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Granger Causality between Government Revenues and Expenditures in Korea*

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This paper investigates the Granger causal relationship between government revenues and expenditures in Korea over the period 1964 to 1992. With due consideration of stationarity of the variables; selection criteria of optimal lag length; and assumptions of error structure such as normality, homoscedasticity and independence, both parametric and nonparametric tests are performed. The multiple rank F test is employed as a nonparametric test. We find that in order for the nonparametric test to be superior to the parametric test, at least one of the error structure assumptions should be violated in the parametric test and at the same time all those assumptions must be satisfied in the nonparametric test. In this context, the nonparametric test is not a substitute for but a complement to the parametric test when testing for Granger causality. We find that in the Korean data both parametric and nonparametric test results support the unidirectional causal relationship from government revenues to expenditures.

I. Introduction

In the field of public finance, the majority of the Granger causality tests have been conducted in two directions. The first one is on the relationship between economic growth and government expenditures. Wagner's law states that as economy grows, government expenditures also increase. On the other hand, the Keynesian effective demand principle states that as government expenditures increase so does national income. Therefore tests for these two different hypotheses have comprised one of the major research topics in public finance. For example, 63 countries were studied by Ram (1986) and the Canadian case has been analyzed by Sahni and Singh (1984) and Afxentiou and Serletis (1991), Greece by Karavitis (1987), India by Holmes and Hutton (1990a), G-7 countries by Hsieh and Lai (1994). The second one is on the relationship between government revenues and expenditures. Manage and Marlow (1986), Blackley (1986) and Anderson *et al*. (1986) investigated the relationship in the case of the US federal government; Marlow and Manage (1987) and Joulfaian and Mookerjee (1990a) concentrated on US state governments, Provopoulos and Zambaras (1991) used data for Greece; Joulfaian and Mookerjee (1990b) studied OECD countries. While these studies have examined causality patterns between revenues and expenditures, no consensus exists as to whether revenues cause expenditures or vice versa. At the US federal level, a finding of expenditures to revenues causality has obtained by Anderson *et al*. (1986). However, Blackley (1986) and Manage

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and Marlow (1986) found revenue increases led to spending increases.

Several methodological problems have been found in many of the studies mentioned above. To put it concretely, causality tests have been performed without due consideration of stationarity of the series; the existence of cointegration; the selection criteria of optimal lag length; and the error structure assumptions.

In this paper, we perform the Granger causality test between government revenues and government expenditures in Korea with the above considerations in mind. Both parametric and nonparametric tests are performed. The analysis uses annual data of the central government for the period 1964 to 1992 from the IMF's International Financial Statistics Yearbook (1994).[1]

The plan of this paper is as follows. In the next section we discuss the econometric methodology concerning the Granger causality, which includes unit root and cointegration tests, error structure and seemingly unrelated regression (SUR). Results for both the parametric and the nonparametric tests are given in section 3. Concluding remarks are in the final section.

II. Econometric Methodology

Since the Granger causality test is relevant only when the variables involved are either stationary or nonstationary but cointegrated,[2] the Augmented Dickey-Fuller (1981, hereafter ADF) unit root test has been performed for government revenues (REV) and government expenditures (EXP).

The regression equation for ADF test is as follows.

$$\Delta Y_t = a + bT + cY_{t-1} + \sum_{i=1}^{p} d_i \Delta Y_{t-i} + \varepsilon_t, \tag{1}$$

where ΔY indicates the first differenced series of Y, T is a time trend, and Y_t denotes either REV or EXP at time t. Since we do not know a priori whether the intercept and the time trend should be included in Equation (1), we need some statistical criteria. In this paper, both Akaike (1974) criterion (hereafter, AIC) and Schwarz (1978) criterion (hereafter, SC) are adopted.[3] The functional form to be selected is the one where both AIC and SC are minimized. And the lag length p is chosen such that the error term, ε_t, is white noise.

In Equation (1), the null hypothesis (H_0) is $c = 0$ and the alternative hypothesis (H_1) is $c < 0$. If we cannot reject H_0, then the variable has a unit root and it is a nonstationary series. If all variables have been proven to be nonstationary and integrated of order 1, I(1),

1. The figures are expressed in billions of won.
2. See Granger (1988a) for more details.
3. The formulas for AIC and SC are as follows:

$$AIC = \ln \hat{\sigma}^2 + \frac{2k}{N}, \quad SC = \ln \hat{\sigma}^2 + \frac{k \ln N}{N},$$

where $\hat{\sigma}^2 = \frac{e'e}{N}$, e is residual vector, N is the number of observations, k is the number of parameters to be estimated.

the first differenced series of these variables are I(0), or stationary processes. In this case, we can perform the Granger causality test with these first differenced variables. Note that even when the two variables are I(1), their linear combination can still be I(0). In this case, it is said that these two variables are cointegrated. The test for cointegration begins with the regression of one of the following two equations.

$$Y_{t1} = \alpha_0 + \alpha_1 Y_{t2} + \varepsilon_t, \tag{2}$$

$$Y_{t1} = \beta_0 + \beta_1 T + \beta_2 Y_{t2} + \varepsilon_t, \tag{3}$$

where Y_{ti}(i = 1, 2) is one of two variables analyzed (REV and EXP). As is the case in Equation (1), the choice between Equations (2) and (3) depends on the values of AIC and SC, calculated from an OLS regression. One potential problem in cointegration regression is that when the dependent variable is changed, the result concerning cointegration can also be changed. In this respect we choose the equation with the higher R^2, following the advice of Banerjee *et al*. (1986). The Engle-Granger (1987) cointegration test is simply the unit root test for $\hat{\varepsilon}_t$ calculated from one of the two Equations, (2) and (3). The regression equation in this case is:

$$\Delta \hat{\varepsilon}_t = \gamma_0 \hat{\varepsilon}_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta \hat{\varepsilon}_{t-i} + \eta_t. \tag{4}$$

If the null hypothesis, $H_0: \gamma_0 = 0$, is accepted from a regression of Equation (4), then we can conclude that the two variables are not cointegrated. In this case we can perform the Granger causality test with the stationary series of these two variables. However if the null hypothesis is rejected in favor of the alternative hypothesis, $H_1: \gamma_0 < 0$, then these variables are cointegrated, and for the Granger causality test we can use the first differences of the I(1) variables with the additional error correction term in the regression equation.[4]

If the variables REV and EXP are both I(0), then the regression equations for Granger causality test are:

$$\mathrm{EXP}_t = \alpha + \sum_{i=1}^{m} \beta_i \mathrm{EXP}_{t-i} + \sum_{j=1}^{n} \gamma_j REV_{t-j} + u_t, \tag{5}$$

$$REV_t = a + \sum_{i=1}^{r} b_i REV_{t-i} + \sum_{j=1}^{s} c_j \mathrm{EXP}_{t-j} + v_t. \tag{6}$$

In Equations (5) and (6), lag lengthes m, n, r, s are determined so as to minimize both AIC and SC. For Equation (5), we regress EXP only on its lagged variables of various

4. The error correction term is the lagged variables of residuals from the cointegrating regression. For theoretical discussions and empirical applications on cointegration and Granger causality, see Granger (1986, 1988a, 1988b).

lag length without including REV. And we select $m = m^*$ where both AIC and SC are minimized. Next we fix the value of m at m^* and keep on adding the lagged variables of REV until we obtain the lag length n^* where AIC and SC are minimized. Then the overall optimal lag length in Equation (5) will be (m^*, n^*). If the value of m based on AIC is different from that based on SC, then for each of two different lags, the lagged variables of REV are added and the overall optimal lag length is determined where AIC and SC are minimized. That is, if $\tilde{m} \equiv \arg\min AIC(m, n=0)$ and $\bar{m} \equiv \arg\min SC(m, n=0)$, then (m^*, n^*) will be the unique solution to the following two constrained optimization problems:

$$\min AIC(m, n) \ \ s.t. \ \ m = \tilde{m} \ \text{ or } \ \bar{m},$$

$$\min SC(m, n) \ \ s.t. \ \ m = \tilde{m} \ \text{ or } \ \bar{m}.$$

And if $\tilde{n} \equiv \arg\min AIC(m^*, n) \neq \bar{n} \equiv \arg\min SC(m^*, n)$, then the Granger causality test is performed for both lags, $(m^*, \tilde{n})$ and $(m^*, \bar{n})$.[5] The same procedures are applied to Equation (6) to obtain the optimal lag length.

In Equation (5), the null hypothesis, $H_0: \gamma_1 = \gamma_2 = \ldots = \gamma_n = 0$, means that government expenditures are not Granger caused by government revenues, and in Equation (6) the null hypothesis, $H_0: c_1 = c_2 = \ldots = c_s = 0$, is that government revenues are not Granger caused by government expenditures. The tests for these hypotheses can be performed by a traditional F test resulting from an OLS regression for each equation. Consider the test for $H_0: \gamma_1 = \gamma_2 = \ldots = \gamma_n = 0$ in Equation (5). First of all, the sum of squared residuals in Equation (5)(SSR_1) and sum of squared residuals under H_0 (SSR_0) are calculated as follows:

$$SSR_1 = \sum_{t=g^*+1}^{N} \tilde{u}_t^2, \ \ SSR_0 = \sum_{t=m+1}^{N} \bar{u}_t^2. \tag{7}$$

where $\tilde{u}_t$ and $\bar{u}_t$ are residuals from OLS regressions and N is the original sample size, and $g^* \equiv \max(m, n)$.[6] The F statistic for the Granger causality test is as follows:

$$F = \frac{(SSR_0 - SSR_1)/n}{SSR_1/(N - g^* - m - n - 1)}.$$

This F statistic has F distribution with n and ($N - g^* - m - n - 1$) degrees of freedom under

5. Of these two different lags, the long lag length is preferred by Holmes and Hutton (1990a), whereas Guilkey and Salemi (1982), and Judge *et al.* (1985) are in favor of the short lag based on SC.
6. When we calculate SSR_1, even though the original sample size is N, the effective sample size becomes N-g^* due to the inclusion of lagged variables.

the null hypothesis. The same procedures are applied to tests for another null hypothesis. However in the tests for these hypotheses the error terms should be the Gaussian white noise processes, that is each error term has normal distribution with mean 0, equal variance (σ^2), and zero covariance (Hamilton (1994), p.43, p.305).

If the error terms, u_t and v_t in Equations (5) and (6) satisfy the normality, homoscedasticity, and independence assumptions and there exists contemporaneous correlation between them, so that the covariance matrix of these two error terms are not diagonal, then we can obtain efficient estimators through a joint estimation technique such as seemingly unrelated regression (SUR) rather than through individual OLS estimation.[7]

The parametric tests mentioned above depend on the assumptions of error structure such as normality, homoscedasticity, and independence. Since the nonparametric test does not depend upon such assumptions it can be a desirable alternative when at least one of the assumptions is violated in the parametric test. In this paper the multiple rank F test is utilized as a nonparametric test for Granger causality.[8] To perform the multiple rank F test, all the variables including lagged variables in the parametric test should be transformed to the corresponding rank representation. The optimal lag length of each variable is chosen in the same manner as the parametric test.

III. Empirical Results

Both parametric and nonparametric results of the Granger causality test are summarized as follows. In the latter case, the multiple rank F test has been employed.

1. Parametric Test

As we can see in Table 1 the unit root tests for natural logarithm of government revenues (LREV) and natural logarithm of government expenditures (LEXP) indicate that at $\alpha=0.1$ LEXP has no unit root thus is stationary. On the other hand LREV has a unit root and is thus a nonstationary process. In order to check whether LREV is integrated of order 1, that is LREV $\sim$ I(1), we perform the unit root test for the first differenced series of LREV(DLREV). The null hypothesis that the variable DLREV has a unit root is rejected at $\alpha=0.1$. Therefore DLREV is a stationary process. In Table 1, p indicates lag length of the first differenced variables in the right-hand side of Equation (1). In cases of LEXP and DLREV, only the intercept is included in the regression, on the other hand in case of LREV both the intercept and the time trend are included in the regression.

According to the ADF test results described in Table 1, the Granger causality test can be performed with two stationary series, LEXP and DLREV in Equations (5) and (6).

7. The Granger causality test using SUR has been tried in Huang and Tang (1992). However they have not investigated the validity of the assumptions of error structure (normality, homoscedasticity, independence) in each equation.
8. See Olejnik and Algina (1985) and Holmes and Hutton (1990a, 1990b) for more details of the multiple rank F test.

Table 1 ADF Unit Root Test

Variable	Lag Length (p)	Coefficient	Critical Value (α = 0.1)
LREV	1	-2.5040	-3.13
LEXP	0	-3.1515	-2.57
DLREV	1	-3.5721	-2.57

To perform the Granger causality test between government revenues and expenditures, the selection of optimal lag length is essential. When the dependent variable is LEXP, the optimal lag length, which is chosen by the method described in the previous section, is $m=1, n=4$. When the dependent variable is DLREV, there exist two optimal lag lengthes; $(r=5, s=1)$ and $(r=5, s=5)$. The former case, $(r=5, s=1)$ is based on SC, and the latter $(r=5, s=5)$ is based on AIC. The causality test results are summarized in Table 2. The mark "$\rightarrow$" indicates the direction of the Granger causality. The F-value is the statistic for the Granger causality test and df stands for degrees of freedom. Test results show that there exists a causal relationship from government revenues to government expenditures at $\alpha=0.01$, but not vice versa. The Jarque-Bera (1987) statistic (hereafter, J-B) is for the normality test of the error term, which has a χ^2 distribution with two degrees of freedom under the null hypothesis that the distribution is normal.[9] All J-B values cannot reject the null hypothesis at the conventional significance level. When the error term is normally distributed and its covariance is zero, it is independently distributed. Therefore the test for independence of the error term reduces to the test for serial correlation in the error term. The test for the serial correlation can be performed with a Q-statistic developed by Ljung-Box (1979), which has a χ^2 distribution with L degrees of freedom under the null hypothesis that there is no serial correlation up to L lags.[10] In Table 2 the values of the Q-statistic are calculated up to maximum lag length based on effective sample size. Since all these values are statistically insignificant at $\alpha=0.05$, we cannot reject the null hypothesis that there is no serial correlation in the error term.

There are various forms of heteroscedasticity in the error term. Because the testing methods of heteroscedasticity are mainly based on the specific forms of heteroscedasticity, we may reach a wrong conclusion that there is no heteroscedasticity if we test for it by employing a particular method, while there exists another untested form of heteroscedasticity in the error term. Therefore only after as many tests as possible are performed, can we decide whether there is heteroscedasticity or not. In this paper, the Breusch-Pagan (1979) (hereafter, B-P) statistic, the ARCH statistic developed by Engle (1982), and the Glejser (1969) statistic

9. $J-B = N[\frac{g_1^2}{6}+\frac{g_2^2}{24}]$ where N is the number of observations, g_1 is the coefficient of residual skewness, g_2 is the coefficient of excess kurtosis.

10. $Q = N(N+2)\sum_{j=1}^{L}\frac{r_j^2}{N-j}$, where $r_j = \frac{\sum_{t=j+1}^{N} e_t e_{t-j}}{\sum_{t=1}^{N} e_t^2}$, N is the number of observations, and e_t is the residuals from OLS regression.

are calculated so as to determine whether there is heteroscedasticity in the error term. We accept the validity of the assumption of homoscedasticity in our analysis, only if none of these statistics reject the null hypothesis that there is homoscedasticity in the error term. We perform the B-P test based on the assumption that error variance is a linear function of explanatory variables. The test statistic has a χ^2 distribution with degrees of freedom equal to the number of explanatory variables under the null of homoscedasticity. The ARCH test is based on the assumption that error variance at time t is a function of error variances of previous periods. In this paper, we test whether the error variance at time t is related to the error variance at time $(t-1)$; this is denoted ARCH(1). The test statistic has a χ^2 distribution with 1 degree of freedom under the null hypothesis of homoscedasticity. The Glejser test is based on the relationship between the absolute value of the OLS residuals and the explanatory variables, and its statistic has a χ^2 distribution with degrees of freedom equal to the number of explanatory variables. According to Table 2 in the regression of DLREV on LEXP at lag length $(r=5,\ s=1)$, both the B-P and the Glejser statistics indicate that there is no homoscedasticity in the error term. In this case we cannot rely upon the test results. Remaining two cases satisfy the assumption of homoscedasticity.

Table 2 The Granger Causality Test (Parametric Test)

	DLREV → LEXP	LEXP → DLREV	
Optimal Lag Length	m = 1 n = 4	r = 5 s = 5	r = 5 s = 1
F-value(df)	6.0347**(4, 18)	1.8432(5, 12)	3.3850(1, 16)
J-B	0.3432	0.4586	1.3462
Q-value	Q1 = 1.40 Q2 = 1.70 Q3 = 1.71 Q4 = 6.19 Q5 = 10.54 Q6 = 11.14 Q7 = 11.54	Q1 = 0.72 Q2 = 2.55 Q3 = 4.05 Q4 = 4.06 Q5 = 4.13 Q6 = 6.05	Q1 = 0.14 Q2 = 2.72 Q3 = 4.03 Q4 = 5.13 Q5 = 6.42 Q6 = 8.25
B-P(df)	8.801(5)	8.545(10)	14.508*(6)
ARCH	1.567	0.323	1.613
Glejser(df)	8.230(5)	10.367(10)	18.348**(6)
LR	6.2702*		
F-value(SUR)(df)	5.7171**(4, 29)	1.9000(5, 29)	

* and ** indicate statistically significant at $\alpha=0.05$ and at $\alpha=0.01$, respectively.

If the covariance matrix of two error terms in Equations (5) and (6) is a diagonal matrix, then we can obtain efficient estimators through an OLS estimation of individual equations. But if it is not a diagonal matrix, then we can get efficient estimators through a GLS method, such as SUR estimation. However, even in this case, if the explanatory variables in each equation is identical, then an OLS and a SUR estimation are the same. In order to perform the SUR estimation, all the assumptions of error structure must be satisfied. As can be seen in Table 2, these assumptions are satisfied both in the regression of government expenditures on government revenues and in the regression of government revenues on government expenditures at lag $(r=5,\ s=5)$. The test for the diagonality of covariance matrix of error terms can be performed by likelihood ratio (LR) test. When there are two equations to be estimated, the LR statistic has a χ^2 distribution with 1 degree of freedom under the null of diagonal covariance matrix. The LR statistic indicates that the null hypothesis cannot be accepted at $\alpha=0.05$. The test results using SUR estimation are exactly identical to those from OLS estimation of individual regression equations. There exists a causal relationship from government revenues to government expenditures at $\alpha=0.01$ but not vice versa.

2. Nonparametric Test

The Granger causality test above depends on the assumptions of error structure. When these assumptions are satisfied the parametric test is relevant, but if one of these is violated, test results cannot be relied upon.[11] If one assumption or more is violated, we can perform the nonparametric test such as a multiple rank F test.[12] Nonparametric test results are summarized in Table 3.

When the dependent variable is LEXP, we cannot rely on the test results because the assumptions of normality and homoscedasticity are violated at $\alpha=0.05$. When the dependent variable is DLREV, all the assumptions of error structure are satisfied. Therefore the causality test results are reliable. At $\alpha=0.05$, the Granger causal relationship does not exist from government expenditures to government revenues.

Table 3 The Granger Causality Test (Nonparametric Test)

	DLREV → LEXP	LEXP → DLREV
Optimal Lag Length	m = 4 n = 3	r = 1 s = 1
F-value(df)	2.9430(3, 17)	2.2022(1, 24)
J-B	6.5016*	2.8942
Q-value	Q1 = 0.86 Q2 = 2.05 Q3 = 3.79 Q4 = 4.03 Q5 = 6.53 Q6 = 6.57 Q7 = 7.71	Q1 = 0.03 Q2 = 1.49 Q3 = 1.61 Q4 = 7.09 Q5 = 7.09 Q6 = 11.28 Q7 = 11.43 Q8 = 12.63
B-P	14.778*(7)	2.681(2)
ARCH	1.097	1.403
Glejser	18.043*(7)	1.574(2)

* indicates statistically significant at $\alpha=0.05$.

11. However, the Granger causality test is still valid under the asymptotic ground even if the error term does not satisfy some of the classical assumptions.
12. In order for the causality test results of nonparametric test to be superior to those of parametric test in terms of reliability, at least one of the assumptions of error structure should be violated in the parametric test and at the same time the error term in the nonparametric test should satisfy all of the assumptions of normality, homoscedasticity, and independence. All of these assumptions have been checked in Holmes and Hutton (1990a).

IV. Summary and Comments on Further Research

Until now, we have investigated the Granger causal relationship between government revenues and government expenditures utilizing the annual data from 1964 to 1992 in Korea. We have employed parametric and nonparametric tests for Granger causality. Holmes and Hutton (1990a, 1990b) found that the multiple rank F test is by far superior to the parametric test when the assumptions of error structure are violated. They also found that little statistical power is lost by using the multiple rank F test rather than the parametric F test when all parametric assumptions have been met. So we are likely to be misled that it is always safe to perform the nonparametric test. However when we test for Granger causality we have to perform the F test for the null hypothesis, whether we use the original variables or rank-transformed variables. This time, all the assumptions of error structure should be satisfied. Therefore in the strict sense, in order for the nonparametric test to be superior to the parametric test, at least one of the error structure assumptions should be violated in the parametric test, and at the same time all those assumptions must be satisfied in the nonparametric test. In this context, the nonparametric test is not a substitute for but a complement to parametric test in the case of the Granger causality test.

For Korea we have found that both OLS estimation and SUR estimation yield the same test result that there exists a causal relationship from government revenues to government expenditures at the conventional significance level. We can only rely on the nonparametric test result that there is no causal relationship from government expenditures to government revenues, which support the parametric test result.

Directions for further research should be as follows. First, we can include a control variable such as national income and perform the Granger causality test and check the differences with this study. Second, besides the Granger causality test, other parametric tests such as Sims (1972) test, Geweke-Meese-Dent (1983) test can also be performed and compared with the results obtained in this paper. Third, a comparison of such causal relationship using the same kind of data set, but from other countries, would be interesting.

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