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A causal analysis of several economic time series

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A CAUSAL ANALYSIS OF SEVERAL ECONOMIC TIME SERIES

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A causal analysis of several economic time series

by

William George Colclough, III

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TABLE OF CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

Page

CHAPTER I. EMPIRICAL RESEARCH, PROBLEMS, AND CAUSALITY TESTS

In recent years, an enormous amount of effort has gone into quantitative economic research. This type of analysis has been greatly enhanced by the continued development of more sophisticated computers. This quantitative research has been undertaken in an attempt to clarify and illuminate many complex economic relationships. Traditionally, the research has taken a two step form. First, a model is specified which is consistent with economic theory. Then, using a consistent procedure, the parameters of the model are estimated. In other words, as stated by Pierce (1977a, p. 11), "The estimation has been empirical while the specification has been theoretical."

Basic Problem

The problem with this approach concerns the first step. Suppose that the a priori model specification is incorrect in that it does not reflect how the real world actually works. If this is the case, then the estimation procedure will not produce consistent results. The end result is a model which does not accurately portray the interactions of the economic variables.

As an illustration, suppose the relationship between X and Y is being evaluated. Further, assume that economic theory dictates that variable X is related to variable Y in the following manner:

$$Y_t = \theta X_t + \beta_{11} Y_{t-1} + \beta_{12} X_{t-1} + \varepsilon_{1t} \tag{1.0}$$

Further, assume that θ, β_{11}, and β_{12} are all estimated using ordinary least squares. But suppose the actual relationship between X and Y is

$$Y_t = \theta X_t + \beta_{11} Y_{t-1} + \beta_{12} X_{t-1} + \varepsilon_{1t} \tag{1.1a}$$

$$X_t = \gamma Y_t + \beta_{21} Y_{t-1} + \beta_{22} X_{t-1} + \varepsilon_{2t} \tag{1.1b}$$

where ε_{1t} and ε_{2t} are independent, serially uncorrelated random variables with zero means and variances of σ_1^2 and σ_2^2, respectively. Unless γ is equal to zero, the parameter estimates obtained for Equation 1.0 are biased and inconsistent.

To show the inconsistency and bias, the reduced form of model 1.1 must be derived. By solving for Y_t and X_t in terms of Y_{t-1}, X_{t-1}, ε_{1t}, and ε_{2t}, the following reduced form can be derived:

$$Y_t = \frac{\beta_{11} + \theta\beta_{21}}{(1-\theta\gamma)} Y_{t-1} + \frac{\beta_{12} + \theta\beta_{22}}{(1-\theta\gamma)} X_{t-1} + \frac{\varepsilon_{1t} + \theta\varepsilon_{2t}}{(1-\theta\gamma)} \tag{1.2a}$$

$$X_t = \frac{\gamma\beta_{11} + \beta_{21}}{(1-\theta\gamma)} Y_{t-1} + \frac{\gamma\beta_{12} + \beta_{22}}{(1-\theta\gamma)} X_{t-1} + \frac{\gamma\varepsilon_{1t} + \varepsilon_{2t}}{(1-\theta\gamma)} \quad (1.2b)$$

Regression theory dictates that the expected value of $X_t\varepsilon_{1t}$ must be zero, in order to avoid any simultaneous equation bias in fitting Equation 1.0. Using Equation 1.2b, the expectation of $X_t\varepsilon_{1t}$ is

$$E[X_t\varepsilon_{1t}] = E[(\frac{\gamma\beta_{11}+\beta_{21}}{(1-\theta\gamma)} Y_{t-1} + \frac{\gamma\beta_{12}+\beta_{22}}{(1-\theta\gamma)} X_{t-1} + \frac{\gamma\varepsilon_{1t}+\varepsilon_{2t}}{(1-\theta\gamma)})\varepsilon_{1t}] = \frac{\gamma\sigma_1^2}{1-\theta\gamma} .$$

Therefore, the expectation of the estimated parameters is not the actual parameter for a finite sample. Or, in other words, if the parameters of Equation 1.0 are estimated using ordinary least squares, then the parameter estimates are biased. Since the bias persists, even for the infinite sample, the parameters are also inconsistent.

In order to avoid inconsistent and biased empirical parameter estimates, the underlying relationship between the variables needs to be investigated. Basically, three hypotheses are of interest with respect to the relationship between two variables. The first consideration is that of "contemporaneous exogeneity" or in terms of the model 1.1 is γ equal to zero. If contemporaneous exogeneity exists,

($\gamma=0$), then a regression of Y on X will produce unbiased and consistent parameter estimates. In terms of the model 1.1, the second hypothesis of concern is if both γ and β_{21} are equal to zero. This case is referred to as the hypothesis that "Y does not cause X." Y is said not to cause X in the sense that a policy seeking to control Y by minimizing the error in Equation 1.0 does not effect the X variable. The third hypothesis of concern is if $\gamma\beta_{11} + \beta_{21}$ is equal to zero. This hypothesis is referred to as the situation where "Y does not cause X in the Granger (1969) sense." To understand this hypothesis, refer to Equation 1.2b in the reduced form model. As long as $\gamma\beta_{11} + \beta_{21}$ is equal to zero, then an optimal prediction of X does not involve Y. These three hypotheses are the most significant, when considering the relationship between two variables.[1] In the past, these hypotheses have been evaluated on the basis of economic theory, thus implying a theoretical specification.

Causality Tests

The problems associated with theoretical specification have been addressed in the literature in recent years. The result has been the development of a new type of econometric testing procedure. This econometric innovation

[1]For a more detailed presentation see Jacobs, Leamer, and Ward (1979).

has been referred to as "causality testing" or "exogeneity testing." These procedures are empirical tests of the basic relationship between two variables. Indirectly, they are empirical tests of specification. Thus, the application of these procedures allows the empirical data to dictate the model specification, as compared to allowing economic theory or economic intuition to dictate the model specification.

Essentially, three types of causality tests have appeared in the literature. The three tests can be attributed to Sims (1972), Haugh (1976), and Sargent (1976). All of these tests are bivariate tests. They are bivariate in the sense that the direction of causation is tested between only two time series variables at one time. All of the tests claim the concept of causality developed by Granger as their basis.

The application of the causal testing procedures has grown substantially since the original introduction of Sims' test in 1972 and the subsequent development of the alternative procedures. The test procedures have been used to investigate the relationships among a wide variety of economic time series. For example, Sims' original work investigated the relationship between money and income. Williams, Goodhart, and Gowland (1976), using a modified version of the Sims' method, investigated the relationship between money and income in the United Kingdom. The investigation was further expanded to other market economics by DyReyes, Starleaf, and Wang (1980). In another application, Kraft and Kraft (1977) tested the causal relationship between several determinants of stock prices (i.e., money supply, rate of change in the money supply, corporate interest rate, and a measure of risk) and stock prices. Still another example of an application was an investigation of the relationship between the money supply and bank reserves by Feige and McGee (1977). All of these studies attempt to analyze the basic relationship between economic time series using the causal tests.

Research Objective

A significant percentage of the empirical work being done involves or uses monetary aggregates. Therefore, the fundamental relationship between these variables is of great concern and should be investigated. In this study I will investigate the relationships among the following variables:

1. Demand deposit component of the money supply
2. Commercial bank time deposits
3. Federal funds rate
4. 90-day Treasury bill rate

5. Unborrowed reserves
6. Unborrowed monetary base

The investigation will involve the application of Sargent's (1976) and Sims' (1972) causal testing procedures. Thus, the primary purpose of this study is to allow the empirical data to indicate the relationships among these variables.

This study will also produce a secondary result. A certain amount of debate has developed with respect to which of the procedures is most appropriate. In general, the application of these tests to various economic time series has not produced very consistent results. The set of variables to be tested in this study is a subset of those tested by Pierce (1977a) using basically the Haugh (1976) procedure. So, by applying the Sargent and Sims procedures to the same set of variables, a comparison of the different procedures can be made.

CHAPTER II. CAUSAL TESTING METHODOLOGY

Granger's Definition of Causality

In the interest of causal investigation, Granger (1969) provides testable definitions of causality and feedback. Following Granger's notation, let:

$\bar{Y}_t$ = set of all past values of Y;

$\bar{\bar{Y}}_t$ = set of all past and present values of Y;

$\bar{U}_t$ = all of the information in the universe up to and including time t-1;

$\overline{U_t - Y_t}$ = all of the information in the universe apart from the specified series Y_t accumulated up to and including time t-1;

$\sigma^2(X/\bar{U})$ = minimum predictive error variance of X_t given $\bar{U}_t$;

$\sigma^2(X/\overline{U-Y})$ = minimum predictive error variance of X_t given $\bar{U}_t$ apart from $\bar{Y}_t$;

$\sigma^2(X/\bar{U},\bar{\bar{Y}})$ = minimum predictive error variance of X_t given $\bar{U}_t$ and $\bar{\bar{Y}}_t$.

Granger (1969, p. 428) proposes the following definitions:

Causality. If $\sigma^2(Y/\bar{U}) < \sigma^2(Y/\overline{U-X})$, we say that X is causing Y. In other words, we are better able to predict Y_t using all available information than if the information apart from X_t had been used.

Feedback. If $\sigma^2(Y/\bar{U}) < \sigma^2(Y/\overline{U-X})$ and, $\sigma^2(X/\bar{U}) < \sigma^2(X/\overline{U-Y})$, we say that feedback is occurring. In other words, Y_t is causing X_t and also X_t is causing Y_t.

Instantaneous Causality. If $\sigma^2(Y/\overline{U},\overline{X}) < \sigma^2(Y/\overline{U})$, we say that instantaneous causality is occurring. In other words, the current value of Y_t is better "predicted" if the present value of X_t is included in the "prediction" than if it is not.

If, in fact, one variable does cause another, then Granger (1969) also demonstrates how cross-spectral methods can be used to describe the relationship between the two variables. However, if instantaneous causality exists between the variables, these methods lose their capability of meaningful description.

Granger's definitions are only relevant for stationary time series. The definitions could be generalized, such that the nonstationary case is included. Then the definitions would be in reference to a specific time, or in other words, the existence of causality would have to be referenced with respect to time. The introduction of nonstationary time series only complicates the primary purpose of the definitions. Therefore, Granger constrains his definitions to stationary time series.

The definitions can be illustrated with a simple two variable case. Consider the following model:

$$X_t + c_o Y_t = \sum_{j=1}^{\infty} a_j X_{t-j} + \sum_{j=1}^{\infty} c_j Y_{t-j} + u_t \qquad (2.0a)$$

$$Y_t + b_o X_t = \sum_{j=1}^{\infty} b_j X_{t-j} + \sum_{j=1}^{\infty} d_j Y_{t-j} + v_t \qquad (2.0b)$$

If $b_o \neq 0$ or $c_o \neq 0$, then a situation of instantaneous causality exists. Y is said to be causing X, if $c_o \neq b_o \neq 0$, and at least one c_j is not equal to zero. Suppose $c_o \neq b_o \neq 0$, and at least one c_j and one b_j are not equal to zero, then a situation of feedback exists.

The empirical application of these definitions presents a problem. Granger himself acknowledges that prediction based upon all of the information in the universe is unrealistic. He suggests that the universal information set be constrained to an information set containing only relevant data. Thus, causality is indicated relative to the chosen information set.

The constraining of the information set to only "relevant" information weakens the causal test conclusions. Intuitively, causation relative to some information set is ambiguous. Using the definitions as a causal test criteria under a constrained information set really involves the use of necessary conditions. Therefore, it is possible to reject the hypothesis of causality between two variables. But, a failure to reject the hypothesis only supports the conclusion of causality, it does not in fact prove the conclusion.

Empirical Test Procedures

Several empirical techniques have been developed to test for causality between two variables based upon Granger's (1969) definitions. Basically three bivariate procedures have evolved: Sims' (1972) regression method, Sargent's (1976) regression technique, and Haugh's (1976) cross-correlation procedure. Other procedures have been used, but they are essentially modifications of the three basic procedures. For example, Williams, Goodhart, and Gowland (1976) used a modified version of the Sim's procedure.

Basis for Sims' test procedure

Consider the jointly covariance-stationary pair of stochastic processes X and Y. As long as they are purely linearily indeterministic, they can be expressed as

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} A(L) & B(L) \\ C(L) & D(L) \end{bmatrix} \begin{bmatrix} u_t \\ v_t \end{bmatrix} \qquad \begin{matrix} (2.1a) \\ (2.1b) \end{matrix}$$

where u_t and v_t are mutually and serially uncorrelated random variables with zero means and finite variances. The function A(L) is a polynomial in the lag operator L, where

$$L^n K_t = K_{t-n}$$

and

$$A(L) = \sum_{j=0}^{\infty} A_j L^j$$

$$A_o = 1.$$

B(L), C(L), and D(L) are similar in definition. Sims (1972) has shown that as long as A(L) is equal to zero, then Y is said not to be causing X in terms of Granger's (1969) definitions. And X is said not to cause Y as long as D(L) is equal to zero.

As a further illustration of these concepts, consider an alternate form of the bivariate process shown in 2.1. The process can be written as

$$X_t = E(L)Y_t + F(L)u_t \qquad (2.2a)$$

$$Y_t = G(L)X_t + H(L)v_t \qquad (2.2b)$$

where E(L), F(L), G(L), and H(L) are polynomials in the lag operator L analogous to those just defined with one exception.[1] E_o and G_o are not constrained to equal one. Again, u_t and v_t are mutually and serially uncorrelated random variables. In terms of Granger's definitions of causality, Y is causing X as long as some E_j is not equal to zero. Similarly, X is causing Y as long as some G_j is not

[1] In order to get this form it must be assumed that A(L), B(L), C(L), and D(L) are all invertible.

equal to zero. If some E_j and some G_j are not equal to zero, then a feedback relationship exists. This type of relationship is also referred to as bidirectional causality.

Consider the unidirectional case where all of the C_j are equal to zero in model 2.1. The structure of the model then becomes

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} A(L) & B(L) \\ 0 & D(L) \end{bmatrix} \begin{bmatrix} u_t \\ v_t \end{bmatrix} \qquad \begin{matrix} (2.3a) \\ (2.3b) \end{matrix}$$

An alternate expression for this model is[2]

$$X_t = M(L)Y_t + N(L)u_t \qquad (2.4a)$$

$$Yt = O(L)v_t \qquad (2.4b)$$

In this case Y is said to be causing X. However, X is not causing Y, so there is unidirectional causation from Y to X. Or, in other words, Y is simply a stochastic process which is exogenous with respect to X.

The existence of this type of unidirectional or bi-directional causality has important implications in the application of certain estimation techniques. In a least squares regression model it is assumed that the independent variables are independent of the disturbance term. Or, the right-hand side variables in an ordinary least

[2]Invertibility is assumed again.

squares regression are assumed to be exogenous. Consider model 2.2. If X_t is regressed on Y_t, the resulting parameter estimates will be biased. The bias exists because Y_t is not independent of the disturbance term $F(L)u_t$, as indicated by the relationship shown in Equation 2.2b. The same type of situation exists if Y_t is regressed on X_t. Now, consider model 2.4. If X_t is regressed on Y_t, unbiased estimates of the parameters are obtained. Y_t is independent of the disturbance term. Due to the nature of economic variables it is important to consider causality before employing the commonly used estimation techniques.

General procedure

The stochastic process of model 2.2 exhibits bidirectional causation. Consider regressing X_t on the future, current, and past values of Y, where the time series data used conforms to the stochastic process. The future values of Y should be significant, because of the causation shown in Equation 2.2b. Similarly, if Y_t is regressed on the future, current, and past values of X, the future values of X should be significant in explaining the variation in Y_t. The significance is implied by Equation 2.2a.

Model 2.4 exhibits unidirectional causation. If X_t is regressed on the future, current, and past values of Y, the future values of Y should not have significant explanatory power. The insignificance is indicated in Equation 2.4b, where Y_t is not caused by X_t. And, if Y_t is regressed on the future, current, and past values of X, the future values of X should have significant explanatory power. They should be significant because there is unidirectional causation from Y to X.

This significance or lack of significance provides the basis for Sims' (1972) test procedure. In order to test for causality, two regressions must be run. These regressions provide a F-statistic with which the statistical significance of the future values of a variable can be tested. For example, if you wanted to test if X causes Y, a regression of X_t on the future, current, and past values of Y is performed. A second regression of X_t on the current and past values of Y is performed. From these regressions, the explanatory power of the future values of Y can be tested. All of the possible outcomes of Sims' test method for a two variable process are listed in Table 2.1.

Essentially, Sims has developed an equivalence relationship. Consider the general bivariate process 2.1. It was shown that X does not cause Y as long as all of the C(L) or D(L) are equal to zero. Now, consider the two-sided regression,

$$X_t = \sum_{j=-\infty}^{\infty} a_j Y_{t-j} + e_t, \qquad (2.5)$$

Table 2.1. Possible outcomes of Sims' test procedure (two variable process)

Regression Equation	Significance of Future Values	Causal Indication
Y on future, current, and past X	significant	Unidirectional causation from Y to X; Y is exogenous relative to X
X on future, current, and past Y	insignificant	
Y on future, current, and past X	insignificant	Unidirectional causation from X to Y; X is exogenous relative to Y
X on future, current, and past Y	significant	
Y on future, current, and past X	significant	Bidirectional causation between X and Y; X is not exogenous relative to Y; Y is not exogenous relative to X
X on future, current, and past Y	significant	
Y on future, current, and past X	insignificant	No causality; independence between X and Y
X on future, current, and past Y	insignificant	

of X_t on future, current, and past values of Y. Sims has shown that C(L) = 0 or D(L) = 0 is equivalent to all of the future a_j's equalling zero.

Necessary vs. sufficient conditions

As mentioned earlier, Sims' (1972) test method is only a necessary condition for strict exogeneity. The test in itself does not prove causality or strict exogeneity. To see this, consider the model

$$X_t = R(L)X_{t-1} + u_t \tag{2.6a}$$

$$Y_t = S(L)X_{t-1} + T(L)Y_{t-1} + v_t \tag{2.6b}$$

where u_t and v_t are serially uncorrelated white noise processes with zero means and finite variances. The function R(L) is a polynomial in the lag operator L, where

$$R(L) = \sum_{j=0}^{\infty} R_j L^j .$$

S(L) and T(L) are similar in definition. Equation 2.6a indicates that Y fails to cause X. Now, suppose

$$v_t = \gamma u_t + \delta_t^{\gamma} \tag{2.7}$$

where γ is a fixed scalar and δ_t is a stochastic process. By substituting 2.6a into 2.7 you get

$$v_t = \gamma [X_t - R(L)X_{t-1}] + \delta_t^{\gamma} . \tag{2.8}$$

And substituting 2.8 into 2.6b, you get

$$[1 - T(L)L]Y_t = [\gamma + S(L)L - \gamma R(L)L]X_t + \delta_t^{\gamma}. \qquad (2.9)$$

Further, assume that R(L) is invertible. Then X_t can be expressed as an infinite moving average of the following form:

$$X_t = \lambda(L)u_t \qquad (2.10)$$

The covariance between δ_t^{γ} and current and future values of X is

$$E[\delta_t^{\gamma}X_{t+j}] = E[(v_t - \gamma u_t) \sum_{k=0}^{\infty} \lambda_k u_{t+j-k}]$$

$$= \lambda_j(E[v_t u_t] - \gamma E[u_t^2]). \qquad (2.11)$$

In general, λ_j is not equal to zero, so to insure that future and current values of X are strictly exogenous (i.e., $E[\delta_t^{\gamma}X_{t+j}] = 0$)

$$\gamma = \frac{E[v_t u_t]}{E[u_t^2]}. \qquad (2.12)$$

Or γ must equal the population regression coefficient of v_t on u_t.

The following expression is obtained by eliminating the lagged Y's from 2.9:

$$Y_t = [1-T(L)L]^{-1}[[\gamma+S(L)L-\gamma R(L)L]X_t + \delta_t^{\gamma}] \qquad (2.13)$$

Note that this expression is dependent upon γ. In this case, Sims' test would indicate that X causes Y and Y fails to cause X. In other words, X is exogenous relative to Y. However, if the relationship shown in 2.7 exists, the conclusion of exogeneity may not be valid. With this specific relationship it was shown that the condition 2.12 must be satisfied to insure exogeneity. Therefore, Sims' test can be used to reject the hypothesis of exogeneity, but it can not be used to prove the hypothesis.[3]

Limitation of instantaneous causality

Another limitation of the Sims' (1972) test method occurs when instantaneous causality is present. As an illustration consider the following model,

$$Y_t = X_t + u_t \qquad (2.14a)$$

$$X_t = v_t \qquad (2.14b)$$

where u and v are mutually and serially uncorrelated stochastic processes. In this case, X is contemporaneously causing Y, but X is also exogenous with respect to Y. Information on X and Y would only reveal that they are correlated. Sims' test method would not discern whether the causation ran from X to Y or Y to X or in both directions. So, when there is evidence of contemporaneous causation, the direction of causation can not be determined

[3]The theoretical development of this concept is taken from Sargent (1979).

using Sims' test method.

Basis for Sargent's test procedure

Consider the bivariate model 2.3 in which Y is said to cause X. Assuming D(L) is invertible, then Equation 2.3b can be written as

$$D(L)^{-1}Y_t = v_t \tag{2.15}$$

And by substitution, the following expression can be determined:

$$X_t = B(L)D(L)^{-1}Y_t + A(L)u_t \tag{2.16}$$

Now, if we premultiply 2.16 by $A(L)^{-1}$, and normalize the expression such that $A_o = 1$, then

$$X_t = \alpha(K)Y_t + \beta(K)X_t + u_t$$

$$= \sum_{i=0}^{\infty} \alpha_i Y_{t-1} + \sum_{i=0}^{\infty} \beta_i X_{t-i-1} + u_t \tag{2.17}$$

where

$$\alpha(K) = A(L)^{-1}B(L)D(L)^{-1}$$

and

$$[1-K\beta(K)] = A(L)^{-1}$$

Equation 2.17 implies that if X_t were regressed on past X and past Y, the α_i's should be significant.

By a similar analysis, the bivariate model 2.1, in which bidirectional causation exists, could be expressed in the following form:

$$X_t = \sum_{i=0}^{\infty} a_i Y_{t-i} + \sum_{i=0}^{\infty} b_i X_{t-i-1} + u_t \qquad (2.18a)$$

$$Y_t = \sum_{i=0}^{\infty} c_i X_{t-i} + \sum_{i=0}^{\infty} d_i Y_{t-i-1} + v_t \qquad (2.18b)$$

In this case, if X_t were regressed on past X and past Y, the a_i's should be significant. This would indicate in the Granger (1969) sense that causation exists from Y to X. And if Y_t were regressed on past X and Y, then the c_i's should be statistically significant. This would in turn indicate that causation also runs from X to Y.

General procedure

Sargent's (1976) procedure is based upon the significance of the past values of the variable in question. As was the case in Sims' (1972) procedure, two regressions must be run in order to test for causality. These regressions provide an F-statistic with which the statistical significance of the past values of a variable can be tested. For example, suppose you wanted to test if Y causes X. In order to do this, X_t is regressed on past Y and past X. And, another regression is run with X_t on past X alone. If the explanatory power of the past Y is significant, then the data are consistent with the hypothesis that Y causes X. All of the possible outcomes of Sargent's test method are listed in Table 2.2.

Table 2.2. Interpretation of Sargent's test results

Regression Equation	Significance of the lagged causal variable	Causal Indication
Y on lagged Y's and lagged X's	significant	Unidirectional causation from X to Y; X is exogenous relative to Y
X on lagged X's and lagged Y's	insignificant	
Y on lagged Y's and lagged X's	insignificant	Unidirectional causation from Y to X; Y is exogenous relative to X
X on lagged X's and lagged Y's	significant	
Y on lagged Y's and lagged X's	significant	Bidirectional causation between X and Y; X is not exogenous relative to Y; Y is not exogenous relative to X
X on lagged X's and lagged Y's	significant	
Y on lagged Y's and lagged X's	insignificant	No causality; independence between X and Y
X on lagged X's and lagged Y's	insignificant	

Basis for Haugh's procedure

Consider two covariance-stationary stochastic processes X and Y. If X and Y are purely linearily indeterministic, then they will have an autoregressive representation of the form

$$Y_t = J(L)Y_{t-1} + u_t \qquad (2.19a)$$

$$X_t = K(L)X_{t-1} + v_t \qquad (2.19b)$$

where u and v are white noise processes satisfying

$$E[u] = 0$$

$$E[v] = 0$$

$$E[u_s u_t] = \sigma_u^2, \quad t = s$$
$$= 0 \quad t \neq s$$

$$E[v_s v_t] = \sigma_v^2, \quad t = s$$
$$= 0, \quad t \neq s.$$

J(L) and K(L) are polynomials in the lag operator L, analogous to those defined in previous sections. By the structure of the model X and Y can only be related if u and v are related. Therefore, the relationship between u and v is studied for evidence of a causal relationship.

One method of investigating the relationship between u and v, is to study the cross-correlations between u and v. The cross-correlation between u and v is defined in the following manner:

$$\rho_{uv}(h) = \frac{E[u_{t-h}v_t]}{(E[u_t^2]E[v_t^2])^{1/2}} \qquad h \gtrless 0 \tag{2.20}$$

Implications about the causality between X and Y can be drawn from these cross-correlations. For example, suppose $\rho_{uv}(h) = 0$ for all h, then u and v are independent processes. This, in turn, implies that X and Y are independent. Or, suppose $\rho_{uv}(h)$ is not equal to zero for some h greater than zero, then the data are consistent with the hypothesis of Y causing X. All of the possible outcomes of this type of analysis are listed in Table 2.3.

General procedure

Haugh's (1976) procedure involves fitting each of the time series with a univariate model. Using these models, estimates of the u and v series can be obtained. And, using the u and v series, sample cross-correlations can be computed with the following formula:

$$r_{\hat{u}\hat{v}}(h) = \frac{\sum_{t=1}^{n-h} \hat{u}_{t-h}\hat{v}_t}{(\sum_{t=1}^{n} \hat{u}_t \sum_{t=1}^{n} \hat{v}_t^2)^{1/2}} \tag{2.21}$$

Hypotheses about $\rho_{uv}(h)$ can be tested using the estimated cross-correlations. In order to do this, the sampling distribution of $r_{\hat{u}\hat{v}}(h)$ must be known. It has been demonstrated that if the two residual series, u and v, are assumed

Table 2.3. Interpretation of cross-correlations between u and v[a]

Cross-correlations	Interpretation
$\rho_{uv}(h) \neq 0$ for some $h > 0$ $\rho_{uv}(0) = 0$ $\rho_{uv}(h) = 0$ for all $h < 0$	Consistent with unidirectional causation from Y to X; X does not cause Y; Y is exogenous relative to X; X is not exogenous relative to Y
$\rho_{uv}(h) = 0$ for all $h > 0$ $\rho_{uv}(0) = 0$ $\rho_{uv}(h) \neq 0$ for some $h < 0$	Consistent with unidirectional causation from X to Y; Y does not cause X; Y is not exogenous relative to X; X is not exogenous relative to Y
$\rho_{uv}(h) \neq 0$ for some $h > 0$ $\rho_{uv}(0) = 0$ $\rho_{uv}(h) \neq 0$ for some $h < 0$	Consistent with bidirectional causation between Y and X; Y is not exogenous relative to X; X is not exogenous relative to Y
$\rho_{uv}(h) = 0$ for all $h > 0$ $\rho_{uv}(0) = 0$ $\rho_{uv}(h) = 0$ for all $h < 0$	Independence between Y and X; Y does not cause X; X does not cause Y

[a]Source: DyReyes et al. (1980).

Table 2.3 (Continued)

Cross-correlations	Interpretation
$\rho_{uv}(h) \neq 0$ for some $h > 0$ $\rho_{uv}(0) \neq 0$ $\rho_{uv}(h) = 0$ for all $h < 0$	Consistent with contemporaneous bidirectional causation between Y and X; consistent with past Y causing X; past X does not cause Y
$\rho_{uv}(h) = 0$ for all $h > 0$ $\rho_{uv}(0) \neq 0$ $\rho_{uv}(h) \neq 0$ for some $h < 0$	Consistent with contemporaneous bidirectional causation between Y and X; consistent with past X causing Y; past Y does not cause X
$\rho_{uv}(h) \neq 0$ for some $h > 0$ $\rho_{uv}(0) \neq 0$ $\rho_{uv}(h) \neq 0$ for some $h < 0$	Consistent with bidirectional causation between Y and X; Y is not exogenous relative to X; X is not exogenous relative to Y
$\rho_{uv}(h) = 0$ for all $h > 0$ $\rho_{uv}(0) \neq 0$ $\rho_{uv}(h) = 0$ for all $h < 0$	Consistent with contemporaneous bidirectional causation between Y and X; past Y does not cause X; past X does not cause Y

to be independent and not autocorrelated, then the cross-correlation estimates are approximately normally distributed with zero mean and variance of N^{-1}. Given this result and using a null-hypothesis of independence, a sample statistic can be derived. This statistic

$$S = N \sum_{h=-M_1}^{M_2} r_{\hat{u}\hat{v}}^2(h) \qquad (2.22)$$

is approximately distributed as a chi-square with $|M_1| + |M_2| + 1$ degrees of freedom. M_1 represents the number of future lags and M_2 represents the number of past lags.

<u>Limitation of instantaneous causality</u>

Haugh's (1976) procedure is subject to the same limitation as Sims' (1972) and Sargent's (1976) procedures with respect to contemporaneous causation. If the hypothesis of $\rho_{uv}(0) = 0$ is rejected, then it is concluded that contemporaneous causation exists. And, as was the case with the other methods, this conclusion is consistent with three different hypotheses. The three different possibilities are that X causes Y; or that Y causes X; or that there is bidirectional causation between X and Y.

Bias in Haugh's procedure

Haugh's (1976) test is biased toward the conclusion of independence, except in a very special case. Suppose you wanted to test if X causes Y. The Haugh procedure is based upon postulating a model,

$$Y = A(L)Y + B(L)C(L)X + v, \qquad (2.23)$$

where A, B, and C are polynomials in the lag operator L and v is uncorrelated with the past values of Y and X. The hypothesis of independence is represented by B(L) equalling to zero. The first step in the Haugh procedure is to model the Y and X series. Essentially, you are estimating the filters A(L) and C(L) such that A(L)Y and C(L)X are both serially uncorrelated. Then holding A(L) and C(L) fixed, you estimate B(L) to see if it is significant. This is equivalent to estimating the regression 2.23 with B(L) set equal to zero, and then testing for the contribution of X to the regression by looking at the correlation between C(L)X and the residuals from the original regression equation. Least squares regression theory indicates that this procedure is biased toward the null-hypothesis, in this case B(L) = 0. Therefore, Haugh's procedure is biased towards the hypothesis of independence.[4]

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[4]The theoretical development of this concept is taken from Sims (1977, p. 24).

CHAPTER III. CAUSAL TESTING: PROCEDURAL CONSIDERATIONS

This chapter provides a general overview of some of the considerations involved in the actual empirical application of the regression causality tests. Accompanying the presentation of the important considerations, is a description of the alternative procedures available to deal with each of the considerations.

Nonstationarity

The theory just presented in Chapter II assumes the time series in question are stationary. When applying the causal test procedures, the assumption of stationarity must be considered. In practice, using actual empirical data, nonstationarity may be encountered for any number of reasons. For example, the mean of the time series may be a nonconstant function of time or the variance of the time series may be a nonconstant function of time. Many economic time series display an upward trend, implying the mean is not constant or is a function of time. Therefore, the problem of nonstationarity is real when working with actual empirical data and as such must be dealt with.

One common method of analysis is to decompose the time series into arbitrary components. The traditional model of an economic time series is

$$Y_t = T_t + S_t + E_t \qquad (3.0)$$

where T_t is the trend component, S_t is the seasonal component, and E_t is the random component. The random component, E_t, is assumed to be a stationary time series. In the case of causality testing, the E_t series is the series which should be used in the test procedures. As would be expected, a number of different techniques have been developed to remove the trend and seasonal components from a time series in order to isolate the random component.

Trend Component

Two methods of removing the trend component have been widely used in the empirical applications that have appeared in the literature. The first procedure involves regressing the original time series on a deterministic linear time trend. The resulting residual series contains only the seasonal component and the random component. A second alternative which has been used is based upon the assumption that the parameters of the linear time trend are stochastic. If this alternative assumption is made then first or second differences, as suggested by Box and Jenkins (1976), can be used to remove the trend.

A closely related consideration with respect to the trend, is the assumption that the time series has a zero mean. In order to compensate for the fact that the series is unlikely to have a zero mean, a constant term should be included in each of the regression equations.

Seasonal Component

In terms of estimating distributed lags, distortion due to the seasonal component may appear for basically two reasons. The first possibility occurs, when seasonally unadjusted data are used in the estimation. In this case, the coefficients in the lag distribution may be distorted in both their size and shape. This in turn, may cause fallacious inferences to be drawn about the significance of the effect of the independent variable. Thus, it is desirable to consider the seasonal component in order to eliminate this type of bias. The second possibility can occur when the two series being used have been adjusted using different procedures. In this case, the possibility exists that the adjustment procedure has amplified or even induced seasonal bias in the lag distribution. Therefore, it is extremely important to consider the seasonal component in a time series.

The treatment of distortion due to seasonal noise in the regression causality tests can be divided into two broad categories. The study can begin with seasonally unadjusted data or the study can begin with officially adjusted data. Each possibility is discussed in detail in the following paragraphs.

Seasonally unadjusted data

Basically, two options are available if the study is started with seasonally unadjusted data. The first possibility is that each of the series be filtered to remove the seasonal component. Then, the causality tests are performed using the adjusted series. The second alternative is to perform the procedures using the unadjusted data.

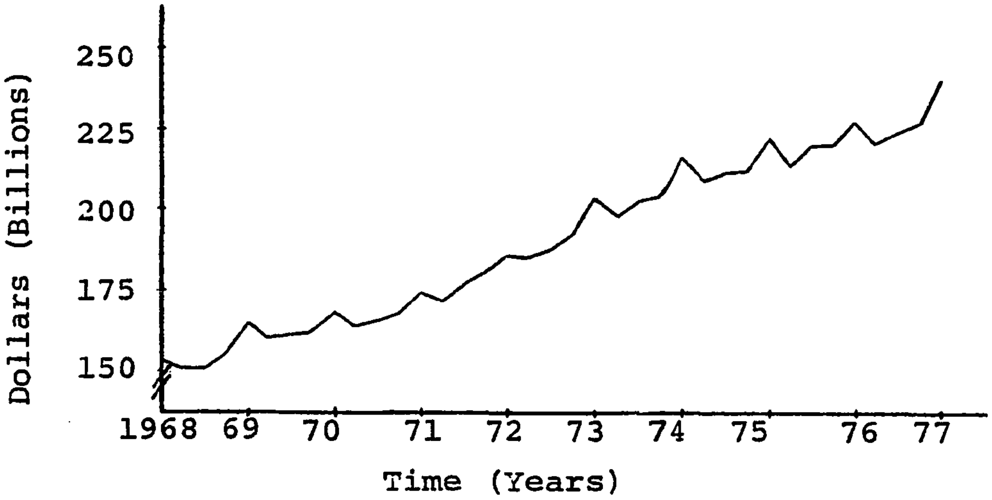
The first possibility mentioned above was that of adjusting each of the series under investigation. If this option is chosen, both types of potential distortion can be eliminated. In other words, the seasonal noise can be filtered out in such a manner that the coefficients in the distributed lag are not biased or do not have spurious significance. The filtering of seasonal noise can be accomplished in two different manners.

The filtering can be done in the frequency domain. Normally, economists think of time series data in the "time domain" sense. The time domain is in reference to the index set of the representation. An alternative representation of the time series can be obtained from the Fourier transform of the correlation function of the time series. In this case, the index set of the resulting representation is frequencies of various trigonometric functions. Thus, the time series can be thought of in a "frequency domain" sense. As an illustration, refer to the graphs on the following page. In Panel A, seasonally unadjusted monthly observations of the demand deposit component of the money supply for the United States from 1968 to 1977 are plotted. This representation is in the time domain because the domain is time. In Panel B, the spectral density of the same series is plotted. This is the frequency domain representation because the domain of the representation is frequencies.

To perform the filtering process in the frequency domain, an explicit judgement has to be made about the "seasonal band" width. The idea of a seasonal band is discussed in the context of spectral analysis. If the time series is thought of in the frequency domain sense, then certain frequencies are considered to be "seasonal frequencies." For example, consider monthly data, then some of the seasonal frequencies are $\pi/6$, $\pi/3$, $\pi/2$, $\pi/6$, and π radians. The period associated with each of these frequencies is listed in Table 3.1.

And, in order to remove the seasonal component from the time series under consideration it must be filtered such that the spectral density is approximately zero for some band around each of the seasonal frequencies. The width of this band is called the "seasonal band width". So, this

Panel A: Time Domain



Panel B: Frequency Domain

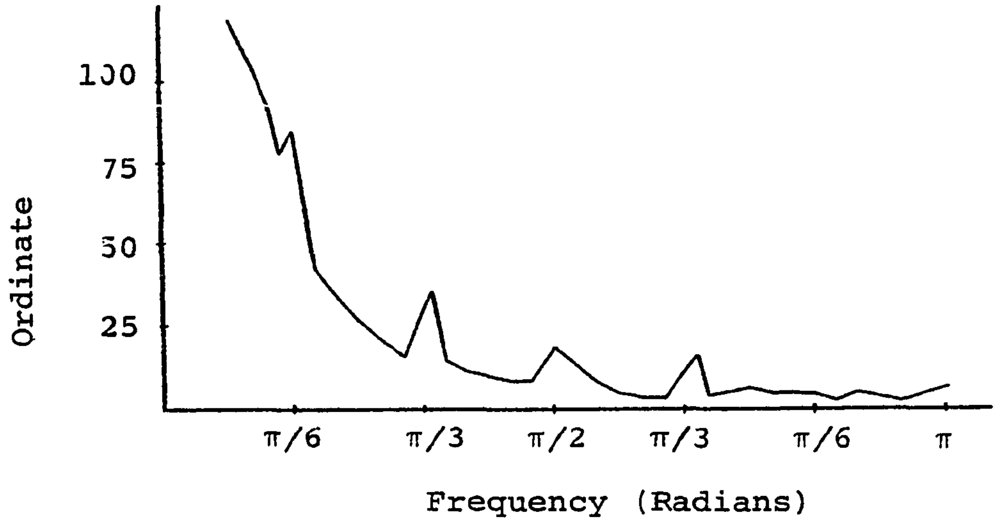


Figure 3.1. Demand deposit component of the money supply (1968-1977)

Table 3.1. Seasonal frequencies for monthly data

Frequency	Period
$\pi/6$	12 months
$\pi/3$	6 months
$\pi/2$	4 months
$2\pi/6$	3 months
$5\pi/6$	2.4 months
π	2 months

seasonal adjustment procedure involves the following steps:

1. choose the seasonal band width;
2. Fourier transform the original series;
3. set the transform equal to zero for the chosen width around the seasonal frequencies; and
4. inverse Fourier transform the filtered series.

This procedure is essentially a regression analysis in the frequency domain and has been used in a number of the more recent causal applications, for example, the paper by Sargent (1976).

In terms of adjusting the time series or filtering out the seasonal component, the second possibility is to filter the data in the time domain. If the time domain procedure is used, then the time series is regressed upon a set of cosine and sine variables. The residual series resulting from this regression is then the corrected series. Pierce (1977a) used this type of technique in his analysis. It is worth noting that the frequency and time domain procedures are equivalent.

Each of the procedures just outlined allows for a consistent degrees-of-freedom correction. The use of a seasonal adjustment procedure which allows for a degrees-of-freedom correction has important implications with respect to causal testing. The conclusions drawn from the test procedures are based upon critical values of test statistics. And, obviously, these critical values depend upon the appropriate degrees-of-freedom. Therefore, the test conclusions are sensitive to the degrees-of-freedom. Although very little attention has been paid to this consideration in the casual testing literature, it is an important consideration.

The degrees-of-freedom correction is simply a matter of subtraction when the filtering is done in the time domain. The correction is somewhat more complicated if the filtering is done in the frequency domain. In this case, the correction suggested by Sims (1974) is based upon the chosen seasonal bandwidth. The correction suggested is to reduce the degrees-of-freedom by a factor of $[1 - (\frac{3\delta}{2\pi})]$, where δ is the seasonal bandwidth. This loss of degrees-of-freedom is implied by the equivalence of the time and frequency regression procedures. In other words, the choice of a bandwidth implies a certain number of sine and cosine waves in a time domain sense. Note that this correction is also a function of the sample size. For example, suppose the sample consists of eighty quarterly observations and a bandwidth of $\pi/8$ is chosen for the seasonal adjustment. The implied correction is a loss of fifteen degrees-of-freedom. An important point to note is that this correction is based upon an explicit judgment about δ and, if this judgement is not made, the necessary correction can't be applied.

The other major choice with respect to starting with seasonally unadjusted data is to proceed with the tests using the unadjusted data. The alternative choice which was just discussed is to filter the data. Basically, this choice involves assuming the seasonal noise in the dependent variable can be attributed or explained by the seasonal noise in the independent variable. Seasonal dummies can also be included as independent variables if there is a seasonal pattern in the dependent variable which can not be attributed to the independent variable. Using unadjusted data in the causal regression procedures has a number of disadvantages and advantages.

The major disadvantage of this type of procedure is that the seasonal noise in the time series may produce seasonal bias in the estimated lag distribution. This type of bias can be detected in two manners. The first possibility is by visual observation of a time domain plot of the estimated lag distribution. The second method is to compute the absolute value of the Fourier transform of the estimated lag distribution and check for peaks or dips at the seasonal frequencies. This type of bias should not be present if the alternative procedure of filtering the data is used.

Two major advantages are associated with this type of procedure. First of all, any distortion due to the time series being adjusted by different procedures is avoided. As has been noted this potential problem is also avoided by starting with unadjusted data and adjusting it yourself (provided you adjust the data correctly). The process of adjusting each of the series involved in the study is a computationally complicated procedure. Therein lies the second advantage of using unadjusted data. By using unadjusted data you avoid a great deal of computational work which may not even be necessary in terms of the qualitative results of the causality study.

Officially adjusted data

The other major method of procedure with respect to seasonal adjustment is to use data which has been seasonally adjusted at the source or in other words, officially adjusted data. As was noted earlier, this method of analysis may produce distorted results if the two variables in question have been adjusted differently. Another problem with this type of procedure is the inability to correct the degrees-of-freedom. So, to begin with, nonseasonalized data are the most desirable from the standpoint of eliminating distortion due to seasonal bias and a proper accounting of the degrees-of-freedom. However, to start with, nonseasonalized data involves a significant amount of additional computational work. Therefore, data which have been seasonally adjusted at the source has been used in a number of different studies involving causality. For example, the Williams, Goodhart, and Gowland (1976) study of causality between money and income in the United Kingdom used officially adjusted data.

Serial Correlation

The assumption of an uncorrelated error structure must be approximately correct in order to ensure a reasonable degree of accuracy in the F-tests used in the causality tests. For example, suppose there is evidence of negative first-order serial correlation in the regression disturbances. Then, the appropriate F-test would be biased in favor of the null-hypothesis. Or, consider the other possibility, suppose positive first-order serial correlation exists. In this situation the F-test would be biased against the null-hypothesis. Therefore, it is important to consider the possibility of nonseasonal as well as seasonal serial correlation which was just discussed in the previous section.

Several tests exist with which serial correlation can be detected. The most common test is the use of the Durbin-Watson (1950) d-statistic. This statistic can be used to test for first-order serial correlation, when none of the independent variables is a lagged dependent variable. When applying Sargent's (1976) test, some of the regressors are lagged dependent variables, so the d-statistic is not appropriate. A more appropriate statistic is Durbin's (1970) h-statistic, when lagged dependent variables are included as regressors. The possibility of higher order serial correlation may exist and should be considered. Neither the Durbin-Watson d- or the Durbin h-statistic are capable of detecting departures from serial independence of degree greater than one. Several test methods are available to test for serial correlation of degree greater than one. Tests on the periodogram of the regression disturbances are one possibility. Two such tests are Fisher's (1929) Kappa test and Bartlett's (1966) Kolmogorov-Smirnov test. Fisher's test searches out the largest periodogram ordinate and determines if it is reasonable given the assumption of white noise. The Bartlett test is based upon the normalized cumulative periodogram. This test applies the Kolmogorov-Smirnov test of the hypothesis that the sample distribution function was selected from a uniform (0,1) distribution. In other words, we are performing a test of the hypothesis that the regression disturbances form a white noise series. Several other tests are available; however, the two tests just mentioned are available in the SAS software package.

Once the existence of serial correlation has been established, a correction should be employed. Again, a variety of correction procedures are available and have been used. Three basic procedures have appeared in the causality literature. One possibility is to employ a prechosen filter. For example, Sims used the filter $1-1.5\ L + .5625\ L^2$ with quarterly data. This type of filter was suggested by Nerlove (1964) in an earlier work. A problem may arise with using a prechosen filter, if the filter inadequately removes the serial correlation. If this is the case, then the results could be subjected to the "spurious regression" phenomenon suggested by Granger and Newbold (1974). A more popular approach as compared to using a prechosen filter is to estimate the appropriate filter with the estimated regression residuals from the initial regression. This procedure involves calculating the sample residual autocorrelation function from the residuals. Then, from the estimated error model, a filter can be calculated and used to transform the time series. The third alternative, which has received the most attention in the more recent literature, is to use a spectral analysis type procedure. For example, Feige and Regalia (1979) used this type of procedure in a recent working paper. This type of procedure is essentially the use of Generalized Least Squares in the frequency domain. An example of this type of method is the Hannan (1970) efficient procedure. The following are the steps involved in using this procedure:

(i) Estimate the regression equation with OLS

(ii) Fourier transform the estimated residuals and estimate the spectral density ($\hat{s}_{\hat{u}}$)

(iii) Divide the Fourier transform of each time series by $\hat{s}_{\hat{u}}$

(iv) Inverse Fourier transform the corrected time series

(v) Re-estimate the regression equation with OLS

Each of the basic procedures just mentioned have been used in the application of causality tests. The two procedures using the estimated residuals are more desirable in terms of adequate correction for serial correlation. However, they are computationally more complicated than the use of a prechosen filter. Therefore, in certain situations, the use of a prechosen filter may be desirable.

Time Interval Between Observations

The test procedures described in the previous chapter test for causal effects which take at least one period to show themselves. Even if unidirectional causality is not shown, instantaneous causality may exist. Instantaneous or contemporaneous causality can be tested by testing to see if the current value of the variable in question is significant. However, as indicated by Granger (1969), instantaneous causality may be the conclusion when in fact unidirectional causality exists. For example, suppose X affects Y with a lag of one week and the series are observed every two weeks. The tests would show instantaneous causality, when the true relationship was unidirectional causality. On the basis of capturing causal relationships, the data set with the smallest time interval between observations should be chosen from the available data sets.

Lead-Lag Length

Another consideration is the lead-lag structure which is used in the regression equations. In other words, a decision must be made with respect to the number of lead and lag variables to be included in each regression equation. More specifically, when using the Sargent (1976) procedure, the number of lagged values of the dependent and independent variables to be included as regressors in the equation must be determined. In the case of Sims' (1972) procedure, the number of lead and lag values to be included as regressors must be determined. The decision should be based upon a judgement of the lag time involved in any potential causal relationship. An important criterion is to allow the lag length to be long enough to capture any possible causal effect.

A great deal of discrepancy exists in the literature in terms of what a proper lag length is. For example, in his original work, Sims' uses a lead structure of four quarters and a lag structure of eight quarters. Thus, he was allowing for a causal effect between money and income to occur within a length of four quarters. By comparison, consider a paper by Feige and Regalia (1979), in which they tested the relationship between possible policy targets and monetary aggregates. Using weekly data, they used a number of different lead-lag structures. The smallest was a lead of four weeks and a lag of thirteen weeks. This structure allows for a causality effect of at most, one quarter in length. The point is that there is a great deal of potential variability in the choice of a lead-lag structure. Ideally, a number of different structures should be used in order to test the robustness of the causal conclusions.

CHAPTER IV. EMPIRICAL RESULTS

Data

The data used in this analysis are nonseasonally adjusted weekly averages of daily observations from September 18, 1968 to September 20, 1978. This time period involves a total of 523 observations. The following six time series were investigated:

1. Demand deposit component (MDC);
2. Other time deposits (OTS);
3. Unborrowed reserves (UBR);
4. Unborrowed monetary base (UMB);
5. Federal funds rate (RFF); and
6. 90-day Treasury bill rate (RTB).[1]

The figures used were in millions of dollars and were obtained from the Board of Governors of the Federal Reserve System.

The major operational consideration discussed in Chapter III was that the regression causality tests assume the time series are stationary. As a first step, each of the raw series of data was checked to see if it formed a white noise process. This testing was done with the use of Bartlett's (1966) test statistic and Fisher's (1929) Kappa statistic. The results of these tests are summarized in

[1]For a detailed definition of each series see Appendix A.

Table 4.1. Clearly, these results indicate that each of the series cannot be assumed to be white noise.

Table 4.1. Test statistics for stationarity check

Time series	Fisher's Kappa statistic	Bartlett's test statistic
MDC	151.27*	.882*
OTS	160.99*	.907*
UBR	150.47*	.876*
UMB	164.42*	.902*
RFF	176.15*	.925*
RTB	173.45*	.879*

*Indicates significance at the .01 level.

In order to further investigate the time series in question, with respect to stationarity, it was assumed that each of the series fits the time series model form discussed in Chapter III i.e.,

$$Y_t = T_t + S_t + E_t \tag{4.0}$$

where T_t is the trend component, S_t is the seasonal component, and E_t is the random component. Using this model, the hypothesis that each series contained a trend and seasonal component was formed.

The hypothesis of a trend component was not statistically tested. It was further assumed that the trend was deterministic. Given these assumptions, the trend component can be removed from the dependent variable in each regression by including a deterministic trend as an independent variable. The trend variable included in each regression equation was of the form $t = 1,2,...,n$, where n equals the total number of observations in the sample.[2] Also, to insure the series has a zero mean, a constant term was included in each regression.

The hypothesis that each time series contained a seasonal component was tested statistically. This was done by testing to see if a set of variables reflecting seasonal movement significantly explained any of the variation in each of the time series. The variables used to reflect seasonal content were a set of twenty-six variables; twenty-four sine and cosine functions and two binary seasonal dummies for the months of January and December.[3] The sine and cosine functions used were of the form

$$\cos\left(\frac{2\pi\ mt}{365}\right)$$

$$\sin\left(\frac{2\pi\ mt}{365}\right)$$

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[2]It should be noted that some causality studies have not removed the trend, for example, the study by Sargent (1976).

[3]These variables are similar to those used by Pierce (1977a).

where

$m = 1,2,3,4,5,6,7,8,13,17,18,26$

and t is the corresponding Julian date of each observation. The frequency and the period of the cycle associated with each of seasonal variables are shown in Table 4.2.

Table 4.2. Period and frequency for the seasonal variables

m	Frequency	Period of the Cycle (days)
1	$2\pi/365$	365
2	$4\pi/365$	182.5
3	$6\pi/365$	121.7
4	$8\pi/365$	91.3
5	$10\pi/365$	73
6	$12\pi/365$	60.8
7	$14\pi/365$	52.1
8	$16\pi/365$	45.6
13	$26\pi/365$	28.1
17	$34\pi/365$	21.5
18	$36\pi/365$	20.3
26	$52\pi/365$	14

The dummy variables used were binary variables for December and January. They were of the form:

$D_1 = 1$, observation occurred in the month of December

$= 0$, all other months

$D_2 = 1$, observation occurred in the month of January

$= 0$, all other months

The inclusion of these specific dummy variables may appear to be arbitrary. However, their inclusion as seasonal variables is based upon the work done by Pierce (1977a). He found these variables to have significant explanatory power. Therefore, they were included in the test for a seasonal component.

The results of regressing each of the six time series on this set of twenty-six variables are shown in Table 4.3.[4] As can be seen from these results, three of the six variables contain a significant seasonal component. These results are consistent with those of Pierce, except in the case of time deposits. He found a significant seasonal component and this analysis did not indicate a significant seasonal component.

Given this information, the following procedure was employed with respect to the seasonal component and seasonal adjustment. The two causality regression procedures were performed using seasonally unadjusted data and the set of twenty-six seasonal variables just described were included in

[4] Each regression equation also contained a deterministic trend and a constant.

Table 4.3. Test statistics for seasonal component

Time series	F-statistic for seasonal variables[a]	F-statistic for entire model[b]
MDC	15.66*	1,065.6*
OTS	1.18	944.9*
UBR	3.67*	97.5*
UMB	2.74*	2,103.3*
RFF	1.11	1.29
RTB	1.11	1.09

[a]Degrees-of-freedom for each of the statistics are 26 and 469. It should be noted that these statistics are no longer distributed as an F-statistic if the residuals of the regression equation are serially correlated.

[b]Degrees-of-freedom for each of the statistics are 27 and 469.

*Indicates significance at the .01 level.

each regression equation.[5]

This methodology has not been used in any of the actual empirical applications of causality testing. A number of

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[5]When the dependent variable was one of the interest rate series, the additional seasonal variables were not included as independent variables. They were excluded because in the early analysis of the time series no significant seasonal component was found in the interest rate series.

Note that the seasonal variables were included as independent variables in a regression for which the dependent variable was OTS. This was done even though no significant seasonal component was found in the series. This was done because previous studies have found a seasonal component in this series.

advantages and disadvantages are associated with this methodology. The first major advantage is that there is no complex computational work involved in seasonally adjusting the data. The second major advantage is that any chance of spurious dynamics is eliminated. This potential problem exists when using officially adjusted data and was discussed in Chapter III. The third advantage is that a proper accounting of degrees-of-freedom is available. There is one major disadvantage to this procedure. The possibility does exist that the seasonal noise will create bias in the estimated lag distribution. Methods of detecting this type of bias were discussed in Chapter III. If this type of bias is detected, then the two series in question should be seasonally adjusted and the causality tests re-run. The advantages of this procedure seem to outweigh the disadvantages, thus this procedure was employed in this study.

Another empirical consideration of importance was that of serial correlation. The treatment of serial correlation differed between the application of the two different regression procedures. Therefore, the discussion of the treatment of serial correlation is presented with the results of each of the different procedures.

Application of Sargent's Test

Using the OTS and MDC time series for illustrative purposes, the actual procedure used included the following steps:

1. OTS is regressed on past OTS, current and past MDC, a constant term, a trend, and the twenty-six seasonal variables.

2. OTS is regressed on past OTS, a constant term, a trend, and the twenty-six seasonal variables.[6]

3. The residuals were estimated for the regression performed in step 1 and checked for serial correlation.[7]

4. An F-statistic was calculated to test the explanatory power of current and past MDC. It is from this statistic that the causal conclusion is drawn.

The above procedure was used to check for causal implications from MDC to OTS. To complete the analysis between the two time series another set of regressions was estimated to test for causality from OTS to MDC. These regressions were of the same form as shown above, only the MDC and OTS series are reversed.

A point worth noting, is that the contemporaneous term is included in the regression equation and tested for significance with the past values. In a number of actual applications of the Sargent (1976) procedure, the contemporaneous term was excluded. In this study the contemporaneous term was included in the equations to allow for an indication

[6]The seasonal variables were not included when the dependent variable was one of the interest rate series.

[7]Bartlett's test statistic and Fisher's Kappa statistic were used as rough checks for serial correlation.

of instantaneous or contemporaneous causality. The t-statistic indicating the significance of the contemporaneous term is included in Table 4.4. In four of the fifteen pair-wise comparisons there is an indication of a significant contemporaneous relationship. As was indicated in Chapter II, the occurrence of a significant contemporaneous relationship limits the causal conclusion that can be inferred from the data.

The test statistics associated with each of the fifteen pair-wise comparisons are summarized in Table 4.4. The causal implications that can be derived from these statistics are summarized in Table 4.5. The causal conclusions that are shown in Table 4.5 are based upon a significance level of .05.

Serial correlation

As was discussed in Chapter III, the presence of serial correlation in the residuals is an important consideration. Due to the nature of this test procedure, the presence of serial correlation was not expected. The inclusion of lagged dependent variables as independent variables is likely to eliminate any significant serial correlation. In order to test for serial correlation, the residuals were estimated for each of the unrestricted equations. These residuals were then tested to see if they

Table 4.4. Summary of causality test statistics for Sargent's test

Time series[a]	F-statistic for significance of current and past values	Degrees-of-freedom	Bartlett's test statistic[b]	Fisher's Kappa statistic[b]	t-statistic for the contemporaneous term
OTS → MDC	2.12**	14,423	.060	7.99	.963
MDC → OTS	2.98**	14,429	.035	6.60	-.922
UBR → MDC	1.74*	14,429	.077	9.35*	.853
MDC → UBR	8.31**	14,429	.032	5.16	2.00*
UBR → OTS	1.77*	14,429	.029	6.85	-.316
OTS → UBR	1.57	14,429	.037	8.60*	-.430
UMB → MDC	3.34**	14,423	.058	9.18*	3.84**
MDC → UMB	10.19**	14,423	.027	5.59	4.96**
UMB → OTS	2.02*	14,429	.037	6.14	-.076
OTS → UMB	2.37**	14,423	.025	6.89	-.363
UMB → UBR	48.32**	14,429	.040	5.64	23.5**
UBR → UMB	49.72**	14,429	.049	7.96	23.9**
RFF → MDC	1.33	14,423	.074	7.13	.658
MDC → RFF	2.05*	14,455	.021	3.87	-.844
RFF → OTS	1.42	14,429	.030	6.59	-1.18
OTS → RFF	1.54	14,455	.015	4.58	-1.21

[a] → indicates causal relationship tested is from the left variable to the right variable.

[b] Test statistic is based upon 250 periodogram ordinates.

* Significant at the .05 level.

** Significant at the .01 level.

Table 4.4 (Continued)

Time series[a]	F-statistic for significance of current and past values	Degrees-of-freedom	Bartlett's test statistic[b]	Fisher's Kappa statistic[b]	t-statistic for the contemporaneous term
RFF → UBR	1.23	14,429	.038	7.50	.707
UBR → RFF	1.00	14,455	.017	4.88	.371
RFF → UMB	2.16 **	14,423	.040	7.12	.072
UMB → RFF	1.13	14,455	.015	5.23	.969
RTB → MDC	1.55	14,423	.075	7.58	.359
MDC → RTB	.97	14,455	.021	4.65	1.38
RTB → OTS	4.64**	14,429	.037	7.76	-.306
OTS → RTB	1.17	14,455	.014	4.17	-.290
RTB → UBR	1.40	14,429	.040	6.54	1.10
UBR → RTB	1.20	14,455	.013	4.30	.547
RTB → UMB	2.01*	14,423	.036	6.51	.268
UMB → RTB	1.09	14,455	.018	4.20	.580
RTB → RFF	2.28**	14,455	.014	4.83	3.03**
RFF → RTB	4.73**	14,455	.028	4.85	2.78**

Table 4.5. Summary of the causal relationships implied by Sargent's test

Series	Series[a]				
	MDC	OTS	UBR	UMB	RFF
OTS	↔				
UBR	C[b]	→			
UMB	C	↔	C		
RFF	←	—	—	→	
RTB	—	→	—	→	C

[a]Notes: — indicates independent series,
→ indicates left-margin variable causes top variable,
← indicates top variable causes left-margin variable,
↔ indicates bidirectional causation between left margin variable and top variable.

[b]C indicates a significant contemporaneous relationship implying no causal conclusion.

formed a white noise series. The test-statistics corresponding to each of the pair-wise comparisons are listed in Table 4.4. As can be seen from Table 4.4, there are only three instances where the test statistics indicate the presence of serial correlation.[8] Initially, serial correlation was indicated in the estimated residuals of several of the regression equations when the dependent variable was either the MDC, UBR, or UMB series. In order

[8]The critical values for Bartlett's test statistic were derived using the relationship developed by Birnbaum (1952).

to investigate the cause of the serial correlation, the periodograms of the estimated residuals for equations with MDC or UMB as the dependent variable were observed. Three significant peaks were found. For example, a large peak was found at a frequency of 2.769 radians. The period associated with this frequency is 2.3 weeks. This indicates that a seasonal factor of approximately two weeks still remains in the MDC and UMB series. In order to remove the remaining serial correlation, the appropriate regressions were re-estimated with three additional sets of seasonal variables included as independent variables. After this correction, only three of the Fisher test statistics indicated any significant serial correlation. Therefore, no further correction was deemed necessary or pursued.

Lead-lag length

Another consideration which was discussed in Chapter III was the lead-lag length to be used. In the application of Sargent's (1976) test it is necessary to choose the lag length for past values of the dependent variable and past values of the independent variable to be included in the regression equation. It is desirable to make the length generous enough to capture any potential causal effects. However, there are a number of potential problems to a large lag length. An increased number of lags results in an additional loss of observations, increased potential of colinearity among the independent variables, and increased computational expense. All of these factors were considered in the choice of the lag length. The test statistics presented in Table 4.4 are based upon a lag length of twenty-six time periods for past values of the dependent variable and a length of thirteen time periods for past values of the independent variable. A number of the pairwise comparisons were also run using a different lag structure. This set of causality tests were run with a lag length of thirteen time periods for past values of the dependent variable and thirteen time periods for past values of the independent variable. The test statistics for the different lag lengths are compared in Table 4.6. This comparison was not done to provide unrefutable evidence with respect to the robustness of the causal conclusions. Rather, they are offered as an indication of the potential sensitivity of the causal implications to the lag length chosen.

The causal implications of Sargent's procedure using different lag lengths are summarized for comparison in Table 4.7. These conclusions are based upon a significance level of .05. As can be seen from this comparison, there are three discrepancies in the causal conclusions. The implied relationships between RTB and MDC, RFF and OTS, and

RFF and MDC all change. This occurrence indicates that the causal conclusions may be sensitive to the lag length actually used in the empirical application. Given the relative magnitudes of the test statistics shown in Table 4.6 are the same, this issue was not explored further in this research. However, this is a source of potential problem and will be explored in future research to strengthen this study.

Table 4.6. Comparison of F-statistics for different lag lengths of the dependent variable[a]

Time series[b]	26-weeks	13-weeks
RFF → MDC	1.54	1.84*
MDC → RFF	2.05*	3.04**
RFF → OTS	1.42	1.72*
OTS → RFF	1.54	1.71
RFF → UBR	1.23	1.20
UBR → RFF	1.00	1.21
RFF → UMB	2.02*	2.06*
UMB → RFF	1.13	1.22
RTB → MDC	2.03*	1.57
MDC → RTB	.97	.99
RTB → OTS	4.64**	3.90**
OTS → RTB	1.17	1.16
RTB → UBR	1.40	1.36
UBR → RTB	1.20	1.12
RTB → UMB	1.99*	1.78*
UMB → RTB	1.09	1.09

[a]→ indicates the causal relationship being tested is from the left variable to the right variable.

[b]This comparison was done without the additional seasonal variables suggested by the tests for serial correlation.

*Significant at the .05 level.

**Significant at the .01 level.

Table 4.7. Comparison of causal implications using different lag lengths of the dependent variable

Series	Series[a] MDC	OTS	UBR	UMB
<u>26-week</u>:				
RFF	←	—	—	→
RTB	→	→	—	→
<u>13-week</u>:				
RFF	↔	→	—	→
RTB	—	→	—	→

[a]— indicates independent series,
→ indicates left margin variable causes top variable,
← indicates top variable causes left margin variable,
↔ indicates bidirectional causation between left margin variable and top variable.

Application of Sims' Test

Using the OTS and MDC time series for illustrative purposes, the actual procedure used included the following steps:

1. OTS is regressed on future, current, and past MDC, a constant term, a trend and the twenty-six seasonal variables.

2. The residuals are estimated for the regression performed in step 1. And the autocorrelation function is estimated from these residuals.

3. Using the autoregressive parameters estimated in step 2, a filter is estimated and the independent and dependent variables used in step 1 are filtered.

4. Using the filtered data the regression performed in step 1 is repeated.

5. Using the filtered data, OTS* is regressed on current and past MDC*, a constant, a trend and the twenty-six seasonal variables.[9]

6. The residuals are estimated for the regression performed in step 4 and checked for serial correlation.

7. The F-statistic for the significance of future MDC was calculated. This statistic is the basis for the causal conclusion to be drawn from this test.

The above procedure was used to check for causal implications from OTS to MDC. To complete the analysis between the two time series, another set of regressions was estimated to test for causality from MDC to OTS. The procedure used is the same as was just listed, only the MDC and OTS series are reversed.

The test statistics associated with each of the fifteen pairwise comparisons are summarized in Table 4.8. Included with these statistics are the t-statistics with which the significance of the contemporaneous term can be tested. The causal implications that can be drawn from these statistics are summarized in Table 4.9. All of these conclusions are based upon a significance level of .05.

[9] The asterisk on MDC and OTS indicated that they are filtered series. The constant, trend and seasonal variables are also filtered series.

Table 4.8. Summary of causality test statistics for Sims' test

Time series[a]	F-statistic for significance of future values	Degrees-of-freedom	Bartlett's test statistic[b]
OTS → MDC	2.42**	13,412	.029
MDC → OTS	2.09*	13,410	.035
UBR → MDC	1.16	13,415	.072
MDC → UBR	10.46**	13,410	.033
UBR → OTS	1.16	13,415	.050
OTS → UBR	1.47	13,410	.045
UMB → MDC	2.69**	13,410	.039
MDC → UMB	4.80**	13,410	.034
UMB → OTS	1.45	13,410	.033
OTS → UMB	2.19**	13,410	.029
UMB → UBR	2.87**	13,410	.046
UBR → UMB	2.98**	13,415	.062
RFF → MDC	.53	13,440	.084
MDC → RFF	3.04**	13,410	.040
RFF → OTS	1.27	13,440	.034
OTS → RFF	.68	13,410	.036
RFF → UBR	1.03	13,440	.064
UBR → RFF	1.06	13,410	.035
RFF → UMB	1.90*	13,440	.057
UMB → RFF	.98	13,410	.030
RTB → MDC	1.14	13,440	.047
MDC → RTB	1.56	13,410	.038

[a]→ indicates the causal relationship being tested is from the left variable to the right variable.

[b]Test statistic is based on 243 periodogram ordinates.

*Significant at the .05 level.

**Significant at the .01 level.

Fisher's Kappa statistic[b]	Frequency of the largest cycle	t-statistic for the contemporaneous term
10.13**	2.907	1.35
9.37*	2.386	-.377
7.07	-	.142
8.68*	.834	.756
8.51*	-	-1.17
11.55**	2.907	-.658
7.74	-	1.38
8.74*	.834	4.22**
4.97	-	-.418
10.95**	2.907	-.737
6.97	-	21.81**
7.15	-	18.78**
11.78**	.026	-2.00
8.52*	.834	-1.93
8.12	-	-.333
12.44**	2.907	-1.66
10.35**	.026	.601
9.05*	2.412	.930
9.99**	.026	-.643
6.28	-	.820
4.94	-	1.09
9.33*	.834	.474

Table 4.8 (Continued)

Time series[a]	F-statistic for significance of future values	Degrees-of freedom	Bartlett's test statistic[b]
RTB → OTS	3.98**	13,440	.035
OTS → RTB	1.06	13,410	.039
RTB → UBR	1.10	13,440	.037
UBR → RTB	1.37	13,408	.027
RTB → UMB	1.54	13,440	.045
UMB → RTB	1.32	13,410	.031
RTB → RFF	1.37	13,440	.039
RFF → RTB	4.71**	13,440	.026

Fisher's Kappa statistic[b]	Frequency of the largest cycle	t-statistic for the contemporaneous term
4.68	-	.482
10.79**	2.907	-.282
4.97	-	.321
8.47*	2.881	.610
4.91	-	-.136
7.42	-	1.11
4.44	-	2.28*
5.26	-	1.40

Table 4.9. Summary of the causal relationship implied by Sims' test

Time series	Series[a]				
	MDC	OTS	UBR	UMB	RFF
OTS	↔				
UBR	←	—			
UMB	C[b]	←	C		
RFF	←	—	—	→	
RTB	—	→	—	—	C

[a]— indicates independent series,
→ indicates left margin variable causes top variable,
← indicates top variable causes left margin variable,
↔ indicates bidirectional causation between left margin variable and top variable.

[b]C indicates a significant contemporaneous relationship implying no causal conclusion.

Serial correlation

As was noted in Chapter III, the assumption of an uncorrelated error structure must be approximately correct in order to insure a reasonable degree of accuracy in the F-tests used in the causality tests. In the application of Sargent's (1976) test, no significant serial correlation was expected and the empirical results generally supported this expectation. Serial correlation is an expected problem with the application of Sims' (1972) procedure. This change in expectations is based upon two reasons. The first reason is that Sims' procedure does not involve using lagged dependent variables as explanatory variables. The inclusion of these variables in Sargent's test essentially eliminates any significant serial correlation problem. The second reason is that all of the previous applications of Sims' test to actual empirical data have had to deal with the problem of serial correlation. Given the high probability of occurrence in the application of Sims' test, the presence of serial correlation was assumed from the outset.

Three methods of dealing with serial correlation were outlined in Chapter III. The method employed in this study, was that of estimating the residuals from the initial regression equation. Then, using these residuals, a filter was estimated. This filter was then used to transform the time series and the causality test was then performed with the transformed series.[10] Basically, two test statistics were used to check the effectiveness of the filter. These statistics were Fisher's (1929) Kappa statistic and Bartlett's (1966) statistic. If the filter was found to be ineffective,

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[10]The term filtering is used to refer to the following process. Suppose it has been determined that the appropriate filter is 1-.5 L, where L is the lag operator. Using MDC series for illustrative purposes, the filtered MDC series which should be used in the causality test is MDC*, where

$$MDC^* = MDC_t - .5\ MDC_{t-1}$$

All of the filters used in this study were linear. The autoregressive parameter estimates were obtained by solving the Yule-Walker equations. For an explanation of Yule-Walker equations, see Fuller (1976, p. 53).

then the original filter was modified. The new filter was used to transform the original data and the causality test was re-run. And, the test statistics for serial correlation were re-estimated. This procedure was repeated until an appropriate filter was found or until it was determined that the additional computational expense involved in testing a new filter outweighed the possibility of finding a more effective filter. The final filter used in each of the regressions is listed in Table 4.10. The check statistics associated with each of the regressions are listed in Table 4.8.

The modification of the different filters failed to remove all of the serial correlation. The coefficients of the estimated filters summed to one, indicating that first differences should be employed. Also, the periodograms of the estimated residuals of several of the regression equations were observed in order to further investigate this problem. Peaks were found at three specific frequencies. These peaks occurred at frequencies of .026, 1.44, and 2.89 radians. The peaks at 1.44 and 2.89 radians could be removed by adding additional seasonal variables, similar to those already being used in this study.

These additional corrections were used in the appropriate regressions. Also, the necessary filters were re-estimated. Although the Bartlett statistics indicate no further serial

Table 4.10. Empirically estimated filters used for serial correlation correction

Regression equation	Estimated filter
OTS on MDC	$1 - .08L - .26L^2 + .04L^3 - .10L^4 - .02L^5 - .03L^6 - .04L^7 - .06L^8 - .09L^9 + .05L^{10}$
MDC on OTS	$1 + .39L + .14L^2 + .12L^3 + .12L^4 - .03L^5 + .15L^6 + .15L^7 + .10L^8 + .12L^9 + .06L^{10}$
UBR on MDC	$1 - .66L - .12L^2 - .18L^4 - .13L^9 + 13L^{10}$
MDC on UBR	$1 + .30L + .14L^2 + .18L^3 + .03L^4 - .03L^5 + .16L^6 + .15L^7 + .08L^8 - .01L^9 + .02L^{10}$
UBR on OTS	$1 - .53L - .28L^2 - .14L^4 - .10L^9 + .11L^{10}$
OTS on UBR	$1 - .09L - .31L^2$
UMB on MDC	$1 + .33L + .23L^2 + .21L^3 + .04L^4 - .03L^5 - .01L^6 + .12L^7 + .02L^8 - .09L^9 + .01L^{10}$
MDC on UMB	$1 + .39L + .24L^2 + .30L^3 + .07L^4 - .04L^5 + .14L^6 + .15L^7 + .05L^8 - .01L^9 + .05L^{10}$
UMB on OTS	$1 + .41L + .25L^2 + .13L^3 + .02L^4 - .03L^5 + .08L^6 + .13L^7 + .02L^8 - .03L^9 - .03L^{10}$
OTS on UMB	$1 - .05L - .26L^2 + .04L^3 - .08L^4 - .11L^5 - .003L^6 - .02L^7 - .15L^8 - .07L^9 + .08L^{10}$
UMB on UBR	$1 + .16L + .27L^2 + .13L^3 - .10L^4 - .13L^5 + .08L^6 + .02L^7 + .11L^8 + .01L^9 + .08L^{10}$
UBR on UMB	$1 - .79L - .32L^4 + .15L^6$
RFF on MDC	$1 + .10L + .007L^2$
MDC on RFF	$1 + .47L + .34L^2 + .16L^3 + .09L^4 + .02L^5 + .16L^6 + .18L^7 + .17L^8 + .12L^9 + .005L^{10}$

Table 4.10 (Continued)

Regression equation	Estimated filter
RFF on OTS	$1 + .20L + .05L^2 - .02L^3 - .20L^4 - .02L^5 - .04L^6$
OTS on RFF	$1 + .01L - .15L^2 - .05L^3 - .07L^4 - .01L^5 - .10L^6 - .09L^7 - .02L^8 - .03L^9 + .01L^{10}$
RFF on UBR	$1 + .14L + .006L^2$
UBR on RFF	$1 + .42L + .21L^2 + .07L^3 - .03L^4 - .03L^5 + .03L^6 + .12L^7 + .08L^8 - .05L^9 - .06L^{10}$
RFF on UMB	$1 + .15L + .019L^2$
UMB on RFF	$1 + .48L + .35L^2 + .12L^3 + .01L^4 + .03L^5 + .09L^6 + .12L^7 + .10L^8 + .02L^9 - - .03L^{10}$
RTB on MDC	$1 - .13L + .09L^2$
MDC on RTB	$1 + .46L + .37L^2 + .18L^3 + .12L^4 + .005L^5 + .18L^6 + .19L^7 + .14L^8 + .06L^9 - .01L^{10}$
RTB on OTS	$1 - .26L + .12L^2$
OTS on RTB	$1 + .07L - .11L^2 - .01L^3 - .08L^4 - .04L^5 - .08L^6 - .08L^7 - .07L^8 - .07L^9 + .01L^{10}$
RTB on UBR	$1 - .29L + .09L^2$
UBR on RTB	$1 + .40L + .17L^2 + .12L^3 - .08L^4 - .02L^5 + .02L^6 + .08L^7 + .14L^8 - .11L^9 - .07L^{10}$
RTB on UMB	$1 - .28L + .06L^2$
UMB on RTB	$1 + .50L + .35L^2 + .14L^3 - .02L^4 - .05L^5 + .01L^6 + .08L^7 + .08L^8 - .0005L^9 - .04L^{10}$

Table 4.10 (Continued)

Regression equation	Estimated filter
RTB on RFF	$1 - .21L + .15L^2 + .009L^3 + .02L^4 - .03L^5 + .20L^6$
RFF on TRB	$1 + .25L + .12L^2 + .03L^3 - .19L^4 + .02L^5 - .03L^6 + .04L^7 + .12L^8 - .06L^9$

correlation, the Fisher test statistics still indicate some significant cycles. For example, the RFF series still shows a significant peak at a frequency of .026 radians. This suggests that some unexplained long term movement still exists in the RFF series. Also, the MDC series shows a peak at a frequency of .834 radians. The seasonal variables used in this analysis will not adequately remove a seasonal component with a frequency of .026 or .834 radians. Therefore, a more sophisticated set of seasonal variables should be developed and used in the analysis. Due to the significant computational expense involved, no further correction for serial correlation was performed. To strengthen this study, this topic will be pursued in future research.

Lead-lag length

The lead-lag length used in the causality test is another consideration which has been mentioned in this study. When using Sims' (1972) test, it is necessary to choose the number of future and past lags of the independent variable to be included as explanatory variables. Ideally, the lengths should be long enough to capture any potential causal effect. A number of tradeoffs exist with respect to a large number of lags. An increased number of lags results in an additional loss of observations, increased potential of colinearity among the explanatory variables, and additional computational expense. In the application of Sims' test thirteen future lags and twenty-six past lags were used. This allows for a causal effect of at most, thirteen weeks. When Sargent's (1976) test was applied to these time series, different lag lengths were used to test the sensitivity of the results. The Sims' procedure was not performed with different lag lengths. Therefore, no conclusion can be drawn about the sensitivity of the causal implications based upon Sims' test to the chosen lag length.

CHAPTER V. ANALYSES OF EMPIRICAL RESULTS

Comparison of Causal Conclusions

In Chapter II it was noted that basically three different types of causality tests exist, i.e., Sims' (1972) test, Sargent's (1976) test, and Haugh's (1976) cross-correlation procedure. This study involved applying Sargent's test and Sims' test to six economic time series. The causal conclusions derived from this study are summarized for comparison in Table 5.1.

Pierce (1977a) applied the cross-correlation procedure to these six series and several others. His results are summarized along with the results of Sims' procedure in Table 5.2. Also, the results of the Pierce study are summarized with those of the Sargent's procedure in Table 5.3. The causal conclusions presented in Table 5.1 for the Sims' and Sargent's procedures, differ somewhat from those shown in Tables 5.2 and 5.3. Due to the nature of the tests a certain amount of personal judgement is involved in the presentation of the results. The results of this study have been modified in Table 5.2 and Table 5.3 to make them more consistent with Pierce's method of presentation. More specifically, the change is in reference to the occurrence of instantaneous causality. The only time Pierce indicates there was a contemporaneous relationship is when

Table 5.1. Summary of regression results

Series	Series[a]				
	MDC	OTS	UBR	UMB	RFF
<u>Sims' Test</u>					
OTS	↔				
UBR	←	—			
UMB	C[b]	←	C		
RFF	←	—	—	→	
RTB	—	→	—	—	C
<u>Sargent's Test</u>					
OTS	↔				
UBR	C	→			
UMB	C	↔	C		
RFF	←	—	—	→	
RTB	—	→	—	→	C

[a]— indicates independent series,
→ indicates left margin variable causes top variable,
← indicates top variable causes left margin variable,
↔ indicates bidirectional causation between left margin variable and top margin variable.

[b]C indicates a significant contemporaneous relationship implying no causal conclusion.

Table 5.2. Summary of Sims' test and the cross-correlation procedure results

Series	Series[a]				
	MDC	OTS	UBR	UMB	RFF
<u>Sims' Test</u>					
OTS	↔				
UBR	←	—			
UMB	↔	←	↔		
RFF	←	—	—	→	
RTB	—	→	—	—	←
<u>Cross-correlation Procedure</u>[b]					
OTS	↔				
UBR	→	↔			
UMB	→	←	C[c]		
RFF	←	—	→	←	
RTB	—	—	→	→	↔

[a]— indicates independent series,
→ indicates left margin variable causes top variable,
← indicates top variable causes left margin variable,
↔ indicates bidirectional causation between left margin variable and top variable.

[b]Cross-correlation results are those of Pierce (1977a).

[c]Indicates a significant contemporaneous relationship implying no causal conclusion.

Table 5.3. Summary of Sargent's test and the cross-correlation procedure results

Series	Series[a]				
	MDC	OTS	UBR	UMB	RFF
Sargent's Test					
OTS	↔				
UBR	↔	→			
UMB	↔	↔	↔		
RFF	←	—	—	→	
RTB	—	→	—	→	↔
Cross-correlation Procedure[b]					
OTS	↔				
UBR	→	↔			
UMB	→	←	C[c]		
RFF	←	—	→	←	
RTB	—	—	→	→	↔

[a]— indicates independent series,
→ indicates left margin variable causes top variable,
← indicates top variable causes left margin variable,
↔ indicates bidirectional causation between left margin variable and top variable.

[b]Cross-correlation results are those of Pierce (1977a).

[c]Indicates a significant contemporaneous relationship implying no causal conclusion.

this was the only significant relationship found. In the initial presentation of the results of this study, i.e. Table 5.1, the occurrence of a significant contemporaneous relationship is only indicated, even though the results may also support other causal relationships.[1] By comparison, in presenting the results in Tables 5.2 and 5.3, the only time a contemporaneous relationship is indicated is when it is the only significant relationship. It should be noted that this situation never occurred. This modification allows for a better comparison of the results of the different tests.

The results shown in Table 5.1 indicate that the Sargent and Sims tests have generated mixed results in terms of agreement. Different conclusions are reached for four of the fifteen pairwise comparisons. The tests do not agree on the causal relationship between the following pairs:

1. UBR and MDC
2. UBR and OTS
3. RTB and UMB
4. UMB and OTS

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[1]In Chapter II it was noted that when contemporaneous causality is present no definitive causal conclusion can be made. Apparently, Pierce (1977a) has ignored this limitation in the presentation of his results.

The F-statistics for these comparisons are summarized in Table 5.4. The observation that four of the conclusions differ is based upon a significance level of .05. If the significance level is increased to .01, then four discrepancies exist. The differences occur for the following pairs:

1. OTS and MDC
2. RFF and UMB
3. RTB and RFF
4. RFF and MDC

So, in general, it appears that the Sims' and Sargent's tests have produced somewhat different results.

By observing Tables 5.2 and 5.3, it is obvious that there is little agreement between the regression procedures and the cross-correlation procedure, i.e., Pierce's work. In fact, the results are remarkably dissimilar. Only five out of fifteen conclusions are the same when comparing Sims' test results and Pierce's results. Also, only six out of fifteen conclusions are the same when comparing Sargent's test results and Pierce's results. If a .01 significance level is imposed on the regression procedures, the dissimilarity between the regression procedures and the cross-correlation procedure increases.

Table 5.4. F-statistics for pair's showing different causal conclusions

Time series	Sargent's Test	Sims' Test
UMB → OTS	2.02*	1.45
OTS → UMB	2.37**	2.19**
UBR → MDC	1.74*	1.16
MDC → UBR	8.31**	10.46**
UBR → OTS	1.77*	1.16
OTS → UBR	1.57	1.47
RTB → UMB	2.01*	1.54
UMB → RTB	1.09	1.32

*Indicates significance at the .05 level.

**Indicates significance at the .01 level.

Explanation of Different Conclusions

In the following section, a number of explanations are offered to explain the difference between the cross-correlation and regression procedure results. The potential explanations are grouped into two broad categories; Data Sample and Operational Considerations.

Data sample

The most obvious reason for the great difference in the results Pierce (1977a) found, and those indicated by this study, is the difference in the data sample. His data set consisted of weekly observations from September 18, 1968 to April 10, 1974. By comparison, the data set used in this study consisted of weekly observations from September 18, 1968 to September 20, 1978. Thus, this analysis involved an additional four years of observations. Any number of events could have occurred that would effect the causal relationships among the time series. For example, control strategies imposed by central authorities have obviously affected these time series.[2] And, it is highly probable that these strategies have changed over time, thus changing the relationship amongst the time series. Another possibility is that the data series themselves have been modified or transformed. Keeping in mind that the causal inferences are based solely on the data series, a modification of the series could generate a change in the causal conclusions. So, the difference in the time span of the data sets could and probably is one important explanation for the significantly different results.

The proposition that the different time period of the

[2]This topic will be discussed in detail later in the chapter.

data sets affects the results is testable. This could be done two different ways. The first possibility is to apply the regression procedures to the data corresponding to the time period of Pierce's study. As was noted earlier, the possibility does exist that the time series have been adjusted or modified since Pierce used the data. So, if this option were pursued, the exact data set used by Pierce should be investigated with the regression procedures. The other option would be to apply the cross-correlation procedure to the data sample used in this study. This would allow for a comparison of the causal inferences between the two different data samples. Neither one of these options was pursued due to the significant amount of time and expense involved in the computations.

Operational considerations

Several other factors may explain the difference in causal results. A number of these explanations are noted as potential problem areas with this type of causality testing by Zellner (1980).

One of the conclusions of Zellner's (1980, p. 65) paper is that, "mechanical filtering of series can exert a substantial influence on causality tests." Basically, two types of filtering are done in a causality test. The first type of filtering is for nonstationarity. As was discussed in much detail in Chapter III, the Granger (1969) definition of causality assumes stationary series. And, since most economic time series are nonstationary it is necessary to filter the series in an attempt to form a stationary series. The other type of filtering is done to correct for serial correlation or autocorrelation. In the case of a cross-correlation analysis, autocorrelation in the individual series should be removed. And, in the case of a regression analysis, autocorrelation in the disturbances should be removed. There is a difference in the filtering process between this study and Pierce's (1977a) study.

In this study, Granger's definition was not adhered to in the strictest sense. The concept of predictability was used as a basis for causality. However, the series were not directly filtered in an attempt to produce stationary series. Rather, the factors creating the non-stationarity were treated indirectly. This was done by including seasonal and trend variables as independent variables in the regression equations. The alternative is to regress each series on the seasonal and trend variables and calculate the estimated residuals. The estimated residual series would then be used in the causality tests. Pierce used this alternative. For example, consider the time series MDC. In his analysis, he used the stationary series MDC*, where

$$MDC^* = (MDC_t - MDC_{t-1}) - \alpha_t \qquad (5.0)$$

and α_t was a linear combination of seasonal variables similar to those used in this study. So, Pierce attacks the need for stationarity directly with a mechanical filtering process and in this study the need is handled indirectly. In theory, this difference should not affect the results. However, the exact same filtering process was not used by both studies and this may have added to the discrepancy between the results.

The other type of filtering is done to eliminate serial correlation. Pierce accounts for serial correlation by fitting each transformed series with an ARMA model. Since this study used the regression procedures, filtering was done to correct for serial correlation in the residuals. No filtering was done in the application of the Sargent (1976) procedure because of the infrequent occurrence of serial correlation due to the nature of the procedure. Serial correlation was encountered in the application of the Sims' (1972) procedure. To correct for this, a filter was estimated from the residuals and applied to the series.

The effect of the different filtering procedures for serial correlation is difficult to assess. In theory, filtering for serial correlation should not affect the causality tests. However, there is a significant difference between theory and actual practice in this case. Filtering for serial correlation may explain a significant amount of the difference between the Sims' test results and Pierce's results. Specifically, the filters developed in the application of Sims' procedure appear to be only moderately effective in removing serial correlation. For proof of this refer to Table 4.8. Pierce (1977a, p. 16), claims that "checks . . . failed to reveal further serial correlation in the residual series." Therefore, the failure of the filters in this study and the success of Pierce's filters may explain the difference between the Sims' regression procedure results and Pierce's cross-correlation results.

A general conclusion with respect to the influence of filtering for serial correlation can not be reached. On one hand, it seems to be a plausible explanation for the differences among Sims' test results and Pierce's results. Only partial success of the filters in the Sims' procedure may also explain the differences among the two regression procedures. However, it does not seem to be a logical explanation with respect to the Sargent test results versus the Pierce results. Therefore, the filtering done to eliminate serial correlation may have influenced specific causal conclusions, particularly in the Sims' test. But, it is doubtful that the effectiveness or ineffectiveness of this type of filtering would significantly explain the dissimilarities in the test results.

Another source of explanation is that of the length of time allowed for the causal effect to take place. For Sims' regression procedure, the number of future lags included as independent variables determines the length allowed for a causal effect to occur. For Sargent's procedure, the number of past lags of the independent variable determines the allowed length of the causal effect. And, for the cross-correlation procedure, consider the test statistic used to

$$S = N \sum_{h=1}^{J} r^2_{\hat{u}\hat{v}}(h) \qquad (5.1)$$

test the significance of the cross-correlations. This statistic is an alternate expression of the statistic 2.22 developed in detail in Chapter II. In this case, the value J determines the maximum length allowed for the causal effect to occur. For example if J = 10, then the causal relationship has a maximum of ten time periods in which to occur. The choice of this length could obviously influence the causality tests.

A length of thirteen weeks was allowed for the causal effects to occur in this analysis using the regression procedures. This means that thirteen future lags were used in the Sims procedure and thirteen past lags for the Sargent procedure. Pierce's analysis involves a number of different lengths. He indicates that he tried lengths of up to two years and found no significant relationship for a lag of more than thirty weeks. The results presented in Tables 5.2 and 5.3 are based upon a length of ten to thirty weeks. So, there is some difference between the length used in this analysis and the length used by Pierce. This difference may explain the dissimilar test results. This contention is further supported by the evidence found to suggest that the Sargent's procedure results were sensitive to the lag length associated with the lagged dependent variable.

An additional point should be noted with respect to the choice of the lag length in the regression procedures. The theoretical development of Sims' and Sargent's procedures involves an infinite distributed lag.[3] For the actual empirical implementation of the procedure it is necessary to approximate the infinite distributed lag by a finite distributed lag. This finite approximation involves the choice of the number of future lags for Sims' procedure and past lags for Sargent's procedure. Zellner argues that the process of using a finite approximation can generate inconclusive results unless a detailed analysis of the

[3]To see this, refer to Equation 2.5 and Equation 2.17 in Chapter II.

estimated lag distribution is made.[4] So, even if the choice of the length allowed for the causal effect were totally consistent for all three procedures, it is possible that the regression procedures have been affected by using a finite approximation to an infinite lag.

Technical Issues

A number of issues exist, which may or may not influence the results of the causality testing procedures. Two issues seem particularly relevant to this study. These two issues are in reference to monetary policy.

The issue of monetary policy is of particular significance given the nature of the time series being investigated in this study. Pierce (1977a, p. 18) makes two observations which provide some useful insight. First, he states, ". . . any deterministic series" caused "only by it's own past . . . can be perfectly predicted from its own past so there is no room for improvement by using any other variable. Thus, if the money supply grows exactly 5 percent over the sample period, it will show up as unrelated to anything else despite what its actual relationship . . . might be." As an illustration, suppose the monetary authorities peg the federal funds rate and allows it to fluctuate only within a narrow range. Then, the federal funds rate series will show

[4] For a more detailed discussion of this point see Zellner (1980).

very little stochastic variation. The causality tests employed in this study will have trouble discerning any causal relationship involving this series. So, the presence of a monetary policy can effect the causal analysis. In addition to the existence of a monetary policy influencing the results, any change in such a policy could also create problems. For example, suppose the monetary authorities were controlling the federal funds rate and switched to a policy of controlling the money supply during the sample period of the data set. This type of occurrence could influence the causality tests.

The second insight offered by Pierce (1977a, p. 20) is in reference to closed-loop control. As an illustration of this concept, consider the dynamic regression

$$Y_t = V(L)X_t + u_t \tag{5.2}$$

where V(L) is the lag distribution to be estimated.

> In the context of the dynamic regression model 5.2, suppose X has been adjusted to keep Y on a desired path according to the control strategy $X_t = C(L)Y_t$. Then it can be shown that not only is the lag distribution V(L) unidentifiable but that identical residuals and model forecasts can result from[5]
>
> i. a model with V(L) chosen so that the disturbances [U_t's] will be white noise;

[5]For further explanation, see Box and McGregor (1974).

ii. a "model" with V(L) = 0 so that Y is formally related only to its own past;

iii. an infinite number of intermediate models.

> Perhaps this is not surprising; if X is determined from present and past Y then, knowing Y, knowing X in addition tells us nothing new.

Certainly, this type of control has been attempted with the money and interest rate series. Given this type of control has been imposed on some of the series under investigation, it seems plausible to assume the causality tests have been influenced.

To determine the exact influence of monetary policy, either from the creation of an essentially deterministic series or from the closed-loop control situation, would involve a detailed analysis of monetary policies. It is beyond the scope of this study to investigate the possible effects of monetary policy on the causality tests. Even if a detailed study were made, it is doubtful if the results would be of much help. This doubt is based upon the apparent short run imprecision of monetary policy, the inability to determine the exact nature of monetary policy, and the changing nature of monetary policy in a long run framework.

Economic Interpretation

An important part of any econometric study is its contribution to economic knowledge. In terms of this study, the contribution is that of elucidating the causal relationships among the six economic time series studied. The following discussion is an analysis of the results of the causality tests in an economic sense. The basis for this analysis are the results of the regression procedures, using a significance level of .01. These results are summarized for easy reference in Table 5.5. The fact that the causality tests have generated dissimilar results should be kept in mind. Thus, the causal tests do not necessarily provide rigorous proof of the causal relationships suggested in the remainder of this chapter.

The first observation involves the UMB (Unborrowed Monetary Base) and the UBR (Unborrowed Reserves) series. By definition, unborrowed reserves are a major component of the unborrowed monetary base. This means that the two series should essentially move together. Or, in terms of a causality test a contemporaneous relationship should be indicated. Both causality tests in fact show a contemporaneous relationship between UBR and UMB.

The results of the causality tests are inconsistent with the money multiplier model,

Table 5.5. Causal conclusions of the regression procedures[a]

Series	Series[b]				
	MDC	OTS	UBR	UMB	RFF
<u>Sargent's Test</u>					
OTS	↔				
UBR	←	—			
UMB	C[c]	←	C		
RFF	—	—	—	→	
RTB	—	→	—	—	C
<u>Sims' Test</u>					
OTS	→				
UBR	←	—			
UMB	C	←	C		
RFF	←	—	—	—	
RTB	—	→	—	—	←

[a]Results are based upon a significance level of .01.

[b]— indicates independent series,
→ indicates left margin variable causes top variable,
← indicates top variable causes left margin variable,
↔ indicates bidirectional causation between left margin variable and top variable.

[c]C indicates a significant contemporaneous relationship implying no causal conclusions.

$$M = mB \tag{5.3}$$

where

M = some measure of the money supply

B = monetary base

m = money multiplier.

To see this, consider the relationship between MDC (Demand Deposit Component), UMB, and UBR. UBR and UMB are significant components of B. And MDC is a significant component of any of the money stock measures. The above model implies that UBR and UMB should cause or should be exogenous with respect to MDC. However, both of the regression procedures indicate unidirectional causality from MDC to UBR and a contemporaneous relationship between MDC and UMB. These results are consistent with those of a Feige and McGee (1977) causality study involving money supply control and lagged reserve accounting. They found unidirectional causality from M_1 to total reserves using both the cross-correlation procedure and Sims' (1972) procedure. So, my results are consistent with their study, implying the money multiplier model is invalid. As stated by Feige and McGee (1977, p. 547), they support "the view of a monetary authority whose commitment to ease fluctuations in interest rates leads largely to a policy of accommodating reserves to innovations in credit demand."

The tests indicate that there is unidirectional causation from OTS (Other Time Deposits) to UMB. By comparison, independence is indicated between OTS and UBR. This seems to indicate that the other major component of the monetary base, currency in circulation, has a unidirectional causal relationship with OTS. No apparent economic rationale exists to explain this type of relationship. It should be noted that Pierce (1977a) also found a seemingly inconsistent relationship between these three series.

The test results support two conflicting causal relationships between the money supply and interest rates. The first possibility is unidirectional causality from the money supply to interest rates. The Sims' procedure supports this hypothesis. Unidirectional causality is indicated from MDC to RFF (Federal Funds Rate). All of the other test results suggest independence between the money supply and interest rates. The Sargent's (1976) test results indicated independence between MDC and the two interest rate series. Also, both test procedures show no causality from UMB and UBR to the interest rate series.

The relationship shown between the interest rate series and the time deposit series follows traditional economic analysis. It is generally argued that changes in interest rates generate changes in the level of time and savings deposits at commercial banks. With respect to the two interest rate series used in this study, it would be expected that the 3-month Treasury bill rate would exert more influence than the federal funds rate. The Sims' procedure results indicate unidirectional causality from RTB to OTS. Also, the Sargent's procedure results indicate unidirectional causality from RTB to OTS and independence between RFF and OTS. So, the results support the hypothesis of causality from interest rates to time deposits.

The only remaining relationship tested was between the two interest rate series. The federal funds rate is associated with an instrument with a maturity of one day. The Treasury bill rate used was the 3-month rate. Due to the differences in maturity of the instruments, it could be argued that the federal funds rate acts as a leading series with respect to the RTB series. In other words, RFF causes RTB. The Sims' procedure results support this hypothesis by indicating unidirectional causality from RFF to RTB. Sargent's procedure indicates a contemporaneous relationship exists between the two interest rates. This finding does not call for a rejection of the hypothesis. So, the regression results support the hypothesis of causality from RFF to RTB.

The regression procedure results of this study are generally consistent with the following three causal hypotheses:

1. Unidirectional causality from the federal funds rate to the 3-month Treasury bill rate.

2. Unidirectional causality from the interest rate series to time deposits at commercial banks.

3. Unidirectional causality from the money supply to reserves. This causal pattern is inconsistent with the money multiplier model.

The regression procedures did not produce totally consistent results. Therefore, everyone of the pairwise tests does not necessarily agree with these hypotheses.

The results of Pierce's cross-correlation study are inconsistent with all three of these hypotheses. His results indicate a bidirectional causal relationship between RFF and RTB. With respect to time deposits and interest rates his analysis shows independence. The cross-correlation analysis supports the money multiplier model. He found unidirectional causality from UBR and UMB to the demand deposit component of the money supply. So, the cross-correlation results are different from the regression results in a significant number individual pairwise cases and also in a general analysis of economic relationships.

CHAPTER VI. SUMMARY, SUGGESTIONS FOR FUTURE RESEARCH, AND CONCLUSIONS

This chapter contains a summary of the findings reported in this study; some suggestions for future research; and the conclusions of the study. The summary of findings concentrates on the general causal patterns found amongst the six time series, a comparison of the causality tests, and explanations of the dissimilar findings between the regression and cross-correlation procedures.

Summary

One of the causal patterns found was that of unidirectional causality from interest rates to time deposits at commercial banks. The Sims' (1972) regression procedure supported this conclusion by indicating unidirectional causality from the 3-month Treasury bill rate to time deposits. Sargent's (1976) procedure generated similar results. Both procedures also indicated independence between the federal funds rate and time deposits. These results and those discussed in the following paragraphs are based upon statistical tests using a .01 level of significance.

The second causal pattern indicated was that of unidirectional causality from the federal funds rate to the

3-month Treasury bill rate. Or, in other words, the RFF leads RTB. It was argued that this was consistent with economic theory due to the difference in maturity dates of the two instruments. This conslusion was reached based upon the indication of a contemporaneous relationship by Sargent's procedure and unidirectional causality by Sims' procedure.

The third conclusion reached was in reference to the money multiplier model. The results are not compatible with this model. This conclusion is based upon the relationship shown between MDC, UBR, and UMB. Both procedures indicate unidirectional causality from MDC to UBR. They also show a contemporaneous relationship between UMB and MDC. These results imply that the money supply is exogenous with respect to reserves. Feige and McGee (1977) found similar results using both Sims' regression procedure and Haugh's (1976) cross-correlation procedure. So, causality was found running from money to reserves, not from reserves to money as is implied by the money multiplier model. This finding is consistent with the view that the monetary authority was committed to a policy of easing fluctuations in interest rates from 1968 to 1978.

A secondary result of this study was a comparison of the different types of causality tests: Sargent's regression procedure, Sims' regression procedure and Haugh's cross-correlation procedure. As was noted, there is very little similarity between the results of this study and those of Pierce (1977a). In fact, in a comparison of pairwise results, there is agreement in only five cases. This suggests that a distinct difference exists between the two regression procedures and the cross-correlation procedure. Also, the regression procedures did not produce totally consistent results, which suggests a difference between the regression techniques. It is doubtful that the difference is as dramatic as suggested by this study.

A number of explanations were offered to explain the dissimilar results. Basically, four general explanations were suggested. These included:

1. Differences in the data sample.
2. Differences in filtering.
3. Differences in the length allowed for the causal effect to occur.
4. Effects of monetary policy.

All of these explanations seem plausible. In theory, differences in filtering should not cause problems. However, test statistics indicated that the filtering used in this analysis was not totally effective in removing serial correlation. The presence of serial correlation may have caused the causality test procedures to generate different results.

The exact effect on the causality tests is difficult to assess.

Future Research

Some additional research would strengthen this study and the investigation of the relationship between the three types of causality tests. Specifically, three topics need to be explored.

Differences in the data sample used in this study and Pierce's (1977a) study should be considered. Two investigations would provide valuable insight. The first analysis would be to apply the regression procedures to the data set used by Pierce. The second analysis would be to apply the cross-correlation test to the data set used in this study. These analyses would show if the dissimilar results can be attributed to differences among the testing procedures or to changes in the data. They would also indicate if any changes in the causal relationships had occurred.

The second topic of concern is the length of the time period allowed to capture any causal relationship. In this analysis it was found that the Sargent (1976) procedure results were sensitive to the number of lagged dependent variables included as explanatory variables. Also, differences in the causal effect length was suggested as one of the causes of the discrepancy between this study and Pierce's. Based upon these reasons, it would be of value to perform the two regression procedures with a number of different lengths.

Serial correlation is the third topic which should be explored. The Sims' regression procedure should be performed with the corrections suggested in Chapter IV. These corrections should remove any remaining serial correlation. This analysis would eliminate any bias in the causal test results due to the presence of serial correlation. Thus, a more exact comparison could be made of the three different causality tests.

Conclusions

The major conclusions of this type of study are the causal relationships implied by the data. The three general causal patterns found were summarized in the beginning of this chapter. Using these patterns as a basis, it was suggested that from 1968 to 1978 the data are consistent with the hypothesis of the monetary authority pursuing a policy of easing interest rate fluctuations.

In a number of investigations, this type of causality testing has produced inconsistent and inconclusive results. Given the differences between the regression results in this study and the dissimilarity with Pierce's analysis, this investigation falls into the inconsistent result pattern. This implies one of two conclusions. The first possibility is to conclude that the mechanical application of causality tests produces inconsistent and inconclusive results. Along these lines, Zellner (1980) argues that this is a type of "measurement without theory" and should be avoided. The second possibility is to conclude that the causality tests do produce consistent results. However, the tests are extremely sensitive to operational considerations, such as the time period of the data sample and the length allowed for the causal effect. Based upon the incompatibility of the two regression procedure results, the first conclusion seems more acceptable. This implies causality testing as an econometric tool should be used with careful consideration.

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APPENDIX: MNEMONICS AND SERIES DESCRIPTIONS

MDC

This series is the Demand Component of the Money Stock. It is primarily the sum of demand deposits at all commercial banks other than those due to domestic commercial banks and the United States Government, less cash items in the process of collection and Federal Reserve float. This series contains other less significant modifications.

OTS

This series consists of all time and savings deposits at commercial banks less all Certificates of Deposit issued by weekly reporting commercial banks in denominations of $100,000 or more.

UMB

The Unborrowed Monetary Base series is the monetary base minus member bank borrowings at the Federal Reserve discount window. The data on the monetary base have been adjusted for breaks due to changes in reserve requirements. The figures used are a weekly average.

UBR

The Unborrowed Reserve series is total reserves of member banks minus borrowings. Waivers are included in this series for the period from November 15, 1972 through June 30, 1974. During this period banks were allowed to waive penalties for reserve deficiencies associated with adjusts to Regulation J. Regulation J was amended effective November 9, 1972.

RFF

The Federal funds rate is the rate at which excess reserves on deposit with the Federal Reserve banks are traded by member banks. The figures used are a seven day weekly average.

RTB

The Treasury bill rate is the rate at which 90-day Treasury Bills are discounted in the open money market. The figures used are a weekly average.