Government Size and Real GDP: A Causality Test

Edward Day
Department of Economics
University of Central Florida
Orlando, FL 32816-1400

Mark C. Strazicich
Department of Economics
University of North Texas
Denton, TX 76203-1457

Junsoo Lee
Department of Economics
University of Central Florida
Orlando, FL 32816-1400

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Abstract

We empirically examine the relation between the major components of government size and national output in the United States. The focus of our testing methodology is the Toda and Phillips (1993) causality test, which is employed as a safeguard when dealing with nonstationary cointegrated time series. Overall, we find that government size is cointegrated with and Granger causes real GDP, but real GDP does not cause government size. In addition, while the size of government investment increases real GDP, the size of government consumption has the opposite effect.

JEL Classification: E6, H1, C1

Key Words: Government Size, Real GDP, Causality Test

Corresponding author: Mark Strazicich, Department of Economics, University of North Texas, P.O. Box 311457, Denton, TX, 76203-1457. Telephone: 940-565-2220. Fax: 940-565-4426. Email: strazicich@unt.edu.

1. Introduction

The goal of this paper is to increase understanding of the relation between the size of government and national output. Few people dispute the need for government and most agree that a growing economy is associated with a larger government. However, recent evidence suggests that expansion in the relative size of government may reduce economic growth. (See, for example, Peden and Bradley, 1989; Barro, 1997; and Gwartney, Lawson, and Holcombe, 1998). As government expands beyond its core functions of national defense, police, courts, and establishing property rights, growth-inhibiting factors may arise. Indeed, the impact of government on real GDP is an old question-echoed in the decision by Chief Justice Marshall in 1808 that "... the power to tax is the power to destroy..." (McCulloch vs. Maryland, 1819).

The question of whether government is a positive, benign, or negative factor on the aggregate economy has been frequently examined. Landau (1983) tests the effect of government consumption on economic growth in ninety-six non-communist countries over the period 1961-1976 and finds a universally negative impact on economic growth from greater government spending. Kormendi and Meguire (1985) test a similar proposition using average economic growth over the period 1950-77 in forty-seven countries. They again find that government consumption has a negative impact on economic growth. Peden and Bradley (1989) derive a growth model that includes government spending in the production function and test their hypothesis using U.S. annual post-World War II data. Although they do not examine the time series properties of their data prior to testing, they perform tests in first-differences in case series are nonstationary. They again find a strong negative relationship between the rate of economic growth and the size and growth of government. Using a longer time period of 1929-1986 and a somewhat different method of modeling government in the production function, Peden (1991) confirms previous findings that growth in government spending reduces output growth, but finds a positive impact from government size. Barro (1991) returns to the strategy of Landau and tests a cross-section of ninety-eight countries. He again finds that the relative size of government consumption has a negative impact on economic growth, but the size of government investment is not statistically significant. Gwartney, Lawson, and Holcombe (1998) divide government spending into "core" and "non-core" functions and find that when the size of government grows beyond its core functions (approximately 15-20 percent of GDP) economic growth declines.

Several additional papers examining the relation between government and output growth provide contradictory or mixed results. For example, Grossman (1988) finds that growth in U.S. government spending has a positive impact on output growth, while government size has the opposite effect. Karras (1996) departs from the previous approach and focuses on estimating the "optimal" size of government. He concludes that the size of government consumption is optimal everywhere except in Africa and Asia, where government size is larger and smaller, respectively, than optimal. Karras estimates the optimal size of government for the world as a whole to be approximately twenty-three percent of GDP and finds that government spending is productive on the margin. Ghali (1998) uses time series methods to analyze the relationship between government size and economic growth for ten OECD countries. He finds that growth in government size "Granger causes" output growth, either directly or indirectly, in most countries. Vector auto-regressions indicate the effect is long lasting. Overall, there appears to be no clear consensus on the relation between government size, or growth in government, and national output.

We extend the existing literature in two directions. First, we utilize a relatively more advanced technique to examine the effect of government size on real GDP. Previous works mostly neglect time series properties of the data when formulating the model. It is well known that statistical inference assuming stationary time series can give misleading results when the series is nonstationary. If time series are nonstationary, the asymptotic distribution of the usual Granger causality test can be nonstandard leading to potential problems when using conventional tests. As a remedy, we employ the sequential causality test suggested in Toda and Phillips (1993, hereafter TP). As will be seen in the next section, we find that government size and real GDP are cointegrated. The TP sequential causality test has been shown to be more reliable when dealing with nonstationary time series that are cointegrated, since the cointegration property is utilized in the causality test.[1]

Second, contrary to previous work, we separate government size into its major components. The effect of each government size component is then empirically examined to test its impact on real GDP. The remainder of the paper proceeds as follows. In section 2 we discuss the testing methodology. Section 3 discusses our empirical findings. Section 4 concludes.

2. Testing Methodology

2.1 Econometric Considerations

[1] TP suggest that even the popular causality test based on the error correction model (ECM) may not be a safeguard procedure when dealing with nonstationary time series that are cointegrated.

To examine the relation between government size and national output, we adopt the potentially more robust causality test of TP. During the past decade there has been a tremendous growth in literature dealing with nonstationary time series. Econometric models that incorrectly assume a stationary process have been widely shown to lead to invalid statistical inference. Similar problems of misleading inference can also apply to causality tests. In the presence of nonstationary time series, the asymptotic distribution of the usual Granger causality test is often nonstandard with complicated properties. To promote more reliable inference, we carefully examine the time series properties and relationships among variables prior to formulating our causality test. We adopt the TP causality test, which sequentially examines a set of differing hypotheses to determine an optimal testing procedure. The TP test can be described as follows.

Given a vector time series $X_t = (X_{1t}, X_{2t}, X_{3t})'$ with elements consisting of n_1, n_2, and n_3 dimensional random vectors, respectively, we want to test for causal effects going from X_{3t} to X_{1t}. The series X_{2t} is included to avoid omitting any relevant variables, which could adversely affect the causality test (see Lütkephol, 1982). A vector autoregressive (VAR) model can be described as follows:

$$X_t = \mu + J(L)X_{t-1} + u_t \ , \qquad t = -k+1,..,T \ , \qquad (1)$$

where $J(L) = \Sigma_{i=1}^{k} J_i L^{i-1}$ and L is the lag operator with roots outside the unit circle. The null hypothesis of non-causality is formulated as:

$$H: \quad J_{1,13} = \cdots = J_{k,13} = 0 \ ,$$

where $J_{13}(L) = \Sigma_{i=1}^{k} J_{i,13} L^{i-1}$ is the upper-right sub-matrix of J(L) and is partitioned conformably with X_t. The usual F and likelihood ratio (LR) test statistic for the null hypothesis H can be defined in a straightforward manner. We denote these test statistics as F_{LEV} and LR_{LEV}, respectively, to denote that the data is in levels. A potential problem with these test statistics is that their asymptotic distributions are non-standard with nonstationary time series. In the tests that follow, we conclude that all variables are nonstationary, implying that the conventional Granger-type causality test cannot be performed using data in levels.

To avoid the potential problems noted above, one could consider performing Granger-type causality tests using the VAR model in differences; i.e., by replacing X_t and X_{t-1} in (1) with ΔX_t and ΔX_{t-1}. In this case, we denote the resulting F and LR statistics as F_{DIF} and LR_{DIF}, respectively. However, the VAR model in differences is misspecified if the variables are cointegrated (see Christiano and Ljungquist, 1988). Since cointegration implies utilizing the error correction model (ECM) suggested by Engle and Granger (1987), test statistics based on the ECM may be the relevant choice. We can write (1) in the equivalent ECM format as follows:

$$\Delta X_t = \mu + J^*(L)\Delta X_{t-1} + \underline{J}^* X_{t-1} + u_t \ , \qquad (2)$$

where $J^*(L) = \Sigma_{i=1}^{k} J^*_i L^{i-1}$ with $J^*_i = -\Sigma_{s=i+1}^{k} J_s$ for $i = 1,\ldots, k-1$, and $\underline{J}^* = J(1) - I_n$. The null hypothesis of non-causality is formulated as follows:

$$H^*: \quad J^*_{1,13} = \cdots = J^*_{k,13} = 0 \ \text{ and } \ \underline{J}^*_{13} = 0 \ , \qquad (3)$$

where $J^*_{13}(L) = \Sigma_{i=1}^{k} J^*_{i,13} L^{i-1}$ and $\underline{J}^*_{13}$ are the upper-right sub-matrices of $J^*(L)$ and $\underline{J}^*$, respectively. While it may be widely believed that Granger-type causality test statistics based on the ECM can provide a safeguard method, this is not guaranteed. TP provide evidence that Granger causality tests using the ECM still contain the possibility of incorrect inference. In addition, they might suffer from asymptotic nuisance parameter dependency problems (see TP for further details).

As we have seen, the potentially complicated nature of causality testing requires adopting the appropriate procedure. The sequential Wald tests of TP are designed to avoid potential problems from using the conventional techniques. One salient feature of the sequential Wald test used by TP is that its asymptotic limiting distribution is standard and free of nuisance problems, even if nonstationary variables are included in the system of equations.

TP have suggested a number of test statistics. We first consider Wald statistics testing H and H* denoted as W_{LEV} and W_{ECM}, respectively. (The specific form of the test statistic W_{LEV} and W_{ECM} is shown in TP following eq. (10), p. 1373 and eq. (17), p. 1382, respectively.) Just as the validity of the F and LR tests based on the VAR in levels and the ECM is not guaranteed, the validity of the W_{LEV} and W_{ECM} tests is also not guaranteed. TP decompose $\underline{J}^*$ into equation (2) with $\underline{J}^* = \Gamma A'$, where A is the eigenvector corresponding to the r largest eigenvalue that solves equation (9) in Johansen and Juselius (1990). The required condition for validity of the W_{ECM} test statistic is that the rank(A_3) = n_3, where A_3 is the last row (sub-matrix) in the matrix of cointegrating vectors A. W_{LEV} is valid if the rank(A_3) = n_3, or the rank(Γ_1) = n_1, where Γ_1 is the first row of the matrix Γ. Therefore, one can check the required conditions for validity of each hypothesis as follows:

$$H_1^*: \Gamma_1 = 0 \quad \text{and} \quad H_3^*: A_3 = 0 \ . \qquad (4)$$

TP suggest using W_1* and W_3* to test these hypotheses, respectively. If H_1* is rejected, we can test H* with W_{ECM} or test H with W_{LEV}. If H_3* is rejected, we can test H* with W_{ECM}. If neither H_1* or H_3* is rejected, we test the following hypothesis:

$$H_+^*: J^*_{1,13} = \cdots = J^*_{k,13} = 0 \quad (5)$$

using the W_+* statistic suggested in TP.

2.2 The Model

To test for causality between the size of government (G/Y) and national output (Y), we examine a model based on Peden (1991) and Ghali (1998). All variables are in real terms and defined in Table 1. We define the major components of government size in three ways. In each case, G/Y is separated into its two component parts. We then test for causality between each component of government size and real GDP. In addition, we control for the effect of other variables (X_{2t}) by including private investment spending relative to GDP (a proxy for changes in the capital stock), the total labor force, and the other component of G/Y. The three government size divisions that we employ are described as follows:

Division 1. Government Consumption / GDP and Government Investment / GDP[2]

Division 2. Government Defense Expenditures / GDP and Government Nondefense Expenditures / GDP

Division 3. Federal Government Expenditures / GDP and State and Local Government Expenditures / GDP.

[2] Government investment includes spending on structures and equipment, such as highways, schools, motor vehicles, and computers.

3. Empirical Results

To perform our tests, we examine quarterly U.S. data from 1965:1 to 1999:2.[3] The first step in applying our tests is to determine the order of integration of each variable in order to select the proper specification in the empirical model. We perform unit root tests using both the augmented Dickey-Fuller (ADF) and Phillips-Perron (1988, hereafter PP) procedure. All tests are performed in natural logarithms. A constant and linear time trend term is included in each test as visual inspection reveals that all series may exhibit a trend.

For the ADF test, we use four and twelve augmentation terms, respectively. For the PP test, we employ four and twelve truncation lags in addition to the automatic bandwidth selection procedure of Andrews (1991). In estimating the long-run variance of the PP test we use the Fejer kernel function. Results of testing the null hypothesis of a unit root are shown in Table 2. The results indicate that we are unable to reject the unit root null in any series at the 1% significance level. The results are robust to different numbers of augmentation terms in the ADF test and to different truncation lags in the PP test.[4] For RGDP, the unit root null is rejected at the 5% or 10% level in most cases. Given that it is commonly held that RGDP is a difference stationary series and our rejections are marginal at 5%, we proceed assuming that all the series in Table 2 are nonstationary in levels.

Next, we employ the Johansen (1991) cointegration test to determine if the variables in the system are cointegrated. We wish to determine whether there exists a

[3] All data comes from the DRI-McGraw-Hill BASIC Economic Database.

[4] In results unreported here, we find that all series are clearly stationary in first differences. These results are available upon request.

cointegrating vector between RGDP, PRIVINV, LABOR, and the two component measures of government size in each case. A constant is included in the deterministic term of the Johansen test to capture a possible trend component in the vector error correction model (VECM) with I(1) series. The cointegration test results are shown in Table 3. The trace statistics are reported using "r" to denote the number of cointegrating vectors. We reject the null hypothesis of no cointegration ($r \leq 0$) for all lags tested at the 5% level of significance and in all cases but one at the 1% level of significance. The null hypothesis of no cointegration is rejected at a maximum of one cointegrating vector ($r \leq 1$) at lag length $k = 8$ (at the 5% level of significance). Given the above results showing that variables are cointegrated, our causality tests will be performed using data in (log) levels.

Results using the TP causality test are shown in Table 4. We first look at the W_1* and W_3* test statistics (the last two columns) which test H_1* and H_3* in (4). The hypothesis H_3* is decisively rejected at the 5% level in all cases testing for causality from government size to RGDP, while H_1* is not rejected at the same level regardless of the lag (k) in the system. This result implies that $\text{rank}(A_3) = 1$, $\text{rank}(\Gamma_1) < 1$, and therefore only the W_{ECM} test is valid. The estimated W_{ECM} statistics and their p-values indicate that the null hypothesis H^* is rejected at the 1% level in all cases. These results confirm that government size "Granger causes" real GDP and holds regardless of the measure of spending included in government size. Note that cointegration implies a long-run equilibrium relationship between the integrated variables and also that at least one causal relationship exists.

To test if real GDP might also cause government size, testing was performed interchanging real GDP and total government size (TG). These results are shown in the last row of Table 4. In this case, both H_1* and H_3* are rejected at the 5% level using the W_1* and W_3* test statistics. This result implies that rank(A_3) = 1 and rank(Γ_1) = 1; therefore, both W_{ECM} and W_{LEV} are valid tests. The non-causality hypothesis H^*, however, is not rejected using the W_{ECM} test when k = 4 or 8, but the result from the W_{LEV} test is mixed depending on the choice of k. Overall, these results provide little evidence that real GDP causes government size.

To examine the direction of the causation effect, we look at the signs of the estimated coefficients from the vector error correction model (VECM) in Table 5. The VECM results indicate the long-run positive or negative impact of government size on output in the cointegrated system. Because the variables are in natural logarithms, the estimated coefficients can be interpreted as long-run elasticities of output with respect to each variable. Results show that when government size is separated into federal and state and local components, each has a positive impact on real GDP. The same is true when separating government size into defense and nondefense components; i.e., each has a positive impact on real GDP. When government size is separated into consumption and investment components the results differ. While the size of government investment spending has a positive impact on real GDP, the size of government consumption spending has a negative impact. In all cases, labor and private investment have a positive impact on real GDP. It is also interesting to note that the relative size of state and local spending and nondefense spending each has a much stronger impact on real GDP than the size of federal and defense spending, respectively.

4. Conclusion

The relation between the relative size of government and real GDP is empirically examined using quarterly U.S. data from 1965-1999. Contrary to previous research, we separate total government size into its major components of federal and state and local, consumption and investment, and defense and nondefense. To perform our tests, we employ a variety of time series methods, including unit root tests, cointegration tests, and the causality test of Toda and Phillips (1993). We reject the hypothesis of no causality going from government size to real GDP for all components of government spending. Our results indicate that all government size components are cointegrated and Granger-cause real GDP. Contrary to this, we find little evidence that real GDP Granger-causes government size.

In most cases, we find that government size has a positive impact on real GDP. The exception is when separating government spending into consumption and investment components. We find that the size of government investment spending has a positive impact on real GDP, while the size of government consumption spending has a negative impact. In broad terms, our results support both the traditional Keynesian and monetarist views regarding the impact of government spending. On the one hand, we show that government spending positively affects real GDP, while on the other hand we show that government consumption spending leads to significant crowding out.

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Table 1
Definition of Variables

RGDP	Real GDP
PRIVINV	Private investment/RGDP
LABOR	Total labor force
FDEFCON	Federal Defense consumption spending
FDEFINV	Federal Defense investment spending
FNDEFCON	Federal Nondefense consumption spending
FNDEFINV	Federal Nondefense investment spending
SLCON	State and Local consumption spending
SLINV	State and Local investment spending
GOV	Total Government spending
FED	(FDEFCON+FDEFINV+FNDEFCON+FNDEFINV)/RGDP
STATE	(SLCON + SLINV) / RGDP
TG_CON	(FDEFCON + FNDEFCON + SLCON) / RGDP
TG_INV	(FDEFINV + FNDEFINV + SLINV) / RGDP
DEF	(FDEFCON + FDEFINV) / RGDP
NDEF	(FNDEFCON + FNDEFINV + SLCON + SLINV) / RGDP
TG	GOV / RGDP

Notes: All measures are in real terms.

Table 2
Unit Root Tests

	ADF TEST		PHILLIPS-PERRON TEST[a]		
Series	lag=4	lag=12	lag=4	lag=12	autoband[b]
RGDP	-3.67**	-3.03	-3.51**	-3.36*	-3.47**
PRIVINV	-1.16	-0.28	-0.851	-.641	-0.671
LABOR	-2.30	-1.48	-2.00	-1.95	-2.07
FED	-1.90	-2.82	-1.17	-1.55	-0.97
STATE	-2.87	-1.62	-2.30	-2.15	-2.24
TG_CON	-2.83	-2.36	-2.23	-2.34	-1.96
TG_INV	-1.95	-2.64	-1.68	-1.78	-1.72
DEF	-2.07	-2.96	-1.05	-1.50	-0.94
NDEF	-3.00	-1.76	-2.54	-2.33	-2.29

Notes: All series are in natural logged levels and defined in Table 1. In both unit root tests, we include a constant and trend term, since all series exhibit a possible trend. Critical values are –4.03***, -3.45**, and –3.15* at the 1%, 5%, and 10%, respectively. [a]Employs the Fejer kernel to obtain the long-run variance in constructing the Phillips-Perron test. [b]Employs the automatic bandwidth of Andrews (1991).

Table 3
Johansen-Cointegration Test

	lag	r ≤ 0	r ≤ 1	r ≤ 2	r ≤ 3	r ≤ 4
FED, STATE	k = 2	99.2	60.2	24.8	8.46	.503
	k = 4	80.7	42.3	18.0	7.27	.001
	k = 8	108.6	54.4	27.0	11.3	.537
TG_CON, TG_INV	k = 2	83.6	35.1	18.1	4.68	.567
	k = 4	95.3	42.7	17.8	8.56	.640
	k = 8	88.1	49.5	23.3	10.8	.105
DEF, NDEF	k = 2	85.0	50.9	22.5	8.15	.303
	k = 4	69.3	40.8	20.4	7.49	.014
	k = 8	98.8	51.7	24.6	10.3	.992
FED_CON, FED_INV	k = 2	100.7	30.8	16.3	5.46	.679
	k = 4	90.3	38.8	15.1	4.02	.008
	k = 8	117.1	64.1	27.6	11.4	5.18

Notes: All variables are in natural logs and defined in Table 1. Labor (LABOR), private investment spending (PRIVINV) relative to Real GDP, and a constant term are additionally included in each test. In the VAR or ECM system of equations with I(1) series, the constant term captures a possible trend component. The trace statistics are reported using r to denote the number of cointegrations in the system. Corresponding critical values are:

	r ≤ 0	r ≤ 1	r ≤ 2	r ≤ 3	r ≤ 4
5%	68.5	47.2	29.7	15.4	3.76
1%	76.1	54.5	35.7	20.0	6.65

Table 4
Toda-Phillips Causality Test

Causality Direction Tested	Lags	W_{LEV}	W_{ECM}	W_{+}*	W_{1}*	W_{3}*
FED ® RGDP	k = 4	1.41 (.84)	760. (.0)	1.93 (.59)	.043 (.84)	229 (.0)
(PRIVINV, LABOR, STATE)	k = 8	8.26 (.41)	23984(.0)	5.40 (.61)	.004 (.95)	31.4 (.0)
STATE ® RGDP	k = 4	5.31 (.26)	20.8 (.0)	5.13 (.16)	.043 (.84)	304 (.0)
(PRIVINV, LABOR, FED)	k = 8	20.4 (.01)	234 (.0)	19.0 (.01)	.004 (.95)	4.39 (.04)
TG_CON ® RGDP	k = 4	1.90 (.75)	498 (.0)	1.66 (.65)	1.31 (.25)	51.9 (.0)
(PRIVINV, LABOR, TG_INV)	k = 8	7.29 (.51)	148 (.0)	6.07 (.53)	1.82 (.18)	563 (.0)
TG_INV ® RGDP	k = 4	7.97 (.09)	3000 (.0)	6.20 (.10)	1.31 (.25)	632 (.0)
(PRIVINV, LABOR, TG_CON)	k = 8	25.4 (.0)	3092 (.0)	20.8 (.0)	1.82 (.18)	1335 (.0)
DEF ® RGDP	k = 4	1.17 (.88)	89.5 (.0)	1.29 (.73)	.452 (.50)	309 (.0)
(PRIVINV, LABOR, NDEF)	k = 8	13.7 (.09)	15637(.0)	9.07 (.25)	.005 (.95)	56.2 (.0)
NDEF ® RGDP	k = 4	2.97 (.56)	58.5 (.0)	2.46 (.48)	.452 (.50)	162 (.0)
(PRIVINV, LABOR, DEF)	k = 8	8.41 (.40)	735 (.0)	6.98 (.43)	.005 (.95)	.902 (.34)
RGDP ® TG	k = 4	7.03 (.13)	.963 (.92)	1.82 (.61)	4.40 (.04)	129 (.0)
(PRIVINV, LABOR)	k = 8	24.5 (.00)	8.31 (.40)	18.5 (.01)	9.12 (.03)	2.70 (.10)

Notes: Variables in parentheses in the first column are the control variables included in the causality test. Numbers in parentheses are p-values denoting the significance level. All variables are in natural logs and defined in Table 1.

Table 5
Estimated Cointegrating Vectors

GDP(-1)	1.0000	1.0000	1.0000	1.0000
LABOR(-1)	-1.5681 (-41.97)	-1.0539 (-8.46)	-0.1423 (-5.14)	-0.5513 (-1.76)
PRIVINV(-1)	-0.0995 (-4.60)	-0.0091 (-0.205)	-1.6725 (-34.0)	-0.2785 (-3.65)
FED(-1)	-0.0254 (-1.13)			
STATE(-1)	-0.3802 (-5.61)			
TG_CON(-1)		0.7407 (3.49)		
TG_INV(-1)		-0.3452 (-4.99)		
DEF(-1)			-0.0565 (-2.86)	
NDEF(-1)			-0.5708 (-5.42)	
C	8.5099	3.7126	9.2373	-2.8414

Notes: t-statistics are in parentheses. The cointegrating vectors are taken from the estimation results of the Johansen test. In each case, four lags are used in estimating the error correction model. Note that a negative sign implies a positive impact on real GDP. (-1) denotes the time period (t-1). All regressions include the total labor force (LABOR) and the ratio of private investment spending to real GDP (PRIVINV). All variables are in natural logs and defined in Table 1.