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GOVERNMENT REVENUE AND EXPENDITURE CAUSALITY IN THE PRESENCE OF SEASONALITY IN BARBADOS

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Recent empirical work in the area of government revenue and expenditure has gone beyond standard regression analysis into the realm of Granger causality. This new emphasis is an attempt to resolve the causal relationship between the two variables which remains an unclear theoretical issue[1]. Barro (1974), a supporter of the Ricardian equivalence proposition[2], argues that increased taxes and borrowing (deficits) are the outcomes of higher levels of fiscal expenditures so that causality runs from expenditures to revenues with no feedback. Buchanan and Wagner (1977) explained the growth of government expenditure as a consequence of persistent government deficits. They stated that

> "debt financing reduced the perceived price of publicly provided goods and services. In response, citizen-taxpayers increased their demand for such goods and services. Preferred budget levels will be higher and their preferences will be sensed by politicians and translated into political outcomes" (p.139).

More directly they argued that a smaller proportion of spending financed by direct taxation because of fiscal illusion leads to even greater spending than would occur otherwise.

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1. A causal link was hinted at in the two earliest explanations of government expenditure growth; 'Wagner's law' recognised the importance of revenue as a constraint on government spending whereas the 'displacement effect' suggested government spending first taxes later.

2. This theorem suggests that budget deficits and taxation have equivalent effects on the economy.

Using the approach developed by Borcherding and Deacon (1972) and Bergstrom and Goodman (1973)[3], Niskanen (1978) tested the Buchanan -Wagner conjecture. Niskanen used standard regression analysis to test the hypothesis that "high federal deficits have contributed to a rapid increase in the federal spending" and concluded that "federal deficits have significantly increased the level of federal spending" (p.597). Shibata and Kimura (1986) suggested that "the most that he [Niskanen] could infer from this type of econometric analysis was the possible existence of a (positive) correlation between the size of federal deficits and total federal spending. Obviously, he cannot draw any conclusion about the causal relationship between the variables". The issue in their opinion should be one of causal relation rather than a simple correlation.

That observation has led to a proliferation of causality studies using data from the U.S. Most of these studies used annual data with the exception of Von Furstenberg, Green and Jeong (1986) and Ram (1988,b). Anderson, Wallace and Warner (1986), using federal data for the period 1946-83, found no evidence of a causal relationship running from real revenues to real expenditures, however, real expenditures did cause real revenues. On the other

3. These two studies used a median voter model which focussed on estimating the price and income elasticities for government produced goods. Niskanen (1978) expanded the model to estimate an equation for total federal spending.

hand, Shibata and Kimura (1986) and Manage and Marlow (1986) and Ram (1988,a) found a causal line from revenue to expenditure giving support to the Buchanan-Wagner hypothesis. Holtz-Eakin, Newey and Rosen (1987) using cross-sectional data also found support for the Buchanan-Wagner hypothesis.

With the quarterly data, there are also conflicting results for the U.S. Von Furstenberg, Green and Jeong (1986) found support for the 'spend now tax later' view of the world, while Ram (1988,a) generally supported causation from revenue to expenditure. More recently Ram (1988,b) extended his work to include other developed as well as less developed countries. His results were also conflicting in that "current-price data indicate almost as many cases of causality from revenue to expenditure as of causal flow in the opposite direction" (p. 268).

In this paper we extend Ram's (1988) methodology by employing recently developed tests for unit roots in seasonal data to determine the degree of differencing necessary to achieve stationarity in the variables. The rationale for expecting seasonality is rooted in both institutional and economic factors (see Appendix).

STATISTICAL METHODOLOGY

The search for the causal patterns between government expenditures and government revenues can be done with the help of Granger (1969) concept of causality. Although its exact relationship with the many definitions given by philosophers is not very clear (see Hicks (1979) on this issue), it is fair to say that it is the only definition currently available which can be empirically applied (with known statistical techniques) by practicing social scientists. Granger's definition of causality relates to a dynamic stochastic system in terms of a predictability criterion and is based on the notion that the future cannot cause the past but the past can cause the future. Specifically, if forecasts of GR using past values of GR and GE are better than forecasts obtained using past values of GR alone, GE is said to cause GR in the Granger sense. Causality from GR to GE is defined in a similar way. If GR causes GE and GE does not cause GR then unidirectional causality exists from GR to GE. Where it is found that GR does not cause GE and GE does not cause GR, it is said that GE and GR are either statistically independent or related contemporaneously. If GR causes GE and the hypothesis that GE does not cause GR is rejected the relationship may be characterized by feedback.

The statistical framework for characterizing causality may be developed by considering the following bivariate stationary autoregressive model

$$\begin{bmatrix} GE_t \\ GR_t \end{bmatrix} = \begin{bmatrix} \psi_{11}^{r}(L) & \psi^{n}_{12}(L) \\ \psi^{p}_{21}(L) & \psi^{q}_{22}(L) \end{bmatrix} \begin{bmatrix} GE_t \\ GR_t \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ \eta_t \end{bmatrix} \qquad (1)$$

where $\psi_{ij}^{w}(L) = \sum_{k=1}^{w} \psi_{ijk} L_k$, and L is the lag operator defining $L^k Z = Z_{t-k}$. GE_t and GR_t are government expenditures and revenues respectively for t=1, 2....T. (ϵ_t, η_t) is a bivariate white noise process with zero mean and constant covariance matrix, Ω, and r, n, p, q and w denote the length of the lag polynomials. Sims (1972) has shown that Granger's (1969) definition of causality can be established from the parameters in $\psi_{ij}^{w}(L)$. When $\psi^{p}_{21}(L) = 0$ and $\psi^{n}_{12}(L) \neq 0$ the system depicts unidirectional causality from GR_t to GE_t. If $\psi^{p}_{21}(L) = \psi^{n}_{12}(L) = 0$ then GR_t and GE_t are mutually uncaused or contemporaneously related. Feedback occurs if $\psi^{p}_{21}(L) \neq 0$ and $\psi^{n}_{12}(L) \neq 0$.

Granger (1969), Sims (1972 and Geweke (1981b, 1983) have derived causality testing procedures based on (1) which use Ordinary Least Squares and the conventional Fisher- Snedecor "F" test to see whether $\psi_{ij}^{w}(L)=0$, i=j[1]. As Hsaio (1979, 1981) notes, this approach is potentially problematic because the test of $\psi_{ij}^{w}(L)=0$ is quite sensitive to lag selection[2]. He proposed a test procedure which combines the minimum finite prediction error (FPE) propounded by Akaike (1969a, b) with Granger's (1969) definition of causality, thereby allowing the data to determine the lag structure. Assuming the observations -w+1 to 0 to be fixed for the data set [t:t=(-w+1),....0.....T] where $w \geq \max(r, n, p, q)$ then the FPE for GE_t is defined as

$$FPE_{ge}(r,n) = \frac{T+r+n+1}{T-r-n-1} \times \frac{SSE}{T} \qquad (2)$$

where SSE is the sum of the squares of residuals from the estimated equation

$$GE_t = \psi_{11}^{r}(L)\ GE_t + \psi^{n}_{12}(L)\ GR_t + \epsilon_t \qquad (3)$$

The choice of the lag lengths r,n is based on the minimum FPE when r and n are varied. For example, r and n would be preferred to $(r+\delta)$ and $(n+\gamma)$ respectively if $FPE_{ge}(r,n) < FPE_{ge}(r+\delta, n+\gamma)$.

T is the sample size.

The method used in this paper augments the Hsaio procedure in that an initial testing procedure is used to determine the degree of integration for the strong seasonal variables (see figures 1 and 2). A non-deterministic series X_t is said to be integrated of order (d,D), denoted $X_t \sim I(d,D)$, if the series has a stationary, invertible ARMA representation after one-period differencing d times and seasonally differencing D times. Seasonality, as considered in this paper, may have both deterministic and stochastic components. Thus, if the observed series is GR_t, then it assumed that

$$GR_t = X_t + K_q$$

where X_t is purely stochastic and K_q is the deterministic seasonal component for season q. We remove deterministic seasonality by a prior regression of the levels series on four quarterly dummy variables; the residuals for this regression are then treated in the subsequent analyss as if they are the true X_t. This procedure is justified by Dickey, Hasza and Fuller (1984) for testing a unit root at a seasonal lag and by Dickey, Bell and Miller (1986) for testing a non-seasonal unit root in the presence of deterministic seasonality. The specific methods to test for seasonal integration are given in Dickey-Fuller, Dickey-Fuller-Hasza and Engle-Granger Hylleberg and Yoo (see Appendix for a description of these tests).

The statistical procedure employed involves five six steps. First, determine the orders of integrability of the data series, Y and M, and transform them to their stationary counterparts y and m. Second, treat y as a uni-dimensional autoregressive process and compute its FPE by varying the maximum order of lags from 1 to k. The order which has the smallest FPE is chosen. Third, treat y as the only output of the system and assume m to be the manipulated variable regulating the outcome of y. The FPE criterion is then employed to determine the lag order on m, on the assumption that the lag order of the lag operator on y is the one indicated in the previous step. Fourth, the smallest FPEs of steps 1 and 2 are compared. If the former is less than the latter, a one dimensional autoregressive representation for y is used and it is said that m does not Granger cause y. If the converse is true then m causes y. Fifth, the first three steps are repeated for the m process where y is now the manipulated variable. Finally, combine the single equation specifications to obtain a tentatively identified system. Estimate the system of equations using Full Information Maximum Likelihood (FIML) and perform a sequence of likelihood ratio tests by deliberately overfitting and underfitting the identified system in order to check its adequacy.

EMPIRICAL RESULTS

Data for the paper is quarterly observations spanning the period 1973:11 - 1989:111 and were obtained from the Central Bank of Barbados. The measure of outlay and revenue used is nominal total government expenditures and nominal government revenues. Results for current expenditure are also reported.

The unit roots tests - Augmented Dickey Fuller; Dickey-Hasza-Fuller; Engle-Granger-Hylleberg-Yoo - for seasonal integration suggest a first difference model with seasonal dummies should be used rather than the often used fourth differences Δ_4, or $\Delta_1 \Delta_4$ (see table 1).

Lag order of the variables assuming that they follow uni-dimensional AR processes is given in Table [2]. The equations were estimated in logs with K=12 as the upper bound on the lag structure.

Table 3 gives the case where each variable is fixed at the lag obtained in Table 2. FIML confirmed this.

Comparing Table 2 and 3 we find causality running from TGE $\Rightarrow$ GR but GR $\nRightarrow$ TGE in the Granger sense. GE $\not\Leftrightarrow$ GR.

TABLE 2

FPE OF UNI-DIMENSIONAL PROCESSES FOR
CHANGES IN GOVERNMENT REVENUES AND EXPENDITURES

LAGS	DLGR	DLGE	DLTGE
1	0.007671106	0.008324269	0.00821846
2	0.006688301	0.007812528	0.008427471
3	0.006883018	0.007846553	0.00864328
4	0.006716509	0.008098113	0.008978144
5	0.006913729	0.008202207	0.00926333
6	0.00716899	0.008278917	0.009335429
7	0.007427421	0.008601283	0.009335429
8	0.007712778	0.0089012	0.009621698
9	0.008005616	0.009103071	0.009954497
10	0.008326325	0.009467744	0.010284276
11	0.008662678	0.009721583	0.01064289
12	0.009015849	0.009563773	0.010768584

Note: The underlined values indicate the minimum value of the FPE.

TABLE 3

OPTIMAL LAG OF 'MANIPULATED' AND FPE OF CONTROLLED VARIABLES

Controlled Variables	Manipulated Variable	Optimal Lag	Minimum FPE	Conclusion
DLGR(2)	DLTGE	2	0.006529559	Total Expenditure causes Current Revenue
DLTGE(1)	DLGR	1	0.008507773	Current Revenue does not cause Total Expenditure
DLGR(2)	DLGE	1	0.006836927	Current Expenditure does not cause Current Revenue
DLGE(2)	DLGR	1	0.007976049	Current revenue does not cause Current Expenditure

Note: (a) The values in brackets indicate the order of the AR operator for the controlled variable.

POLICY IMPLICATIONS

The major finding suggests a line of causality from total expenditure to revenue which can be supported by the budgetary framework in Barbados. The presentation of the budgetary proposals to the country is preceded by the 'Barbados Estimates ', that is, the annual (fiscal year) estimates of expenditure and revenue as required under the Appropriations Bill and the Economic Report (Survey) which reviews the performance of the economy during the previous calendar year, See Downes (1988) for a full exposition of the budgetary process. What comes across from the 'Estimates' is a prior determination of expenditure followed by some consideration of the revenue requirement.

The fact that total expenditure and not current expenditure causes revenue suggests that all forms of government expenditure are significant in the determination of government's revenue. This result indicates that government does not differentiate between current and capital expenditure, rather government perceives the tax-payer as having to make contributions to the provision of social and economic services as well as to infrastructural development.

Another significant implication of the findidng relates to the issue of tax reform. According to Bird (1989), "in many countries expenditure reform seems both more needed than, and a necessary pre-condition for tax reform". Thus our empirical finding for Barbados, that expenditure causes revenue, supports Bird's contention for the need to have expenditure reform before tax reform.

FURTHER RESEARCH

Expand the system to a trivariate case, including income as the third variable.

Estimate a VAR system using variance decomposition.

APPENDIX

For Barbados, institutional factors such as the payment of corporation taxes in the first and fourth quarters of the calendar year and the ending of the fiscal year in March contribute to the seasonality in government's revenue and expenditure figures. Between 1976 and 1989, corporation taxes represented 22.4% of tax revenues in the first quarter, reaching a high of 29.0% in 1978 and a low of 14.5% in 1985. For the fourth quarter, the average contribution of corporation taxes to tax revenues over the 1976-88 period was slightly lower at 20.7%, with the high and low points coming in 1978 and 1985 respectively, the same as for the first quarter.

The economic factors such as the high level of activity in the sugar sector during the first quarter and the tourist winter season which runs from December 15 to April 15 also contributed to the peaks in government's figures. While there was some decline in the sugar sector's contribution to GDP, tourism increased from 8.8% in 1976 to 14.0% in 1988. More importantly, the weights of sugar and tourism are much higher in the first and fourth quarters respectively.

Integration Tests

The tests used here, with quarterly data, are:

i) Augmented Dickey-Fuller [$ADF(p)$]: the t-statistic for β in

$$\Delta X_t = \beta X_{t-1} + \alpha_1 \Delta X_{t-1} + \ldots + \alpha_p \Delta X_{t-p} + u_t,$$

$H_0: X_t \sim I(1,0)$ with $H_a: X_t \sim I(0,0)$. The critical values used are given in Fuller (1976, Table 8.5.2) for the regression including an intercept; justification for using these values when seasonal means are removed is provided by Dickey, Bell and Miller (1986, Appendix B).

ii) Dickey-Hasza-Fuller [$DHF(p)$]: the t-statistic for β in the regression

$$\Delta_4 X_t = \beta Z_{t-4} + \alpha_1 \Delta_4 X_{t-1} + \ldots + \alpha_p \Delta_4 X_{t-p} + u_t$$

where $Z_t = \hat{\lambda}(L) X_t = (1 - \hat{\lambda}_1 L - \ldots - \hat{\lambda}_p L^p) X_t$ and L is the lag operator. The $\hat{\lambda}_i$ are the coefficient estimates obtained in the prior regression of $\Delta_4 X_t$ on $\Delta_4 X_{t-1}, \ldots, \Delta_4 X_{t-p}$. $H_0: X_t \sim I(0,1)$; $H_a: X_t \sim I(0,0)$; critical values are given in Table 7 of Dickey, Hasza and Fuller (1984).

iii) Engle-Granger-Hylleberg-Yoo [$EGHY(p)$]: the t-statistics on π_1, π_2 and π_3 in

$$\Delta_4 X_t = \pi_1 Z_{1,t-1} + \pi_2 Z_{2,t-1} + \pi_3 Z_{3,t-2} + \alpha_1 \Delta_4 X_{t-1} + \ldots + \alpha_p \Delta_4 X_{t-p} + u_t$$

where $Z_{1t} = \hat{\lambda}(L)(1 + L + L^2 + L^3) X_t$

$$Z_{2t} = -\hat{\lambda}(L)(1 - L + L^2 - L^3) X_t$$

$$Z_{3t} = -\hat{\lambda}(L)(1 - L^2) X_t$$

and $\hat{\lambda}(L)$ is obtained as for the $DHF(p)$ statistic. The overall null hypothesis here is $H_0: X_t \sim I(0,1)$, but this is broken up using

$$1 - L^4 = (1 - L)(1 + L)(1 + L^2)$$
$$= (1 - \gamma_1 L)(1 + \gamma_2 L)(1 + \gamma_3 L^2)$$

with $\gamma_i = 1$, $i = 1,2,3$. Each π_i represents the difference between the corresponding γ_i and its value under H_0. The alternative hypotheses are $X_t \sim I(1,0)$, corresponding to $\pi_1 = 0$ with π_2 or π_3 non-zero, or $X_t \sim I(0,0)$, when $\pi_1 \neq 0$ and π_2 or π_3 is also non-zero.[1] The critical values are given by Engle, Granger, Hylleberg and Yoo (1987).

(iv) $HF(p)$: the F statistic for testing $\beta = 0$ in

$$\Delta\Delta_4 X_t = \beta_1 Z_{4,t-1} + \beta_2 Z_{5,t-4} + \alpha_1 \Delta\Delta_4 X_{t-1} + \ldots + \alpha_p \Delta\Delta_4 X_{t-p} + u_t \quad (3)$$

where $Z_{4t} = \hat{\lambda}(L)\Delta_4 X_t$ and $Z_{5t} = \hat{\lambda}(L)\Delta X_t$. In this case the $\hat{\lambda}_i$ are the coefficient estimates of $\Delta\Delta_4 X_t$ on $\Delta\Delta_4 X_{t-1}, \ldots, \Delta\Delta_4 X_{t-p}$. The null hypothesis here is $H_0: X_t \sim I(1,1)$, with alternative $H_a: X_t \sim I(0,0)$ or $I(1,0)$ or $I(0,1)$; critical values are obtained by simulation.

(v) The t-ratios on β_1 and β_2 in equation (3), with the same null and alternative hypotheses as in (iv). We refer to these as $OCSB$ t-ratios; the rationale for examining these is discussed below. Critical values are again obtained by simulation.

Hasza and Fuller (1982) discuss using F-type statistics, as in (iv) above, for testing the $I(1,1)$ null hypothesis. They do not, however, consider the case of interest to us, where there is deterministic seasonality but no time trend under the alternative hypothesis. In any case, as Dickey and Pantula (1987) point out, such F statistics are inappropriate in that they are two-sided in nature, whereas the alternative of stationarity is one-sided.

For the non-seasonal case Dickey and Pantula propose starting from the highest level of differencing to be contemplated and testing down to lower levels using a sequence of one-sided t-tests, rather than starting from the lowest level and testing up. Our $OCSB$ t-tests follow the former route. That is, under the $I(1,1)$ null, β_1 provides a test of the non-seasonal unit root, while β_2 examines the unit root at the seasonal lag. Indeed, with $\beta_2 = 0$ the t-ratio on β_1 is an ADF test on the need for a first-order difference in addition to a seasonal difference; similarly, with $\beta_1 = 0$ the t-ratio on β_2 is a DHF test of the seasonal unit root after first differencing.

The two-stage regression carried out for (iv) and (v) results from considering a Taylor series expansion of

$$\lambda(L)(1 - \gamma_1 L)(1 - \gamma_4 L^4) X_t = u_t$$

about $\gamma_1 = \gamma_4 = 1$, with $\beta_1 = -(1 - \gamma_1)$ and $\beta_2 = -(1 - \gamma_4)$. Our proposed test statistics for β_1 and β_2 are analogous to the $EGHY$ t-ratios, although we do not examine the separate roots of $1 - \gamma_4 L^4$.

Below we use critical values for the F and t-statistics of (iv) and (v) obtained using 10,000 replications of 100 observations (approximately our sample size) for the process with true $\lambda(L) = 1$ and seasonal means of zero. Zero starting values were used in generating the series. In these simulations $\lambda(L)$ was not estimated, but the seasonal means were subtracted before calculation of the test statistics. Our simulations are discussed in further detail in Appendix 1.

Despite this prior subtraction of seasonal means, the critical values obtained for our t-ratios (see Table 1) are not very different from the value of -1.95 tabulated by Fuller for the case of testing a unit root with no intercept. Also, our F-test value is similar to 3.26 given by Hasza and Fuller for their two-coefficient F-test without an intercept. Thus, it appears the adjustment for seasonal means has relatively little influence on the distribution of the t-ratios when ΔX_t or $\Delta_4 X_t$ is used in place of X_t and tested for an additional unit root at a lag of a year or a quarter respectively.

It should be made clear that there is an important potential problem in the generality of the ADF test when applied to seasonal data. That is, the ADF statistic with $p \geq 3$ is sufficiently general to include the simple non-stationary seasonal process

$$\Delta_4 X_t = \Delta X_t + \Delta X_{t-1} + \Delta X_{t-2} + \Delta X_{t-3} = u_t$$

so that the ADF statistic on β in (i) above may test $H_0: X_t \sim I(0,1)$ instead of $H_0: X_t \sim I(1,0)$. Admittedly this problem is ruled out in the theory of the test by the assumption that the roots, other than the one being tested, are stationary; clearly, however, this cannot be guaranteed in practice. Similarly, because a unit root at lag four also implies a non-seasonal unit root, acceptance of the $I(0,1)$ null hypothesis for the DHF test may, in fact, be due to a $I(1,0)$ process.

The $EGHY$ test, in looking at the three distinguishable roots implied by Δ_4, separates the non-stationary seasonal and non-seasonal polynomials; therefore, it should assist in interpreting the ADF and DHF test results. Similarly, our $OCSB$ t-ratios should be helpful, since this test regression also embeds the two competing hypotheses.

Notice that our implementation of the DHF and $EGHY$ tests, as outlined above, is different in one respect from that proposed by the original, respective, sets of authors. That is, we use the variable as defined under H_0 as the dependent variable, rather than this variable transformed using $\hat{\lambda}(L)$. The test statistics are invariant to this change, since the p lags indicated by $\hat{\lambda}(L)$ are explanatory variables in the regression. However, where $\lambda(L)$ is unknown, our form has the advantage of being able to indicate over-specification of p.

[1] The other case of interest might be $\pi_1 \neq 0$ with $\pi_2 = \pi_3 = 0$; this may indicate that unit differences had previously been taken whereas seasonal differences were appropriate.

Granger's Method of Causation

① Stochastic System → jointly Stationary series

② Linear Predictor

③ Mean Square Error

Axiom (a) $t+j \Rightarrow t$

(b) Information (No redundancy)

(c) Stability

ISSUES

① Non-stationarity (Trend / Seasonality) △

② Parameterisation
H Siao.