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CAUSALITY TESTING WITH MESSY DATA: SOME PRELIMINARY EXPERIMENTAL EVIDENCE

by

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ABSTRACT

Two tests for bivariate causal ordering are examined using nonstationary data series with known causal structures. Instantaneous causality is often identified when not present due to the presence of the nonstationary components. Increased degrees of error covariance between the series leads to incorrect conclusions and collinearity problems in the tests.

CAUSALITY TESTING WITH MESSY DATA: SOME PRELIMINARY EXPERIMENTAL EVIDENCE

Granger's original contribution of an operational definition of causality in a time series context stimulated much interest. The Granger definition has been employed in analyzing causal relationships between economic time series such as money and income, advertising and consumption, price and quantity variables, and across alternative price series. Though widely applied, the Granger definition has been shrouded in controversy regarding the ability of the test to correctly identify relationships which are consistent with theory.

Nelson and Schwert, Guilkey and Salemi, and Geweke, Meese, and Dent conducted Monte Carlo studies to examine the behavior of alternative tests of Granger causality when known causal relationships are present in the data. In general, they concluded that tests of Granger causality which rely on lagged dependent variables to correct for serial correlation outperform the alternatives in the identification of causal More recently, Zeimer and Collins examined relationships betflows. ween five agricultural price series and three unrelated series, demonstrating that tests of Granger causality can identify causal relationships between series which are counter to theory. Bessler and Kling examined causal relationships between GNP and sunspots in demonstrating the need for post sample testing and stationary input series. Specifically, Bessler and Kling show that identified relationships between a stationary series (sunspots) and a nonstationary series (GNP) fail to hold outside the sample period.

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The work of Zeimer and Collins and Bessler and Kling raises questions regarding the impact of nonstationarity on the outcome of causality tests. The Monte Carlo studies discussed earlier relied on stationary input series, yet there is a growing body of research (including Zeimer and Collins and Bessler and Kling) which dismisses the stationarity issue by "letting the nonstationarity in one series explain the nonstationarity in the other" (Nerlove, Grether, and Carvalho, p. 267). The empirical implications of this procedure need to be examined. There is a need for a Monte Carlo study to examine the behavior of Granger-type causality tests when data are nonstationary and possess known causal structures.

The purpose of this paper is to present some preliminary experimental evidence regarding the impact of nonstationary data on the outcome of causality tests. Data series are examined which were constructed to possess known causal flows and common patterns of nonstationarity. Two tests for causality are used to examine causal relationships between raw data series, first differenced data series, and raw data series with a trend variable included in the regressions. Data series without trend components are examined as a control.

EXPERIMENTAL DESIGN

Table 1 describes the construction of the data series for the experiments. Initial observations were obtained from a random number generator which ran continuously between experiments.¹ Data series of

¹The IMSL subroutine GGNSM was used to generate the bivariate normal random variables.

TABLE 1. EQUATION STRUCTURES TO GENERATE EXPERIMENTAL DATA WITH KNOWN CAUSAL FLOWS AND VARYING ERROR COVARIANCE AND TIME TRENDS.

Independence:

- $X_{t} = .5X_{t-1} + .25X_{t-2} + e_{t} + \lambda TIME$ $Y_{t} = .6Y_{t-1} + .15Y_{t-2} + u_{t} + \delta TIME$
- e_t, u_t distributed N(0,1); $cov(e_t u_t) = 0$ $\lambda = .035; \delta = .035$

 \underline{X} <u>causes</u> \underline{Y} :

$$X_t = .5X_{t-1} + .25X_{t-2} + e_t + \lambda TIME$$

 $Y_t = .6Y_{t-1} + .15Y_{t-2} + u_t + e_{t-1} + \delta TIME$

 e_t, u_t distributed N(0,1); $cov(e_t u_t) = (.1, .5, .9)$ $\lambda = .035; \delta = .035$

Noninstantaneous Feedback:

$$X_{t} = .5X_{t-1} + .25X_{t-2} + e_{t} + u_{t-1} + \lambda TIME$$

$$Y_{t} = .6Y_{t-1} + .15Y_{t-2} + u_{t} + e_{t-1} + \delta TIME$$

 e_t, u_t distributed N(0,1); $cov(e_t u_t) = (.1, .5, .9)$ $\lambda = .035; \delta = .035$

Instantaneous Feedback:

- $X_{t} = .5X_{t-1} + .25X_{t-2} + e_{t} + .5u_{t} + \lambda TIME$ $Y_{t} = .6Y_{t-1} + .15Y_{t-2} + u_{t} + .5e_{t} + \delta TIME$
- e_t, u_t distributed N(0,1); $cov(e_t u_t) = (.1, .5, .9)$ $\lambda = .035; \delta = .035$

100 observations were generated with four possible causal relationships: (1) independence, (2) unidirectional causality, (3) noninstantaneous feedback, and (4) instantaneous causality. The independent data series were generated such that the error covariance was equal to zero. To allow examination of the impact of varying degrees of contemporaneous correlation on the outcome of causality tests, the latter three data series were each generated with error covariances of .1, .5, and .9. Identical data series with no trends were generated as a control.

Two alternative tests of causality are employed in the study. The Geweke and modified Sims procedures, presented in Table 2, rely on the use of lagged dependent variables to correct for serial correlation. The version of the Geweke procedure used was suggested by Geweke and provides two tests for causal relationships between two series. TEST1 is a test of instantaneous causality between X and Y. TEST2 is a test for unidirectional causality from Y to X. The modified Sims test presented in Table 2 differs from previous versions used by Guilkey and Salemi, Nelson and Schwert, and Geweke, Meese and Dent, but is a direct analogue to the Geweke procedure. The modified Sims procedure provides three tests for causal relationships between two series. TEST1 and TEST2 are defined as in the Geweke procedure. TEST3 provides a test for causality from X to Y by testing the coefficients of future values of Y in a regression on X. The procedures can be reversed to test for causality from X to Y.

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TABLE 2. EQUATION SPECIFICATIONS AND HYPOTHESES TESTED BY THE GEWEKE AND MODIFIED SIMS PROCEDURES.

Geweke Procedure:

$$X_{t} = \sum_{j=1}^{p} \theta_{1j} X_{t-j} + \sum_{i=0}^{q} \beta_{1i} Y_{t-i}$$

$$TEST1:^{a} H_{o}: \beta_{10} = 0$$

$$H_{a}: \beta_{10} \neq 0$$

$$TEST2:^{a} H_{o}: \beta_{11} = \beta_{12} = 0$$

$$H_{a}: \beta_{11} \neq 0 \text{ or } \beta_{12} \neq 0$$

Modified Sims Procedure:

$$X_{t} = \sum_{j=1}^{p} \theta_{2j} X_{t-j} + \sum_{k=1}^{r} \phi_{2k} Y_{t+k} + \sum_{i=0}^{q} \beta_{2i} Y_{t-i}$$

TEST3: $H_{o}: \phi_{21} = \phi_{22} = 0$
 $H_{a}: \phi_{21} \neq 0 \text{ or } \phi_{22} \neq 0$
TEST1: $H_{o}: \beta_{20} = 0$
 $H_{a}: \beta_{20} \neq 0$
TEST2: $H_{o}: \beta_{21} = \beta_{22} = 0$
 $H_{a}: \beta_{21} \neq 0 \text{ or } \beta_{22} \neq 0$

^a To simplify comparison of results from the two procedures, the tests are numbered so that TEST2 and TEST3 are identical for the two procedures.

Twenty-five replications of each experiment were computed to generate the preliminary results discussed below. A more thorough investigation will require between 200 and 500 replications, but the examination of a smaller number of the total replications provides a basis for the design of the more extensive experiments. Each replication consisted of the estimation of the Geweke and modified Sims equations in Table 2 for the four data series described above. Within each replication, the regressions were estimated in four ways: (1) using the raw data series; (2) using the raw data series and including a linear trend term in each equation; (3) using first differences of the raw data; and (4) using raw data generated without a trend.

EMPIRICAL RESULTS

The design of the experiments provided an examination of the results of the Geweke and modified Sims procedures when data series are: (1) nonstationary; (2) differenced to obtain stationarity, (3) nonstationary and a trend term is included to account for nonstationary time trends; and (4) when data are stationary. By varying the degree of error covariance between the data series within each case, the impact of contemporaneous correlation on the outcome of tests for causality was also examined.

Table 3 presents the percentage of correct identifications of causal flows by TEST1 and TEST2 using the Geweke procedure. The results of the Geweke procedure are sensitive to the nonstationarity in the data series. For the independent series, both TEST1 and TEST2 are power-

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TABLE 3. PERCENTAGE OF CORRECT IDENTIFICATIONS BY THE GEWEKE PROCEDURE AT THE .05 LEVEL OF SIGNIFICANCE.

Data Series and	Regression Format/Test Statistic ^a									
Error Covariance	RA		TREND V	ARIABLE		DIFF	KVMS			
	Testi	Test2	Testl	Test2		Test2	Testl	Testz		
and Y independent:				X de	pendent					
0	100	87	88	83	92	100	96	83		
Causes Y:										
.1	92	92	96	88	96	88	92	92		
.5	0	0	0	20	0	76	0	12		
.9	0.	0	0	0	n	24	. 0	0		
Noninstantaneous Feedback:										
.1	44	100	80	100	88	100	76	100		
.5	4	75	Ő	100	0	100	0	100		
.9	0.	96	0	96	0	100	0	96		
Instantaneous feedback:						,				
.1	100	0	100	0	100	56	100	0		
.5	100	Ō	100	0	100	38	100	0		
.9	100	0	100	0	100	20	100	0		
X and Y independent:				Y de	ependent ,					
0	96	88	96	100	92	92	96	100		
X causes Y:			•							
.1	92	100	96 ⁻	100	96	100	92	100		
.1	92	100	- 4	96		100	õ	100		
.9	ŏ	100	ō	100	Ő	100	ŏ	100		
Noninstantaneous feedback:										
.1	44	100	03	36	38	100	76	100		
.5	0	96	0	100	. 0	100	0	100		
.9	ŏ	64	- 0	42	0	100	0	60		
Instantaneous feedback:										
.1	100	0	100	0	100	32	100	0		
.5	100	Ō	100	0	100	4	100	4		
.9	100	0	100	0	100	16	100	0		

^aThe four regression formats are: (1) RAW1, raw data series; (2) TREND VARIABLE, regressions using RAW1 series with a linear trend variable included in the equation; (3) IST DIFF, first differences of RAW1; and (4) RAW2, series generated identical to RAW1 but without a trend. TEST1 is a test for instantaneous causality, TEST2 is a test for uni-directional causality from the independent variable to the dependent variable, and TEST3 is a test for uni-directional causality from the dependent variable to the independent variable.

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ful, though the inclusion of a trend term in the regressions significantly increases the percentage of incorrect identifications. In the case where X causes Y, TEST1 often identifies instantaneous causality when it is not present, though the test performance improves as the error covariance is lowered. When testing for Y causes X, when X actually causes Y, TEST2 is often incorrect when the error covariance is high. The test performance improves when the data are differenced, however. TEST2 is almost perfect in identifying causality from Y to X when Y actually causes X in the Y dependent equations, regardless of the degree of error covariance.

The Geweke procedure when X and Y are related by noninstantaneous feedback is also sensitive to the degree of error covariance. Again the ability of TEST1 and TEST2 to correctly identify causal flows diminishes as the degree of error covariance rises. If the data series are related by instantaneous feedback, TEST1 correctly identifies the relationship in all cases, but TEST2 incorrectly identifies unidirectional causality in both directions in all cases, except the first differenced data. Examination of the Geweke procedure when the data are stationary (RAW2) illustrates the ability of TEST1 and TEST2 to correctly identify causal flows, though the tests remain sensitive to the degree of error covariance between the X and Y series.

Table 4 presents the percentages of correct identifications of causal flows by TEST1, TEST2, and TEST3 of the modified Sims procedure. In general, the results for TEST1 and TEST2 are identical to

Data Series and Error Covariance	Regression Format/Test Statistic ^a RAWI TREND VARIABLE IST OIFF RAWZ											
	Testl	RAW1 Test2	Test3		Test2		Testi			Test	RAW2 Test2	Test3
and Y independent:						X dep	endent		•			
0	92	88	88	96	88	96	96	100	100	96	38	96
(causes Y:												
.1 .5 .9	83 0	72 4 0	100 100 100	12 96 0	76 32 0	100 100 100	24 • 0 0	92 76 24	100 100 100	16 96 0	76 24 0	100 100 100
loninstantaneous feedback:												
- 1 - 5 - 9	44 72 0	100 100 96	100 100 100	44 72 0	100 100 100	100 100 26	92 1) 0	100 100 100	100 100 100	36 72 0		100 100 96
Instantaneous feedback:												
.1 .5 .9	100 100 100	0 0 0	96 96 92	100 100 100	0 0 0	96 96 83	100 100 100	56 25 24	96 100 88	100 100 100		96 92 88
(and Y independent:						Y de	pendent					
0	92	96	92	92	96	100	100	92	100	92	96	100
K causes Y:												
.1 .5 .9	96 8 0	96 100 100	92 92 80	96 0 0	100 100 100	96 96 92	92 0 0	100 100 100	100 100 100	96 0 4	100 100 96	92 96 92
Noninstantaneous feedback:												
.1 .5 .9	68 60 0	100 100 63	100 100 100	80 32 0	100 100 63	100 100 92	84 0 0	100 100 100	100 100 56	76 40 0	100 100 64	96 100 92
Instantaneous feedback:								• .				
.1 .5 .2	100 100 100	0	96 100 92	100 100 100	0 0	96 100 92	100 100 100	33 8 16	96 100 83	100 100 100	0 4 0	96 100 92

TABLE 4. PERCENTAGE OF CORRECT IDENTIFICATIONS BY THE MODIFIED SIMS PROCEDURE AT THE .05 LEVEL OF SIGNIFICANCE.

^aThe four regression formats are: (1) RAW1, raw data series; (2) TREND VARIABLE, regressions using RAW1 series with a linear trend variable included in the equation; (3) 1ST DIFF, first differences of RAW1; and (4) RAW2, series generated identical to RAW1 but without a trend. TEST1 is a test for instantaneous causality, TEST2 is a test for uni-directional causality from the independent variable to the dependent variable. and TEST3 is a test for uni-directional causality from the dependent variable to the independent variable. the results for the two tests in the Geweke procedure. TEST3, however, surfaces as a powerful test, with correct identifications in almost all cases. The degree of error covariance has no significant impact on the performance of TEST3 in identifying causal flows between the X and Y series.

A further examination of the impact of nonstationarity and varying error covariances on the Geweke and modified Sims procedures was conducted by examining the regressions for collinearity problems. Evidence of collinearity was found in most of the regressions which used the raw data series with trend. The severity of the problem, as evidenced by high variance inflation factors, condition indeces, and variance proportions, increased as the error covariance was increased. The incidence of collinearity was lower in the raw series with no trend and collinearity was present in only two cases when the data were differenced.

CONCLUDING REMARKS AND SUGGESTIONS FOR FURTHER RESEARCH

Several general conclusions are suggested by this preliminary research. Causality tests do well in identifying causal flows in the data when there is a small degree of contemporaneous correlation present in the series errors. Test performance declines as the degree of error covariance increases, indicating the importance of the inclusion of all relevant variables when testing for causal relationships in economic data. The omission of a third variable which impacts the other two may surface as contemporaneous correlation between the series errors.

With regard to the arguments in the literature to let the nonstationarity in one series explain the nonstationarity in the other series when conducting causality tests, the current research suggests this may not serve the researchers' purpose. Causality tests involving nonstationary time series show a high incidence of identification of instantaneous and unidirectional relationships not present in the data. In short, such procedures may provide good forecasting models, but in the context of identifying the true causal relationships they will fall short.

The Geweke and modified Sims procedures perform equally well when there is a small degree of contemporaneous correlation between the series errors. As the error correlation rises, however, the performance of both tests declines. In some cases, the Sims procedure provides somewhat misleading results due to the high degree of error correlation, though the general ability to correctly test for the significance of future coefficients provides a secondary check on the unidirectional test which leads to the correct conclusions with regard to causal flows. The performance of the test of future coefficients in the modified Sims procedure suggests the test may be a useful alternative to the Geweke procedure, especially if the data possess a strong contemporaneous correlation.

The use of differencing to eliminate nonstationary behavior from the series prior to estimation shows promise. As the degree of contemporaneous error correlation rises, however, even in the differenced

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data instantaneous causality is often identified when it is not present. There are few cases with the differenced data where collinearity is present, and it is always less severe than with the other data series.

Several recommendations can be made both for the future Monte Carlo work and for empiricists interested in testing for causal relationships. The Monte Carlo work needs to address the nonstationarity issue and the contemporaneous correlation issue separately. This will allow the impacts of each on collinearity in the regressions to be identified. There seems little need to further investigate the use of time trend variables in regressions to account for nonstationary components. Adding a time trend variable intensifies collinearity problems and does worsens test results. Series should be examined with different time trends to further examine letting the nonstationarity in one series explain the nonstationarity in the other.

Finally, empiricists interested in testing for causal relationships should keep in mind the issues addressed above. If the decision is made to let the nonstationarity in one series explain the nonstationarity in the other, the results should be cautiously interpreted, particularly with regard to instantaneous causality. Based on these results, it appears that causality tests in the presence of nonstationarity and contemporaneous correlation can be conducted with some confidence, provided the correlation is low and the nonstationarity is taken into account both in the estimation and interpretation.

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REFERENCES

Bessler, D. A., and J. L. Kling. "A Note on Tests of Granger Causality," *Applied Economics*, forthcoming.

Geweke, J. "Inference and Causality in Economic Time Series Models," Handbook of Econometrics Eds. Z. Griliches and M. Intilligator, Amsterdam-North Holland, 1982.

- Geweke, J., R. Meese, and W. T. Dent. "Comparing Alternative Tests of Causality in Temporal Systems: Analytic Results and Experimental Evidence," *SSRI Workshop Series*, No. 7928, University of Wisconsin, Madison, April 1982.
- Granger, C. W. J. "Investigating Causal Relations by Econometric Models and Cross Spectral Methods," *Econometrica*, 37(1969):424-438.
- Guilkey, D. K. and M. K. Salemi. "Small Sample Properties of Three Tests for Granger-Causal Ordering in a Bivariate Stochastic System," *Review of Economics and Statistics*, LXIV(1982):668-680.
- Nelson. C. R. and G. W. Schwert. "Tests for Predictive Relationships Between Time Series Variables: A Monte Carlo Investigation," *Journal of the American Statistical Association*, No. 377 (March 1982), pp. 11-18.
- Nerlove, M., D. M. Grether, and J L. Carvalho. *Analysis of Economic Time Series*, Academic Press, New York, 1979.
- Sims, C. A. "Money, Income, and Causality," American Economic Review, 62(1972):540-552.
- Zeimer, R. F. and G. S. Collins. "Granger Causality and U. S. Crop and Livestock Prices," Paper presented at the annual meeting of the AAEA, West Lafayette, In., 2-5 Aug. 1983.

