

where

$ProvPublicExp_t$ (Total) = Total Provincial Public expenditure at time t

$ExpCom_t$ (SW) = Total Provincial Public expenditure on Compensation of Employees at time t

$ExpGoodsServ_t$ (GS) = Total Provincial Public expenditure on Goods and Services at time t

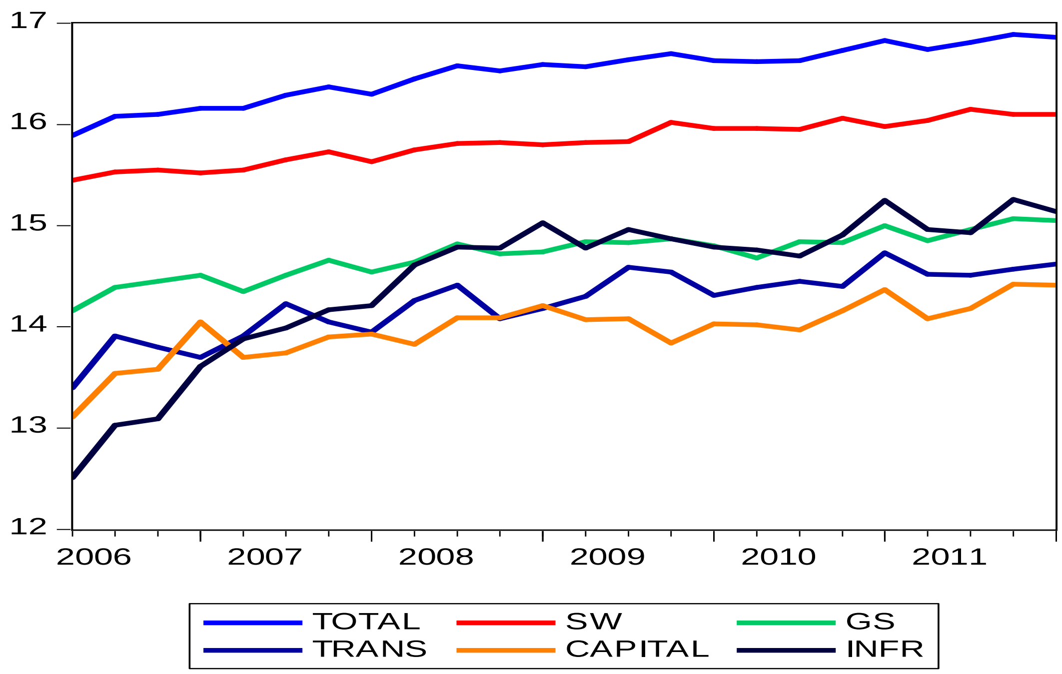
$ExpTrans_t$ (Trans) = Total Provincial Public expenditure on Transfers (Current and Capital) to Municipalities at time t

$ExpCapital_t$ (Capital) = Total Provincial Public expenditure on Capital Purchases at time t

$ExpInfra_t$ (Infr) = Total Provincial Public expenditure on new and upgrading of Infrastructure at time t

Graph 1 displays the quarterly values (in log format and real terms) of total and per component of provincial public expenditure for the indicated period. It is evident that expenditure on salaries and wages are the largest component of provincial public expenditure (50 percent on average), whilst expenditure on capital are the least (8 percent on average). In general, all the components of provincial public expenditure experienced an increasing trend over the period. However it does appear that the various growth trends have been marginally decreasing over the period, with the exception of infrastructure expenditure.

Graph1: Total Provincial Public Expenditure and Total Provincial Public Expenditure per Component (2006 quarter 2 to 2012 quarter 1)



The table below displays the descriptive statistics (in log format and in real terms) for the components of provincial public expenditure.

Table 3: Descriptive Statistics for the Components of Provincial Public Expenditure

	SW	GS	TRANS	CAPITAL	INFR
Mean	15.82333	14.71292	14.24208	13.97500	14.45875
Median	15.82000	14.77000	14.30500	14.04000	14.78000
Maximum	16.15000	15.07000	14.73000	14.42000	15.26000
Minimum	15.45000	14.16000	13.40000	13.11000	12.51000
Std. Dev.	0.211468	0.232182	0.332657	0.295929	0.748513
Skewness	-0.189985	-0.542476	-0.743819	-0.966688	-1.230087
Kurtosis	1.823212	2.693294	2.916155	4.351823	3.500262
Jarque-Bera	1.529209	1.271189	2.220097	5.565368	6.302723
Probability	0.465518	0.529621	0.329543	0.061872	0.042794
Sum	379.7600	353.1100	341.8100	335.4000	347.0100
Sum Sq. Dev.	1.028533	1.239896	2.545196	2.014200	12.88626

Observations	24	24	24	24	24

Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as with 2 degrees of freedom. The reported probability is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null – a small probability value leads to the rejection of the null hypothesis of a normal distribution. With the exception of infrastructure expenditure, the components are normally distributed.

The table below displays the covariance and correlation matrix of the components of provincial public expenditure. It is evident that the components show very high levels of covariance or correlation, i.e., possible violation of the zero correlation assumption as proposed by Wooldridge (2000).

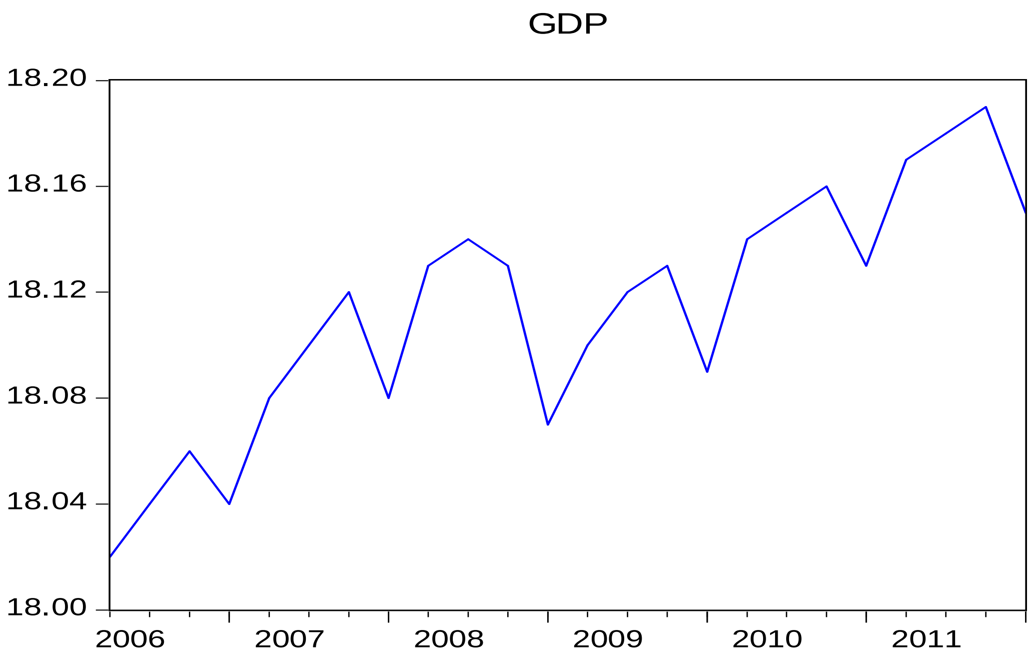
Table 4: Covariance and Correlation Matrix for the Components of Provincial Public Expenditure

Covariance Correlation t-Statistic	SW	GS	TRANS	CAPITAL	INFR
SW	0.042856 1.000000 -----				
GS	0.043353 0.921354 11.11719	0.051662 1.000000 -----			
TRANS	0.059839 0.887616 9.039131	0.067761 0.915451 10.66983	0.106050 1.000000 -----		
CAPITAL	0.045679 0.761674 5.513553	0.058673 0.891056 9.207943	0.072481 0.768290 5.629723	0.083925 1.000000 -----	

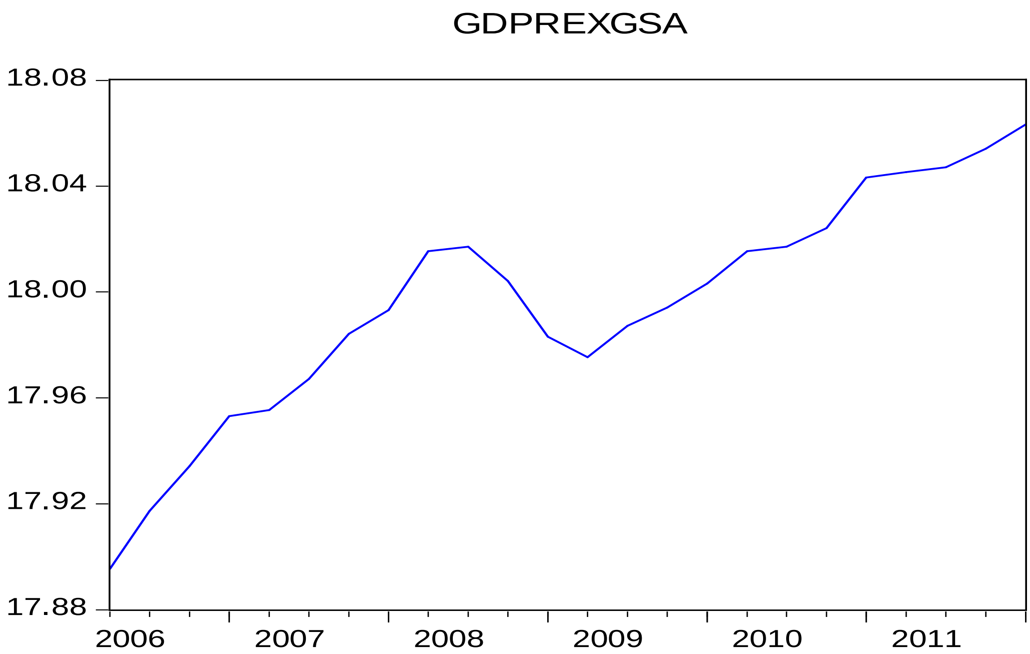
INFR	0.131933	0.152966	0.214719	0.188752	0.536928
	0.869747	0.918439	0.899825	0.889177	1.000000
	8.266462	10.89049	9.674612	9.114823	-----

The behavior of the provincial GDP in log real terms is displayed in the graph below. The GDP series however first needs to be transformed in order to minimize or eliminate possible model misspecification. First the GDP series includes general government services GDP. This has to be excluded (subtracted) from the total GDP series in order prevent biased in the parameters. Second, it is very evident that the GDP series displays high levels of seasonality. The series therefore has to be adjusted for seasonality. This is done by using the ratio to moving average method in EViews. The transformed GDP series are displayed in graph 3.

Graph 2: Total Provincial GDP in log format and in real terms (2006 quarter 2 to 2012 quarter 1)



Graph 3: Transformed Total Provincial GDP in log format and in real terms (2006 quarter 2 to 2012 quarter 1)



In order to test if the assumed relationships indeed exist, it is crucial that the variables be integrated to the same order and that the error terms are stationary. Consider that the two variables Y_t and X_t are both *I*(*d*) (i.e., they have compatible long-run properties). In general, any linear combination of Y_t and X_t will be also *I*(*d*). However, if there exists a vector (1, - β)', such that the linear combination $\boldsymbol{\varepsilon_t = Y_t - \alpha - \beta X_t}$ is indeed *I*(*d* - *b*) , *d* ≥ *b* > 0, then, following Engle and Granger (1987), Y_t and X_t are defined as cointegrated of order (*d*, *b*).

The two variables or time series therefore need to be tested for stationarity to determine their order of integration. To perform the Unit Root test on a AR(p) model, the following regression will be estimated:

$$y_t = \alpha + \delta t + \beta y_{t-1} + \sum_{j=1}^{k} \theta_j \Delta y_{t-j} + u_t$$

where:

y_t = variable to be tested (national GDP and national fuel consumption)

α = constant

t = trend

Δ = lag operated of the dependent variable

u_t = white noise innovation

The ADF Unit Root Test is based on the following three regression forms:

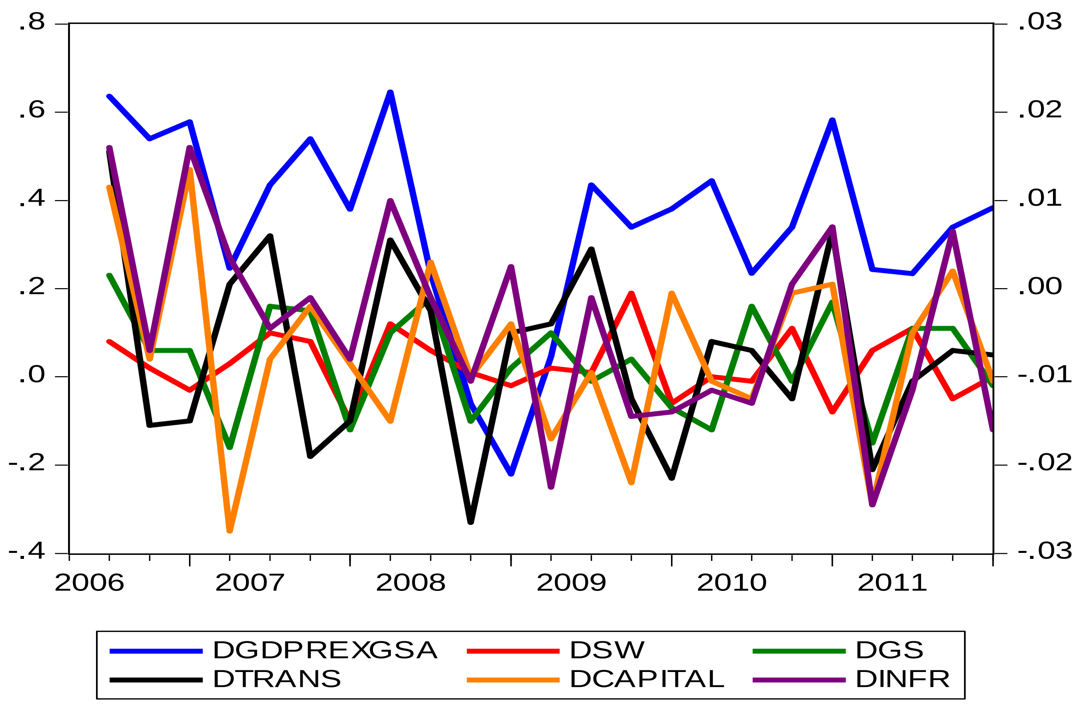
- with constant and trend (τ_τ)
- with constant (τ_μ)
- without constant and trend (τ)

and the testable hypothesis is β = **0** (i.e., p = **1**, y_t has a unit root).

The time series consist of 24 observations and five lags will be included in the test procedures. The Schwarz Info criteria are used to determine the number of lags. Comparing the ADF test statistics with the critical test values at 1 percent, 5 percent and 10 percent levels (tau values) and the F-statistics at the 1 percent, 5 percent and 10 percent levels (phi values) suggests that the variables or time series are non-stationary in log level format. Given that the results clearly show that none of the variables or time series are stationary in level format, the variables need to be transformed in order to determine their level of integration. The non-stationary data therefore needs to be differenced.

Comparing the ADF test statistics of the difference variables with the critical test values at 1 percent, 5 percent and 10 percent levels (tau values) and the F-statistics at the 1 percent, 5 percent and 10 percent levels (phi values) suggests that all the variables or time series are indeed stationary in the differenced format. The results suggest that the variables are stationary and thus integrated to the order of 1 or I(1). The variables in log real stationary format are displayed in the graph below.

Graph 4: Log Real Stationary Format (2006 quarter 3 to 2012 quarter 1)



4. EMPIRICAL ECONOMETRIC MODEL AND ESTIMATION

4.1 A VAR approach

The VAR model that will be estimated is displayed below. We can let the time path of the $\{y_t\}$ be affected by current and past realizations of the $\{c_t, i_t, g_t, s_t$ and $t_t\}$ sequence and let the time path of the $\{c_t, i_t, g_t, s_t$ and $t_t\}$ sequence be affected by current and past realizations of the $\{y_t\}$ sequence. The VAR (in I(1) format) system is as follows:

$$y_t = a_{10} + a_{11}y_{t-1} + a_{12}c_{t-1} + \gamma_{13}i_{t-1} + a_{14}g_{t-1} + a_{15}s_{t-1} + a_{16}t_{t-1} + e_{1t}$$

$$c_t = a_{20} + a_{21}y_{t-1} + a_{22}c_{t-1} + a_{23}i_{t-1} + a_{24}g_{t-1} + a_{25}s_{t-1} + a_{26}t_{t-1} + e_{2t}$$

$$i_t = a_{30} + a_{31}y_{t-1} + a_{32}c_{t-1} + a_{33}i_{t-1} + a_{34}g_{t-1} + a_{35}s_{t-1} + a_{36}t_{t-1} + e_{3t}$$

$$g_t = a_{40} + a_{41}y_{t-1} + a_{42}c_{t-1} + a_{43}i_{t-1} + a_{44}g_{t-1} + a_{45}s_{t-1} + a_{46}t_{t-1} + e_{4t}$$

$$s_t = a_{50} + a_{51}y_{t-1} + a_{52}c_{t-1} + a_{53}i_{t-1} + a_{54}g_{t-1} + a_{55}s_{t-1} + a_{56}t_{t-1} + e_{5t}$$

$$t_t = a_{60} + a_{61}y_{t-1} + a_{62}c_{t-1} + a_{63}i_{t-1} + a_{64}g_{t-1} + a_{65}s_{t-1} + a_{66}t_{t-1} + e_{6t}$$

where

y_t = Provincial GDP (gdprexgsa)

c_t = ExpCapital_t (Capital)

i_t = ExpInfra_t (Infr)

g_t = ExpGoodsServ_t (GS)

s_t = ExpCom_t (SW)

y_t = ExpTrans_t (Trans)

and where it is assumed (i) that $\mathbf{y_t}$, $\mathbf{c_t}$, $\mathbf{i_t}$, $\mathbf{g_t}$, $\mathbf{s_t}$ and $\mathbf{t_t}$ are stationary; (ii) $\mathbf{e_{1t}}$, $\mathbf{e_{2t}}$, $\mathbf{e_{3t}}$, $\mathbf{e_{4t}}$, $\mathbf{e_{5t}}$ and $\mathbf{e_{6t}}$ are white-noise disturbances with standard deviations of σ_y, σ_c, σ_i, σ_g, σ_s and σ_t respectively; and (iii) the error terms are uncorrelated. The equations constitute a first-order VAR since the longest lag length is unity. The structure of the system incorporates feedback since $\mathbf{y_t}$, $\mathbf{c_t}$, $\mathbf{i_t}$. $\mathbf{g_t}$, $\mathbf{s_t}$ and $\mathbf{t_t}$ are allowed to affect each other.

Standard practice in VAR analysis is to report results from Granger-causality. Granger-causality statistics examine whether lagged values of one variable help to predict another variable. For example, if the payment for capital assets does not help predict provincial GDP, then the coefficients on the lags of payment for capital assets will all be zero in the reduced-form provincial GDP equation. Table 5 summarizes the Granger-causality results for the six-variable VAR using different lags. It shows the p-values associated with the F-statistics for testing whether the relevant sets of coefficients are zero. Intuitively the results suggest very little causality between any of the five components of provincial public expenditure and provincial GDP.

Table 5: Pairwise Granger Causality Tests

	Lags	F-Statistic	Prob.
DCAPITAL does not Granger Cause DGDPREXGSA	1	0.78696	0.3861
DINFR does not Granger Cause DGDPREXGSA	1	1.54124	0.2295
DGS does not Granger Cause DGDPREXGSA	1	0.19127	0.6668
DSW does not Granger Cause DGDPREXGSA	1	0.00141	0.9705
DTRANS does not Granger Cause DGDPREXGSA	1	0.00854	0.9273
DCAPITAL does not Granger Cause DGDPREXGSA	2	0.74198	0.4919
DINFR does not Granger Cause DGDPREXGSA	2	1.26599	0.3087
DGS does not Granger Cause DGDPREXGSA	2	0.34072	0.7163
DSW does not Granger Cause DGDPREXGSA	2	0.00473	0.9953
DTRANS does not Granger Cause DGDPREXGSA	2	0.09735	0.9078
DCAPITAL does not Granger Cause DGDPREXGSA	3	0.57709	0.6402
DINFR does not Granger Cause DGDPREXGSA	3	0.81832	0.5065
DGS does not Granger Cause DGDPREXGSA	3	0.83383	0.4989
DSW does not Granger Cause DGDPREXGSA	3	0.15945	0.9217
DTRANS does not Granger Cause DGDPREXGSA	3	0.33966	0.7971
DCAPITAL does not Granger Cause DGDPREXGSA	4	0.15465	0.9565
DINFR does not Granger Cause DGDPREXGSA	4	0.58827	0.6787
DGS does not Granger Cause DGDPREXGSA	4	0.36717	0.8267
DSW does not Granger Cause DGDPREXGSA	4	0.16645	0.9506
DTRANS does not Granger Cause DGDPREXGSA	4	0.20381	0.9305

The estimated VAR model is displayed in the table below. The model will be estimated using EViews and will make use of quarterly data ranging from quarter 2:2006 to quarter 1:2012. Two lags will be included in the model because of data limitations which can be a constraint to the appropriateness of the model. No exogenous variables, except the constant have been included.

Table 6: Estimated VAR model

DGDPREXGSA = C(1,1)*DGDPREXGSA(-1) + C(1,2)*DGDPREXGSA(-2) + C(1,3)*DCAPITAL(-1) + C(1,4)*DCAPITAL(-2) + C(1,5)*DINFR(-1) + C(1,6)*DINFR(-2) + C(1,7)*DGS(-1) + C(1,8)*DGS(-2) + C(1,9)*DSW(-1) + C(1,10)*DSW(-2) + C(1,11)*DTRANS(-1) + C(1,12)*DTRANS(-2) + C(1,13)
DCAPITAL = C(2,1)*DGDPREXGSA(-1) + C(2,2)*DGDPREXGSA(-2) + C(2,3)*DCAPITAL(-1) + C(2,4)*DCAPITAL(-2) + C(2,5)*DINFR(-1) + C(2,6)*DINFR(-2) + C(2,7)*DGS(-1) + C(2,8)*DGS(-2) + C(2,9)*DSW(-1) + C(2,10)*DSW(-2) + C(2,11)*DTRANS(-1) + C(2,12)*DTRANS(-2) + C(2,13)
DINFR = C(3,1)*DGDPREXGSA(-1) + C(3,2)*DGDPREXGSA(-2) + C(3,3)*DCAPITAL(-1) + C(3,4)*DCAPITAL(-2) + C(3,5)*DINFR(-1) + C(3,6)*DINFR(-2) + C(3,7)*DGS(-1) + C(3,8)*DGS(-2) + C(3,9)*DSW(-1) + C(3,10)*DSW(-2) + C(3,11)*DTRANS(-1) + C(3,12)*DTRANS(-2) + C(3,13)
DGS = C(4,1)*DGDPREXGSA(-1) + C(4,2)*DGDPREXGSA(-2) + C(4,3)*DCAPITAL(-1) + C(4,4)*DCAPITAL(-2) + C(4,5)*DINFR(-1) + C(4,6)*DINFR(-2) + C(4,7)*DGS(-1) + C(4,8)*DGS(-2) + C(4,9)*DSW(-1) + C(4,10)*DSW(-2) + C(4,11)*DTRANS(-1) + C(4,12)*DTRANS(-2) + C(4,13)
DSW = C(5,1)*DGDPREXGSA(-1) + C(5,2)*DGDPREXGSA(-2) + C(5,3)*DCAPITAL(-1) + C(5,4)*DCAPITAL(-2) + C(5,5)*DINFR(-1) + C(5,6)*DINFR(-2) + C(5,7)*DGS(-1) + C(5,8)*DGS(-2) + C(5,9)*DSW(-1) + C(5,10)*DSW(-2) + C(5,11)*DTRANS(-1) + C(5,12)*DTRANS(-2) + C(5,13)
DTRANS = C(6,1)*DGDPREXGSA(-1) + C(6,2)*DGDPREXGSA(-2) + C(6,3)*DCAPITAL(-1) + C(6,4)*DCAPITAL(-2) + C(6,5)*DINFR(-1) + C(6,6)*DINFR(-2) + C(6,7)*DGS(-1) + C(6,8)*DGS(-2) + C(6,9)*DSW(-1) + C(6,10)*DSW(-2) + C(6,11)*DTRANS(-1) + C(6,12)*DTRANS(-2) + C(6,13)

The residuals of the estimated VAR model are displayed in the diagram below. Intuitively it appears as if the residuals are stationary and normally distributed, suggesting that the estimated VAR model is appropriate.

The appropriateness of the estimated VAR model will also be tested using a number of diagnostic statistics. Diagram 2 displays the inverse roots of the characteristic AR polynomial. The estimated VAR model is stable or stationary if all the roots have modules less than one and lie inside the unit circle. There is ***kp*** roots, where ***k*** is the number of endogenous variables and ***p*** is the largest lag. The results indeed indicate that the estimated VAR model is stationary.

Diagram 1: VAR Residuals

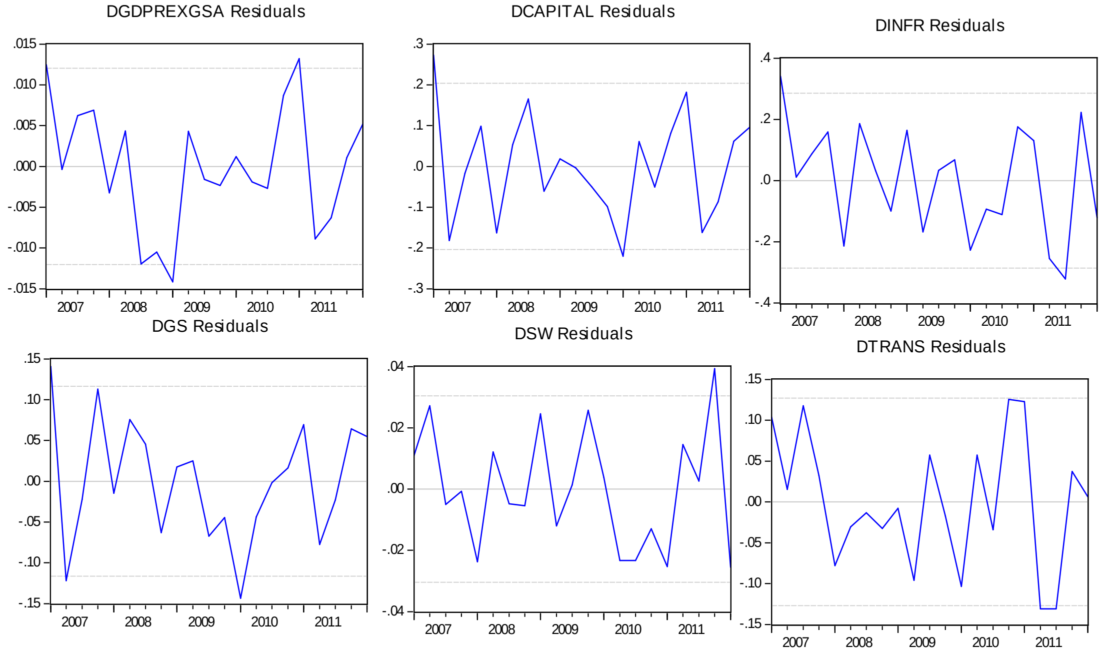
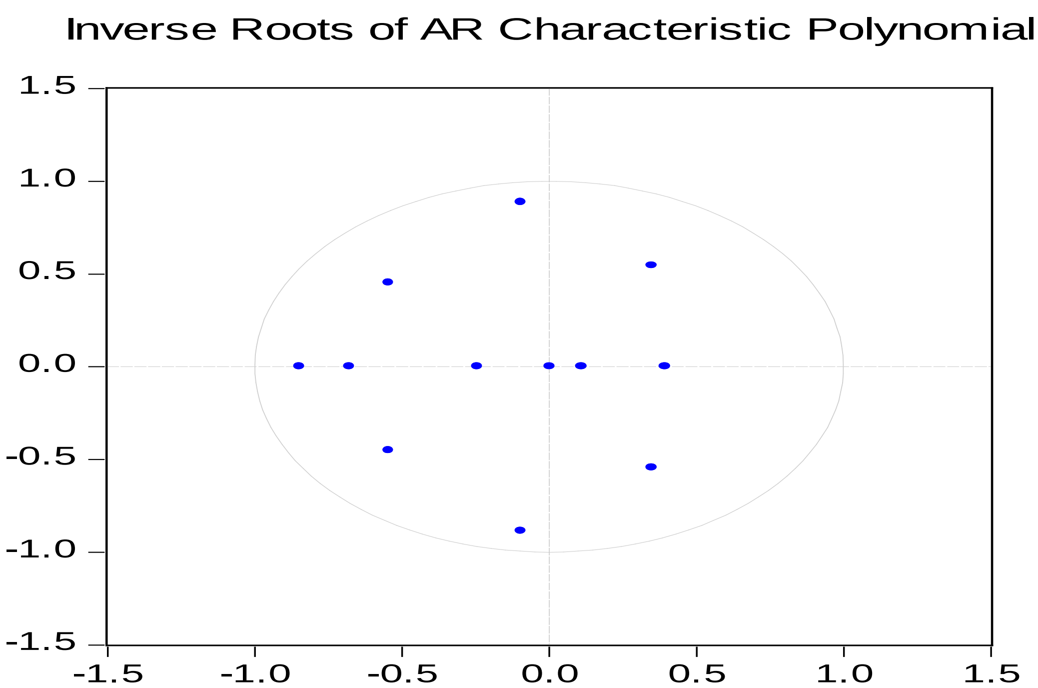


Diagram 2: Inverse Roots of AR characteristic polynomial



The Granger Causality test is used to test whether endogenous variables can be treated as exogenous. For each equation in the VAR, the output displays (Wald) statistics for the joint significance of each of the other lagged endogenous variables in that equation. The statistic in the last row (All in table 7) is the χ^2 statistics for joint significance of all other lagged endogenous variables in the equation. The high p-value (p = 0.9528) suggests that the model is stationary and that there is no problem of spurious Granger causality.

Table 7: VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable: GDP	Chi-sq	df	Prob.
DCAPITAL	1.044199	2	0.5933
DINFR	1.174250	2	0.5559
DGS	0.973231	2	0.6147
DSW	0.038889	2	0.9807
DTRANS	1.406165	2	0.4951
All	3.876765	10	**0.9527**

The table below reports the results of the Portmanteau autocorrelation test. The test computes the multivariate Box-Pierce/Ljung-Box Q-statistics for residual serial correlation up to the specified. The table reports both the Q-statistics and the adjusted Q-statistics (with a small sample correction). Under the null hypothesis of no serial correlation up to lag h, both statistics are approximately distributed χ^2 with degrees of freedom $k^2(h-p)$ where p is the VAR lag order. This test has been constrained by the fact that only 2 lags have been included in the VAR model. In general, evidence of the presence of autocorrelation may indicate that a greater number of lags are needed, but as indicated in this case, lag order selection cannot be performed. The Portmanteau autocorrelation test intuitively suggests some autocorrelation between the residuals.

Table 8: VAR Residual Portmanteau Tests for Autocorrelations

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	39.85664	NA*	41.84947	NA*	NA*
2	62.32856	NA*	66.68686	NA*	NA*
3	94.49248	0.0000	104.2114	0.0000	36
4	131.1619	0.0000	149.5089	0.0000	72
5	151.8522	**0.0035**	176.6650	0.0000	108
6	170.3232	**0.0663**	202.5243	0.0009	144
7	196.0587	0.1956	241.1276	0.0016	180
8	223.0626	0.3564	284.7493	0.0012	216
9	239.3097	0.7072	313.1817	0.0052	252
10	257.1095	0.9046	347.1632	0.0096	288
11	277.6406	0.9706	390.2784	0.0067	324
12	302.4385	0.9877	448.1402	0.0011	360

The table below reports the multivariate LM test statistics for residual serial correlation up to the specified order. The test statistic for lag order h is computed by running an auxiliary regression of the residuals u_t on the original right-hand regressors and the lagged residual u_{t-h}, where the missing first h values of u_{t-h} are filled with zeros. Under the null hypothesis of no serial correlation of order h, the LM statistic is asymptotically distributed χ^2 with k^2 degrees of freedom. The results (all of the p-values are less than 0.05 percent) suggest some degree of serial correlation, which is not ideal but again could be because of the inclusion of only 2 lags for each of the variables.

Table 9: Autocorrelation LM Test

Lags	LM-Stat	Prob
1	235.7433	0.0000
2	NA	NA
3	NA	NA
4	219.7980	0.0000
5	221.2261	0.0000
6	224.3660	0.0000
7	NA	NA

8	217.2229	0.0000
9	NA	NA
10	225.9101	0.0000
11	223.8134	0.0000
12	221.4760	0.0000

The table below reports the multivariate extensions of the Jarque-Bera residual normality test, which compares the third and fourth moments of the residuals to those from the normal distribution. The results (high p-values) suggest that the residuals are indeed normally distributed.

Table 10: Normality Test

Component	Jarque-Bera	df	Prob.
1	0.953431	2	0.6208
2	0.293811	2	0.8634
3	0.968162	2	0.6163
4	0.609554	2	0.7373
5	0.493621	2	0.7813
6	0.004112	2	0.9979
Joint	3.322691	12	**0.9928**

The results of the diagnostic statistics in general support the appropriateness of the estimated VAR model. The estimated VAR model can now be used with a high degree of confidence for structural inference and policy analysis, for example. In structural analysis and policy analysis, certain assumptions about the causal structure of the data under investigation are imposed, and the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized. These causal impacts are usually summarized with impulse response functions and forecast error variance decompositions.

Impulse response traces out the response of current and future values of each of the variables to a one-unit increase in the current value of one of the VAR errors, assuming that this error returns to zero in subsequent periods and that all other errors are equal to zero. The implied thought experiment of changing one error while holding the others constant makes most sense when the errors are uncorrelated across equations, so impulse responses are typically calculated for recursive and structural VARs. The exhibit and table below displays the impulse-response functions for the estimated VAR model over the following 10 quarters.

The impulse-response functions indicate or suggest that infrastructure expenditure and expenditure on goods and services have the biggest impact on the provincial GDP. Transfers and subsidies, compensation of employees and payments for capital assets seems to have negative and short term impacts.

Exhibit 1: Impulse-Response Function (log and first difference format)

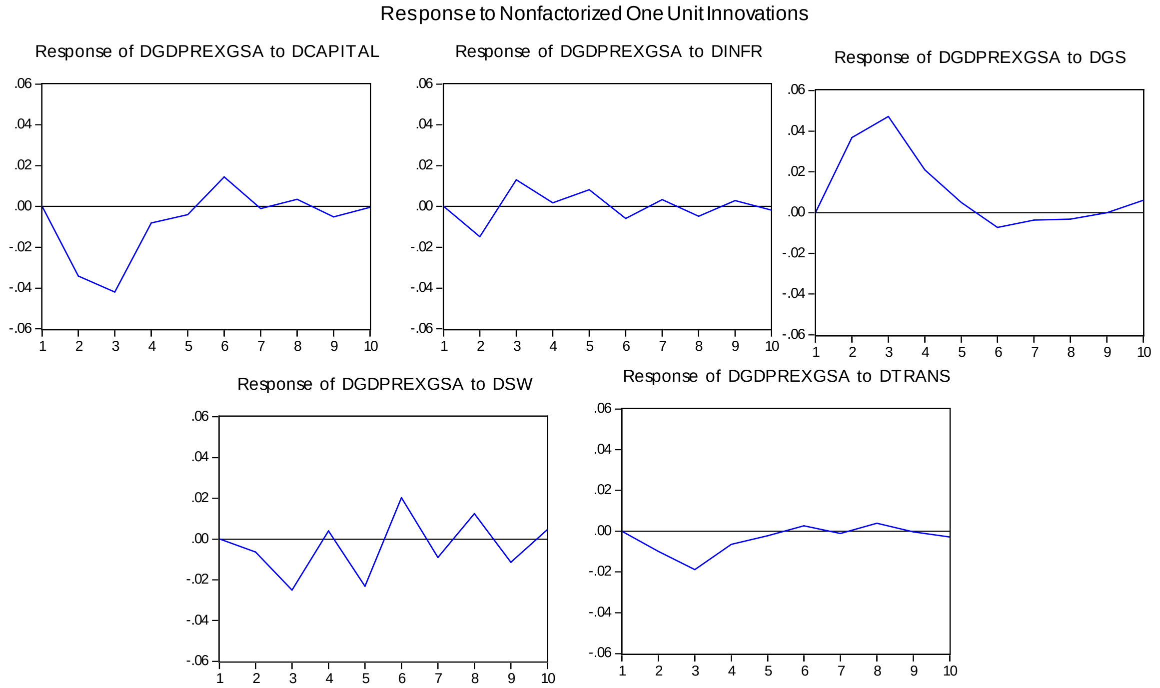


Table 11: Impulse-Response Function (log and first difference format)

Response to Nonfactorized One Unit Innovations					
Period	DCAPITAL	DINFR	DGS	DSW	DTRANS
1	0	0	0	0	0
2	-0.03407	-0.01476	0.03682	-0.00632	-0.00982

3	-0.04198	0.01310	0.04712	-0.02513	-0.01886
4	-0.00818	0.00174	0.02086	0.00401	-0.00647
5	-0.00395	0.00818	0.00490	-0.02326	-0.00231
6	0.01441	-0.00593	-0.00723	0.02021	0.00261
7	-0.00107	0.00328	-0.00370	-0.00909	-0.00103
8	0.00355	-0.00469	-0.00320	0.01247	0.00391
9	-0.00503	0.00284	0.00000	-0.01134	-0.00033
10	-0.00047	-0.00177	0.00606	0.00473	-0.00279
Total	**-0.07677**	**0.00199**	**0.10163**	**-0.03371**	**-0.03509**

While impulse response functions trace the effects of a shock to one endogenous variable on to the other variables in the VAR, variance decomposition separates the variation in an endogenous variable into the component shocks to the VAR. Thus, the variance decomposition provides information about the relative importance of each random innovation in affecting the variables in the VAR. The forecast error decomposition is the percentage of the variance of the error made in forecasting a variable (GDP) due to a specific shock at a given horizon (10 quarters). Thus, the forecast error decomposition is like a partial R^2 for the forecast error, by forecast horizon.

The exhibit and table below displays the variance decomposition for the estimated VAR model. It seems this time around that payments for capital assets has the largest contribution to the variation of provincial GDP of the five provincial public expenditure classifications, whilst the compensation of employees and transfers and subsidies have the lowest contribution to the variation of provincial GDP

The results of the impulse-response and variance deposition functions of the six variable estimated VAR model suggests that expenditure on fixed and current assets has the largest impact on the provincial GDP and that payments for administration have the shortest and smallest impact.

Exhibit 2: Variance Decomposition (log and first difference format)

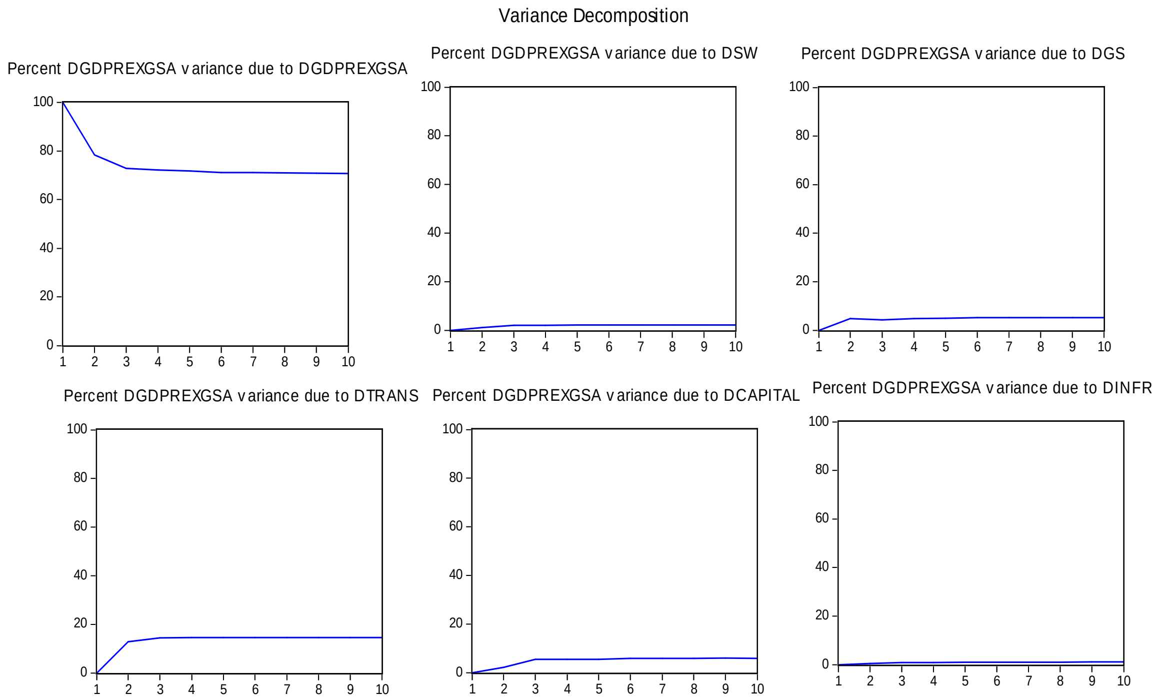


Table 12: Variance Decomposition (log and first difference format)

Variance Decomposition						
Period	DGDPREXGSA	DCAPITAL	DINFR	DGS	DSW	DTRANS
1	100	0	0	0	0	0
2	78.40132	13.64319	5.17470	2.69910	0.01601	0.06569
3	72.84218	14.52377	5.31189	7.02604	0.01987	0.27625
4	72.19098	14.39180	5.26896	7.79897	0.05060	0.29869
5	71.70107	14.51923	5.63100	7.74710	0.10308	0.29852
6	71.15209	14.89189	5.75079	7.76757	0.13740	0.30026
7	71.10573	14.87330	5.80510	7.77056	0.14480	0.30051
8	71.00665	14.85444	5.88572	7.79478	0.14948	0.30894
9	70.91756	14.90979	5.91466	7.78399	0.16543	0.30858
10	70.81108	14.88349	5.95684	7.85870	0.17728	0.31261
Average	**72.23652**	**14.61010**	**5.63329**	**7.13853**	**0.10711**	**0.27445**

4.1 A GMM approach

The regression equation (in matrix format) to estimate the relationship between the provincial GDP and the various components of provincial public expenditure can be expressed as follows:

$$\boldsymbol{Y}\mathbf{t} = \boldsymbol{\alpha}\mathbf{t} + \boldsymbol{\beta}'\mathbf{1}\boldsymbol{X}\mathbf{1t} + \boldsymbol{\beta}'\mathbf{2}\boldsymbol{X}\mathbf{2t} - \mathbf{1} + \boldsymbol{\varepsilon}\mathbf{t}$$

where Y_t = the real economic growth rate at time t, α = constant at time t, X_1, the various components of government expenditure at time t, and X_2, the various components of government expenditure at time t-1 and ε is the error term at time t. β_1 and β_2 are the coefficients to be estimated. The number of lags of the various endogenous variables to be included will depend on the specification of the equation.

Running the regression equation (in I(1) format and including a lagged variable of each independent variable) using OLS yields the following output (table 11). It is noteworthy that none of the components of provincial public expenditure, individually or jointly, is statistically significant, etc.

Table 11: Estimated Regression Equation using OLS

Dependent Variable: DGDPREXGSA
Method: Least Squares
Sample (adjusted): 2006Q4 2012Q1
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DCAPITAL	0.025035	0.035880	0.697753	0.4998
DCAPITAL(-1)	0.016413	0.030049	0.546216	0.5958
DINFR	0.015500	0.023091	0.671248	0.5159
DINFR(-1)	-0.014735	0.020179	-0.730249	0.4805
DGS	-0.038608	0.054236	-0.711850	0.4914
DGS(-1)	-0.032245	0.055970	-0.576120	0.5761
DSW	0.002344	0.069927	0.033523	0.9739
DSW(-1)	-0.001152	0.060580	-0.019012	0.9852

DTRANS	0.018357	0.026099	0.703342	0.4965
DTRANS(-1)	0.039600	0.030838	1.284131	0.2255
C	0.004794	0.004434	1.081255	0.3027

R-squared	0.302894	Mean dependent var	0.006639
Adjusted R-squared	-0.330838	S.D. dependent var	0.010538
S.E. of regression	0.012157	Akaike info criterion	-5.675007
Sum squared resid	0.001626	Schwarz criterion	-5.129486
Log likelihood	73.42508	Hannan-Quinn criter.	-5.546499
F-statistic	0.477953	Durbin-Watson stat	0.916261
Prob(F-statistic)	0.872388		

Including a lagged dependent variable in the above equation and re-estimating using OLS yields the following results.

Table 12: Estimated Regression Equation including lagged dependent variable using OLS

Dependent Variable: DGDPREXGSA
Method: Least Squares
Sample (adjusted): 2006Q4 2012Q1
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DGDPREXGSA(-1)	0.642002	0.270634	2.372217	0.0391
DCAPITAL	0.016759	0.030304	0.553044	0.5924
DCAPITAL(-1)	0.009596	0.025374	0.378185	0.7132
DINFR	0.000152	0.020425	0.007444	0.9942
DINFR(-1)	-0.025988	0.017581	-1.478125	0.1702
DGS	-0.005074	0.047648	-0.106484	0.9173
DGS(-1)	0.005177	0.049537	0.104501	0.9188
DSW	-0.000510	0.058680	-0.008683	0.9932
DSW(-1)	-0.013125	0.051076	-0.256978	0.8024
DTRANS	0.030782	0.022515	1.367202	0.2015
DTRANS(-1)	0.019351	0.027244	0.710280	0.4938
C	0.002326	0.003863	0.602045	0.5605

R-squared	0.553921	Mean dependent var	0.006639
Adjusted R-squared	0.063235	S.D. dependent var	0.010538
S.E. of regression	0.010199	Akaike info criterion	-6.030539
Sum squared resid	0.001040	Schwarz criterion	-5.435425
Log likelihood	78.33593	Hannan-Quinn criter.	-5.890348
F-statistic	1.128870	Durbin-Watson stat	1.796168
Prob(F-statistic)	0.428031		

Although the reliability of the model has significantly improved (adjusted R-squared improved from -0.33 to 0.06), the components of provincial public expenditure is still not statistically significant.

However, Hansen and West (2002) suggest that the above procedure (OLS) may not be appropriate since the independent variables may not be strictly exogenous. Hall (2009) argues that GMM provides a computationally convenient method of obtaining consistent and asymptotically normally distributed estimators of the parameters of statistical models.

Consider the mentioned regression equation, i.e.,

$$\boldsymbol{Y}\mathbf{t} = \boldsymbol{\alpha}\mathbf{t} + \boldsymbol{\gamma}\boldsymbol{Y}\mathbf{t-1} + \boldsymbol{\beta}'\mathbf{1}\boldsymbol{X}\mathbf{1t} + \boldsymbol{\beta}'\mathbf{2}\boldsymbol{X}\mathbf{2t-1} + \boldsymbol{\varepsilon}\mathbf{t}$$

Hansen and Hodrick (2009) demonstrate that the following population moment condition should hold;

$$\boldsymbol{E}[\mathrm{ft,k}(\boldsymbol{Yt} - \boldsymbol{\gamma}\boldsymbol{Y}\mathbf{t-1} - \boldsymbol{\beta}'\mathbf{1}\boldsymbol{X}\mathbf{1t} - \boldsymbol{\beta}'\mathbf{2}\boldsymbol{X}\mathbf{2t-1}] = \mathbf{0}$$

where $(\beta'_1, \beta'_2) = (0, 1)$.

It is relevant to include a set of instrumental variables for GMM estimation. The instruments must satisfy two requirements: First, they must be orthogonal to the error process, which is known as instrument exogeneity; and, second, they must be correlated with the included endogenous variables, more formally known as instrument relevance. It must however be noted that no tests were performed for either instrument exogeneity or instrument relevance.

Estimating the above equation using the GMM estimator and using the independent variables and their lags as instruments (exactly identified, i.e., number of instruments (m) equal the number of endogenous regressors (k)) yields the following results.

Table 13: Estimated Regression Equation including lagged dependent variable using GMM

Dependent Variable: DGDPREXGSA
Method: Generalized Method of Moments
Sample (adjusted): 2006Q4 2012Q1
Included observations: 22 after adjustments
Estimation settings: tol=0.00010, derivs=analytic (linear)
Initial Values: C(1)=0.64200, C(2)=0.01676, C(3)=0.00960, C(4)=0.00015, C(5)=-0.02599, C(6)=-0.00507, C(7)=0.00518, C(8)=-0.00051, C(9)= -0.01313, C(10)=0.03078, C(11)=0.01935, C(12)=0.00233
Kernel: Bartlett, Bandwidth: Fixed (2), No prewhitening
Simultaneous weighting matrix & coefficient iteration
Convergence achieved after: 1 weight matrix, 2 total coef iterations
Instrument list: DGDPREXGSA(-1) DCAPITAL DCAPITAL(-1) DINFR DINFR(-1) DGS DGS(-1) DSW DSW(-1) DTRANS DTRANS(-1) C

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DGDPREXGSA(-1)	0.642002	0.166203	3.862766	0.0031
DCAPITAL	0.016759	0.023214	0.721942	0.4869
DCAPITAL(-1)	0.009596	0.010888	0.881298	0.3988
DINFR	0.000152	0.015075	0.010086	0.9922
DINFR(-1)	-0.025988	0.011559	-2.248344	0.0483
DGS	-0.005074	0.034303	-0.147913	0.8854
DGS(-1)	0.005177	0.025875	0.200059	0.8454
DSW	-0.000510	0.036315	-0.014031	0.9891
DSW(-1)	-0.013125	0.037832	-0.346943	0.7358
DTRANS	0.030782	0.016106	1.911240	0.0850
DTRANS(-1)	0.019351	0.011104	1.742748	0.1120
C	0.002326	0.002768	0.840292	0.4204

R-squared	0.553921	Mean dependent var	0.006639
Adjusted R-squared	0.063235	S.D. dependent var	0.010538
S.E. of regression	0.010199	Sum squared resid	0.001040
Durbin-Watson stat	1.796168	J-statistic	2.80E-45

The adjusted R-square statistics and the coefficients using the GMM estimator and OLS are similar. However, the degree of statistical significance of the independent variables have changed somewhat; for example, in the OLS model the lagged infrastructure expenditure variable is not statistically significant whilst in the GMM model it is. But the coefficient is negative which seems counter-intuitive.

Bond et al. (2001) state that the first-differenced GMM estimator has been found to have poor finite sample properties, in terms of bias and imprecision, in one important case. This occurs when the lagged levels of the series are only weakly correlated with subsequent first-differences, so that the instruments available for the first-differenced equations are weak. They further suggest that the system GMM estimator combines the standard set of equations in first-differences with suitably lagged levels as instruments, with an additional set of equations in levels with suitably lagged first-differences as instruments.

The set of equations in level format with their suitable lagged first-differences as instruments are estimated and displayed in the table below.

Table 14: Estimated Regression Equation level format with their suitable lagged first-differences using GMM

Dependent Variable: GDPREXGOV
Method: Generalized Method of Moments
Sample (adjusted): 2006Q4 2012Q1
Included observations: 22 after adjustments
Kernel: Bartlett, Bandwidth: Fixed (2), No prewhitening
Simultaneous weighting matrix & coefficient iteration
Convergence achieved after: 1 weight matrix, 2 total coef iterations
Instrument list: DGDPREXGOV(-1) DCAPITAL(-1) DINFR(-1) DGS(-1) DSW(-1) DTRANS(-1) C

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPREXGOV(-1)	0.500831	7.839433	0.063886	0.9499
CAPITAL	0.040030	0.963586	0.041542	0.9674
INFR	-0.004770	0.248132	-0.019223	0.9849
GS	-0.140752	1.076233	-0.130782	0.8977
SW	0.121006	1.004374	0.120479	0.9057
TRANS	0.032115	0.708170	0.045349	0.9644
C	8.196741	121.1151	0.067677	0.9469

R-squared	0.853878	Mean dependent var	18.00318
Adjusted R-squared	0.795429	S.D. dependent var	0.035103
S.E. of regression	0.015877	Sum squared resid	0.003781
Durbin-Watson stat	1.326140	J-statistic	-2.21E-21

The level method certainly gives a much higher adjusted R-square statistic as compared with the first difference method (0.79 compared to 0.06), but that is to be expected. However none of the components of provincial public expenditure is statistically significant.

The non-stationary nature of the variables of the above model in all probability caused the significant increase or improvement in the adjusted R-square statistic and as such the results of the model are at best spurious. Differencing the above equation, excluding the lagged independent variable and including the lagged first-differences as instruments, the model is estimated and displayed in the table below.

Table 15: Estimated Regression Equation 1st difference format with their suitable lagged first-differences using GMM

Dependent Variable: DGDPREXGOV
Method: Generalized Method of Moments
Sample (adjusted): 2006Q4 2012Q1
Included observations: 22 after adjustments
Kernel: Bartlett, Bandwidth: Fixed (2), No prewhitening
Simultaneous weighting matrix & coefficient iteration
Convergence achieved after: 4 weight matrices, 5 total coef iterations
Instrument list: DGDPREXGOV(-1) DCAPITAL(-1) DINFR(-1) DGS(-1) DSW(-1) DTRANS(-1) C

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DCAPITAL	-0.059571	0.036748	-1.621094	0.1245
DINFR	0.066853	0.032391	2.063945	0.0556
DGS	0.061295	0.053395	1.147952	0.2679
DSW	0.077631	0.063589	1.220818	0.2398
DTRANS	-0.073135	0.047299	-1.546219	0.1416
C	-0.003449	0.005353	-0.644331	0.5285

R-squared	-0.569891	Mean dependent var	0.003182
Adjusted R-squared	-1.060481	S.D. dependent var	0.016442
S.E. of regression	0.023602	Sum squared resid	0.008913
Durbin-Watson stat	1.996720	J-statistic	0.001336

The adjusted R-square statistic is much lower when using the variables in first difference format compared to level format, but what is very insightful is the fact that the infrastructure expenditure variable is now statistically significant with a positive coefficient as expected. But none of the other government expenditures are statistically significant.

5. SUMMARY AND CONCLUSIONS

Macroeconomics, especially the Keynesian school of thought, suggests that government spending accelerates economic growth. Thus, government expenditure is regarded as an exogenous force that changes aggregate output. John Maynard Keynes was the principle supporter that governments implement counter cyclical fiscal policy in order to achieve full employment. However the literature suggests that there is no general consensus on the topic, with a number of studies yielding different results. There are also a number of studies which argue that in fact government expenditure constrains economic growth.

In general the two principal empirical findings can be summarized as:

- Provincial Government expenditure on infrastructure is positively and significantly correlated with economic growth, while the growth effect of current expenditure is insignificant or marginal at best and of a very short duration.
- At the departmental level, total expenditures in education, health and roads are the only outlays that remain significantly associated with growth and supporting of growth over a long duration.

The above findings in turn support or suggest the following policy implications:

> First, government should ensure that capital expenditure is increased in a manner that it will raise the province's production capacity and accelerate economic growth.
>
> Second, government should increase its investment in transport and communication sectors, since it would reduce the cost of doing business as well as raise the profitability of firms.

Third, government should support and grow the education and health sectors through increased funding, as well as ensuring that the resources are properly managed and used for the development of education and health services.

In this study, we compiled government expenditures by types between 2006 and 2012. We then analyzed trends and impact of various forms of government spending using two different econometric techniques. However, it must be stated that the data limitations are a definite constraint or threat to the reliability of the results. Unfortunately no pre 2006 data are available.

The empirical results of the study indicate that:

The composition of public expenditure matters for growth.
Only infrastructure expenditure contributed positively to economic growth in KwaZulu-Natal.

Some lessons can be drawn from this study:

First, various types of government spending have differential impacts on economic growth, implying greater potential to improve efficiency of government spending by reallocation among sectors.
Second, governments should reduce their spending in unproductive sectors and should increase spending on production-enhancing investments.

Thus, in conclusion, it becomes increasingly important to explore further what portfolio of government outlays is optimal in growth and welfare terms.

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