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TESTING CAUSALITY IN ECONOMICS: A REVIEW

The concept of causality is central to any scientific inquiry. Although it is a popular and widely used concept in almost all branches of science, including economics, the literature on causality does not lack in controversy. In fact, even the meaning of the term 'causality' is under dispute (Zellner, 1979; Holland, 1986; Basmann, 1988). Causality as a concept has its origin in the writings of the ancient Greek philosophers. Aristotle, for example, discussed four 'causes' of a thing in his physics: (1) the material cause, (ii) the formal cause, (iii) the efficient cause, and (iv) the final cause. It is Aristotle's notion of the efficient cause that eventually became central to most discussions of causation in the philosophy of science literature. This is apparent in Locke's definition of causality: "That which produces any simple or complex idea, we denote by the general name 'cause', and that which is produced, 'effect'." Such a simple notion of causality became more complex over time as the philosophers continued their debate on the topic.

Hume emphasized that causation is a relation between experiences rather than one between facts. Since experiences with the same phenomenon can change over time, he argued that causality cannot be verified empirically. About one hundred years later J.S. Mill (1843) argued that causal effects are empirically verifiable, but only through careful experiments. He developed four general methods of scientific experimental inquiry necessary to establish a causal relationship.[1] Despite occasional intensive debates, however, the philosophers have not found a definition of causality that a majority can accept, nor did they produce operational definition that is useful to economists (Granger, 1980; Prioier, 1988).

Economic theory provides causal hypotheses (sometimes explicit, but often implicit) which can be confronted with data. But until recently no suitable method was available to test these hypotheses and most causality decisions required in empirical research were based on the researcher's own judgement (Heien, 1980; Thurman, 1985). The introduction of a testable definition of causality in economics by Granger (1969) inspired a large number of researchers in the 1970s and 1980s to test causal hypotheses in a wide variety of situations. However, the procedures developed for testing for the existence of causality in different instances, are highly controversial. Because of such controversies, causality testing with typical economic and business data remains at the frontier of econometric research. This is reflected in a recent special issue of the Journal of Econometrics (1988) which was devoted to the topic of 'causality' in an effort to promote progress in causality analysis in economics.

The objective of this paper is to provide an overview of the developments in causality testing in economics. The paper is

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1 These are (i) the method of Concommitant Variation; (ii) the method of Difference; (iii) the method of Residues, and (iv) the method of Agreement. See Holland (1986) for a brief discussion of these methods.

organized as follows: Section II provides an exposition of different causality tests. Section III concentrates on the empirical applications of causality testing in economics and in agricultural economics. Section IV is concerned with the limitations of causality testing and finally, Section V concludes the review.

SECTION II
CAUSALITY TESTING: AN OVERVIEW

The definition of causality introduced by Granger (1969) relies on regression analysis and is statistically testable. The notion of predictability is at the heart of Granger causality. The essential idea behind Granger's concept of causality is that if a variable X causes another variable Y, then Y can be better predicted from the past values of X and Y together than from the past values of Y alone, provided the model contains all other relevant information. Sims (1972) developed a slightly different causality test than Granger's and his work has popularized the concept. Geweke et al., (1983) introduced a modified Sims test, while Pierce (1977) introduced a completely different version of causality testing based on correlation analysis of residuals. In this section we present a simple exposition of each of these tests to show their essential characteristics and differences.

The Granger Test

Let {X, Y} represent a joint covariance stationary bivariate time series originating from a purely stochastic process. The test for causality in this bivariate situation, according to Granger, is based on the following equations:

$$Y_t = \alpha_0 + \sum_{j=1}^{J} \alpha_j Y_{t-j} + \delta TR + U_t \tag{1}$$

$$Y_t = \beta_0 + \sum_{j=1}^{J} \beta_j Y_{t-j} + \sum_{i=1}^{M} \gamma_i X_{t-i} + \delta TR + V_t \tag{2}$$

where U_t and V_t are independent, serially uncorrelated random errors with zero means and finite variances; TR is a linear trend variable and the α's, β's, γ's and δ's are parameters. According to Granger (1969) there are four possible causality events in a bivariate situation: (i) either X causes Y; or (ii) Y causes X; or (iii) X causes Y and Y causes X, so a feedback relationship exists between X and Y; or (iv) there is no causality between X and Y.[2] In the above example, if equation (2) is a better predictor of Y_t than equation (1), X is said to cause Y. So, the Granger test of causality involves testing the null hypothesis that $\gamma_1 = \gamma_2 = \ldots = \gamma_m = 0$. The null hypothesis is tested using an F-test calculated by estimating (1) and (2), where

$$F^{*}_{(M,T-P)} = \frac{(SSE_r - SSE_u)/M}{SSE_u/[T-P]}$$

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[2] No causality between X and Y does not necessarily mean that they are statistically independent. Statistical independence requires that the joint probability distribution for X and Y is equal to the product of their marginal probabilities.

where SSE_u and SSE_r are the residual sum of squares from the unrestricted (eq. (2)) and restricted (eq. (1)) regressions. M is the number of restrictions imposed, T is the total number of observations and P=M+J+2 is the number of parameters estimated in the unrestricted regression. The above procedure can be repeated reversing the roles of X and Y to test the hypothesis that Y does not cause X.

The Sims Test

One of the most widely used causality tests in empirical work is the one developed by Sims (1972). According to Sims, if causality runs only one way from current and past values of a list of exogenous variables, then in a regression of the endogenous variable on the past, present and future values of exogenous variables, the future values of the exogenous variables will have zero coefficients. Essentially, Sims developed an equivalence relationship. In a bivariate situation, the hypothesis of no causality from Y to X is equivalent to all of the coefficients on future X's being zero. That is in the following equation:

$$Y_t = \alpha_0 + \sum_{j=-LF}^{LP} \alpha_j X_{t-j} + \delta TR + e_t \qquad (3)$$

[H_0: Y does not cause X is equivalent to the constraint: $\alpha_j = 0$, for all j = -1, -2, ..., -LF] where LP is the length of lagged values and LF is the length of leading values. This significance or lack of significance of the future coefficients provides the basis for Sims' test of causality. In order to test for causality two regressions must be estimated. These regressions provide an F-statistic with which the statistical significance of the future values of a variable can be tested.

The Sims test, like Granger's, requires an uncorrelated error structure in (3) and Sims suggests pre-filtering to eliminate autocorrelated errors or using Generalized Least Squares estimates. In his classic paper Sims (1972) used a quasi-second-differencing of the natural logarithms of the data series to reduce serial correlation in the residuals. In particular, he transformed each data series X_t by $\ln X_t - 2k\ln X_{t-1} + k^2 \ln X_{t-2}$ with the value of k=0.75. Sims believed that this particular filter would flatten the spectral density in most economic time series. To perform Sims' test one also requires the a priori, specification of the lag length, both forward and backward, of the independent variables. Once the data series are properly filtered, the constrained (α_j = 0, for all j= -1, -2, ..., -LF) and unconstrained versions can be estimated using OLS. Then an F-test is calculated as:

$$F^{*}_{(LF,T-P)} = \frac{(SSE_p - SSE_u)/LF}{SSE_u/(T-LF-LP-3)}$$

to test the null hypothesis that Y does not cause X. F^* is an F-Test with LF and T-P (where P = LF+LP+3) degrees of freedom. The above procedure can be repeated reversing the roles of X and Y to test H_0: X does not cause Y. Provided the lag length under H_0 is not too short, F^* converges into a χ^2/LF distribution as the sample size increases (Amemiya, 1973).

The Modified Sims Test

The Modified Sims test is suggested by Geweke et al., (1983). This test is based on OLS estimation of:

$$Y_t = \alpha_0 + \sum_{j=-LF}^{LP} \alpha_j X_{t-j} + \sum_{k=1}^{P} \gamma_k Y_{t-k} + \delta TR + e_t \qquad (4)$$

As in the Sims test, the test that Y does not cause X is equivalent to testing the joint significance of the constraints $\alpha_j = 0$, for all j= -1, -2, ..., -LF. In this case the lagged dependent variables are included to correct for possible serial correlation in the regression. Hence, there is no need to use pre-filtering or a GLS procedure.

To operationalize this test equation (4) is estimated in constrained and unconstrained forms. The hypothesis of no causality is then examined using the following test statistic:

$$F_{(LF,T-P')} = \frac{(SSE_r - SSE_u)/LF}{SSE_u/[T-LF-LP-P-3]}$$

where P' = LF+LP+P+3, the number of parameters estimated from the unrestricted regression. This procedure can be repeated to test the hypothesis that X does not cause Y.

The Haugh-Pierce Test

This test originated from the inadequacy of the Granger-Sims regression technique to determine causal patterns between time series in the presence of autocorrelated disturbances. Consequently, highest priority is given in this test to the removal of serial correlation. If the system under investigation is linear and if all variables or influences are identified within that system, then correlation between two variables implies causation - this is the essential logic underlying the Haugh-Pierce test of causality. The distinguishing features of this test are as follows:

(i) it uses cross-correlation analysis rather than regression analysis on the filtered data to determine the direction of causality;

(ii) separate filters on X_t and Y_t are used to ensure that each series is completely pre-whitened; and

(iii) the filters used are not ad hoc but are empirically determined for each individual series.

Suppose the prechosen filters P(B) and L(B) correspond to the X_t and Y_t processes, so that,

$$U_t = P(B)X_t \ ,$$

and $$V_t = L(B)Y_t \ .$$

The error terms U_t and V_t are free of autocorrelation. The causality patterns between the two original series X_t and Y_t can now be assessed by cross-correlating U_t and V_t as:

$$\rho_{uv}(k) = \frac{E(U_{t-k} V_t)}{[E(U^2_t) \ E(V^2_t)]^{1/2}}$$

where k is the length of lag. Since both series are white noise, the cross-correlation procedure is symmetric (that is, $\rho_{UV}(k) = \rho_{VU}(k)$). Therefore, a single estimate will be sufficient to characterize causality in both directions. The following table gives some major causality patterns and the associated restrictions on the values of $\rho_{UV}(k)$.

Table 1: Causality Patterns and Conditions on Cross-Correlation

Relationship	Restrictions on $\rho_{UV}(k)$
1. X causes Y	$\rho_{UV}(k) \neq 0$ for some $k > 0$
2. Y causes X	$\rho_{UV}(k) \neq 0$ for some $k < 0$
3. Feedback exists between X and Y	$\rho_{UV}(k) \neq 0$ for some $k > 0$ and for some $k < 0$
4. No causality	$\rho_{UV}(k) = 0$ for all k .

Source: Adapted from Pierce (1977).

In practice, however, $\rho_{UV}(k)$s are unknown and are estimated as the residual cross-correlations:

$$\hat{r}_k = r_{\hat{U}\hat{V}}(k) = \frac{E[\hat{U}_{t-k}\ \hat{V}_t]}{[E(\hat{U}^2_t)\ E(\hat{V}^2_t)]^{1/2}}$$

Under the null hypothesis that X_t and Y_t are independent series, Haugh (1976) has shown that the r(k) are asymptotically normally and independently distributed with mean zero and standard deviation $(T)^{-1/2}$, where T is the total number of observations.

Once the residual cross correlations are estimated, each individual estimate is tested for its statistical significance by the following criterion:

$$\left| r_{\hat{U}\hat{V}}(k) \right| \geq 2(T)^{-1/2}$$

Only the significant cross correlations are used to determine the causality patterns. Slightly different versions of the U-test (which has an asymptotic χ^2 distribution) are used to test different causal hypotheses. For example, the null hypothesis that X_t and Y_t are not causally related will be rejected at a particular level of significance if:

$$U_1 = T. \sum_{k=-m}^{m}[r_{\hat{U}\hat{V}}(k)]^2 > \chi^2_{(2m+1)}$$

where $\chi^2_{(2m+1)}$ is the tabular value of the chi-square distribution with 2m+1 degrees of freedom.

Similarly to test, H_0: X does not cause Y we use:

$$U_2 = T. \sum_{k=1}^{m}[r_{\hat{U}\hat{V}}(k)]^2 > \chi^2_m$$

and to test H_0: Y does not cause X, we define:

$$U_3 = T. \sum_{k=-1}^{-m}[r_{\hat{U}\hat{V}}(k)]^2 > \chi^2_m$$

A number of shortcomings are associated with each of these tests. Despite their difficulties, however, each of these tests has been extensively used in a wide range of empirical studies. We turn to these studies in the next section, deferring a discussion of the shortcomings of each test until section IV.

SECTION III
APPLICATIONS OF CAUSALITY TESTING

Economic theory often does not provide any precise causal hypothesis which are easily refuted with empirical data. In cases, where it does provide causal hypothesis, there is often not just one, but a number of competing hypotheses. In the past, economic researchers did not have any operational tool to discriminate among these hypotheses and often they had to resort to intuition to resolve causal questions. In a situation like this it is natural to expect that when an operational tool (even if it is not perfect) becomes available it will receive wide application. This is exactly what has happened in causality testing in economics, since its introduction about two decades ago.

Although Granger (1969) originally introduced the concept of causality testing, much of its current popularity is due to Sims. In the empirical work formal causality testing made its first appearance in the paper by Sims (1972). Given the fact that an intensive debate was going on between monetarists and Keynisians in the early 1970s, Sims (1972) apparently wanted to add some empirical flavour to the debate. Although Sims' results gave limited support to the monetarists, the subsequent work on money-income causality by Barth and Bennett (1974), Goodhart and Gowland (1976), Mehra (1978), Feige and Pearce (1979), Hsiao (1979, 1981) and Layton (1985) with different data sets and/or in different locations indicate that the debate is far from being settled.

In the 1980s, causality testing received increasing attention from economists and agricultural economists. In the economics literature, examples other than the money-income relationship, include relationships between consumer and wholesale price changes (Silver and Wallace, 1980; Colclough and Lange, 1982; Jones, 1986), wages, unemployment and interest rates (Sargent, 1976), money and interest rates (Pierce, 1977), wages and prices (Mehra, 1977), wages, prices and money supply (Barth and Bennett, 1975), trade unions, wages and inflation (Maki, 1985); inflation and relative price changes (Ashley, 1981), advertising and aggregate consumption (Ashley et al., 1980), inflation and productivity (Cecan, 1989), money, stock prices and interest rates (Hashemzadeh and Taylor, 1988), federal expenditures and receipts (Anderson et al., 1986; Manage and Marlow, 1986; Ram, (1988a), state and local governments finances (Marlow and Manage, 1987; Ram, 1988a; Holtz-Eakin et al., 1989). A subset of these studies is summarized in Table 2, with their essential features and major findings.

Examples of causality testing in agricultural economics include examination of lead-lag relationships between wholesale and retail prices (Heien, 1980), wholesale, retail and shipping point prices (Ward, 1982), U.S. and Canadian wheat prices (Spriggs et al., 1982), feed costs and feeder and slaughter cattle prices (Spreen and Shonkwiler, 1981), two price quotes for eggs (Bessler and Schrader, 1980b), turkey parts and whole bird prices of turkey (Bessler and Schrader, 1980a), livestock prices, livestock slaughter and income (Bessler and Brandt, 1982), different grain prices (Grant et al., 1983), the chicken and the egg (Thurman and Fisher, 1988), and wheat acreage allotments and acreage supply response (Weaver, 1980). In addition, Blank (1985) applied causality tests to examine the price discovery process operating in the international tobacco market and Lee and Cramer (1985) used it to examine price leadership in the world wheat market. The essential characteristics of these studies along with their major findings are summarized in Table 3.

Tables 2 and 3 bring out some interesting features of causality testing in economics and agricultural economics. While Sims' test appears to be the most popular test in the economics literature, the Haugh-Pierce test appears to have received prominence in agricultural economics. Secondly, 20 out of 22 studies reported in Table 2 and 11 out of 12 studies in Table 3 have chosen lag-lengths arbitrarily. In general, arbitrary choices are seldom optimal. Thirdly, one of the basic assumptions in causality testing is that the random error terms should be serially uncorrelated. To ensure this, most of the studies reported in Tables 2 and 3 employ different types of prefiltering - ranging from simple first differencing to complex ARIMA procedures. However, only in a few cases were empirical tests used to see if prefiltering adequately removed serial correlation from the data set. Moreover, a few studies did not use any prefiltering at all, instead they used lagged dependent variables in the regression analysis. Finally, how robust and reliable are the reported results of causality tests? One way to examine this is to compare the results of similar studies conducted in different contexts using different data sets.[3] Although we cannot examine any of the

[3] A more appealing approach from economic modeling point of view is to evaluate post-sample performance of the causality model. In this approach the data series is divided into two parts; the first part is used to estimate the model and the second part is used to examine the post-sample performance (in terms of predictability) of the model. Although this approach has been known to the model

results in Table 3, because none of the exercises has been replicated, we can compare some of the results presented in Table 2. For example, in studying money-income relationships, Sims (1972) found unidirectional causality running from money supply to income with U.S. data, Goodhart and Gowland (1976) found exactly the opposite causal direction with U.K. data. Similarly, while Silver and Wallace (1980) found unidirectional causality running from wholesale prices to consumer prices, Colclough and Lange (1982) found bidirectional causality between the two series. Conflicting causality results have also been reported by Anderson et. al., (1986) and Manage and Marlow (1986) concerning federal finances in the U.S. Such conflicting causality conclusions raise questions about the robustness of causality testing in economics. Questions can also be raised about the sensitivity of causality results to changes in lag-lengths, as long as the chosen lag-lengths are arbitrary. These questions lead us to a critical evaluation of causality testing in economics, which is presented in the following section.

SECTION IV
EVALUATION

In the test of Granger causality, researchers need to develop forecast equations for Y_t with or without X_t. The forecast equations should be free from any specification bias and be optimal

builders for at least three decades, none in the causality literature, except Ashley et al., (1980) has used this approach.

in the sense that the resulting forecasts are as accurate and efficient as possible. When the forecasts are efficient the forecast errors will have zero mean and the smallest variance and are serially uncorrelated. It is against this background that the current status of causality testing in economics and agricultural economics can be evaluated. In particular, we will concentrate on the issues of prefiltering, detrending, lag-length selection, functional forms and model specification in causality testing.[4]

In general, prior to performing a causality test, both X_t and Y_t have to be transformed to create a white noise error term. This is necessary because the F-test - the most commonly used test statistic in causality analysis - is particularly sensitive to the presence of auto-correlation in the data set. Since most time series in economics and business tend to be nonstationary and serially correlated, adequate data filtering is essential to the validity of causality tests. Although no universal filter has been found, some researchers apparently believe that such a filter exists. Sims (1972), for instance, suggested an *ad hoc* prefilter $(1 - 0.75L)^2$, and claimed that this filter approximately flattens the spectral density function of most economic time series and hence regression residuals would be white noise with this prefiltering. Although some researchers have naively applied this

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[4] This list is by no means exhaustive. There are other issues like statistical mean independence or orthogonality and causality, appropriateness of deriving structural parameters from reduced form causal models, and prior restrictions and causality testing. For a good discussion on these issues see Conway et al., (1984).

particular filter to correct for autocorrelation there is no reason, a priori, to expect that such a filter will create uncorrelated error structures in all economic time series. In fact, Belongia and Dickey (1982) using monthly data of the U.S. money stock (M1), manufacturing wage rates (W), and the GNP deflator (DEF) for the period from January 1961 to December 1977, have shown that the Sims filter did not transform any of these series to white noise. In recent years, however, more researchers are using empirically determined prefilters based on knowledge of the parameters of autocorrelation. A few studies have also used ARIMA filtering. Empirical filters are certainly adequate in removing autocorrelation, but are they causality preserving? This question is especially relevant for Box-Jenkins ARIMA methods. Residuals resulting from different ARIMA models show quite different patterns of causal relationships (Schwart, 1979). This implies that if the proper ARIMA model is not chosen in a particular case, the prefiltering may not be causality preserving.

Some researchers such as Sargent (1976), Mehra (1977), Guilkey and Salami (1982) and Jones (1986) have also included trend variables in the regressions used to determine causality directions. The purpose is to induce stationarity to the time series. But is detrending causality preserving? Kang (1985) has shown that causality tests are sensitive to detrending, especially if it is accompanied by differencing. In such cases, one can derive quite different causality conclusions. If, however, ARIMA residuals are used in the test, detrending will not alter the qualitative results of causality testing.

As shown in section II, the two variables X_t and Y_t typically enter a regression equation with lagged terms, as in the case of the Granger test, or with lagged and leading terms for the Sims and the Modified Sims tests. The true lengths of these lagged and leading terms in a particular situation are unknown and have to be determined by the researcher. The literature on causality shows that most researchers have arbitrarily chosen the lengths of lagged and leading terms; with some choosing a fixed length while others have tried different lag lengths (see Tables 1 and 2). But what are the implications of these arbitrary choices for causality testing? Tests of causality hypotheses are critically dependent on unknown lag-length parameters and the arbitrary choice of lag-lengths can produce misleading results (Guilkey and Salami, 1982; Geweke, 1984; Thornton and Batten, 1985). Moreover, an arbitrary choice of lag-lengths ignores the important role that model specification should play in causality testing. To remove the arbitrariness in lag-length selection Hsiao (1979) has suggested the use of Akaike's (1970) final prediction error (FPE) criterion to determine the optimum lag lengths. This procedure has been used by Anderson et. al., (1980), Hsiao (1981), and Thornton and Batten (1985) among others. There are other statistical criteria, for example, the Bayesian estimation criterion suggested by Geweke and Meese (1981) which could also be used to select the optimal lag-lengths. However, as emphasized by Thornton and Batten (1985), models selected by different statistical criteria can yield contradictory causal conclusions. Hence the problem of appropriate lag length specification can not be circumvented easily by using statistical criteria. The choice of the proper statistical criterion is also important.

Most of the applications of causality testing in economics involve only two variables. For instance, Sims (1972), Goodhart and Gowland (1976), Hsiao (1979) and Layton (1985) among others, used only money supply and income variables to determine the causal patterns. But in reality money supply not only depends on income, but also on interest rates, levels of economic activity etc. When these variables are not included in the regression analysis, the model is misspecified. If examined closely, such specification bias also exists in most of the causality models used in agricultural economics. If a model is not properly specified the estimated parameters will be biased (since most business and economic data tend to be correlated). More importantly, however, specification errors render the causality test results uninterpretable, if not totally invalid (Jacobson et. al, 1979; Rowley and Jain, 1986; Lutkepohl, 1982).

Finally, in causality testing most researchers have used linear functional forms, either with levels or logs of the variables, while a few researchers have selected a functional form which renders the time series stationary. But are the results of causality tests sensitive to changes in the functional forms of the regressions? Using the generalized functional forms allowed by a Box-Cox transformation, with quarterly U.S. data of GNP, money-supply and wages for the 1949-75 period, Roberts and Nord (1985) have demonstrated that by varying the functional form of the test regressions it is possible in some cases to support unidirectional causality in either direction between two variables. This implies that arbitrary decisions concerning the functional form of the test regressions may render the tests unreliable in identifying causal relationships.

In the above discussion of the current status of causality testing, little was said about the Haugh-Pierce test.. This was not incidental. Although none of the causality tests currently in use are perfect, the Haugh-Pierce test suffers from more problems than the others. By construction, this test has an inherent bias in favour of the null hypothesis, except in the special case when the omitted variables are uncorrelated with the included variables (Sims, 1977). Moreover, once the innovations of X_t and Y_t are significantly correlated, there is no way for the data to shed light on the truth or falsehood of the causal assumption (Ling, 1982). So, the cross-correlation approach may not be appropriate in determining causal relationships. Since the Haugh-Pierce test is the most popular test in agricultural economics (see table 3), all of these causality results are suspect.

Conclusions

Although the concept of Granger causality is relatively new it has received considerable attention from economists and agricultural economists. Several other causality tests have also been developed and applied to a wide range of topics. However, the above evaluation has revealed that there are several problems associated with the current approaches to causality testing and that the conclusions of causality tests may not be reliable if the investigators do not appreciate and make allowance for these issues. Causality results are particularly sensitive to prefiltering, detrending, omitted variables, choice of lag-length or functional forms. These problems highlight the fact that despite its current popularity designing a causality test and interpretating the test results is not a trivial matter. Although the sensitivity of causality results to prefiltering, detrending etc. is discouraging, causality testing will remain a tool for model identification in economics, especially in situations where the theory is ambiguous. If so, in which direction should causality analysis move in the future? Based on the preceding discussion we offer the following suggestions. First, use ARIMA filters with or without detrending, instead of an ad hoc filter.[5] Second, use the Akaike FPE criterion to select the optimal lag lengths if bias is a major concern. If not, then there are alternatives like Hannan-Quinn's criterion (HQC) and the Schwarz Bayesian criterion [Schwarz (1980)] (SBC). Theoretically, AIC, HQC and SBC all have the desired asymptotic power for Granger Causality

[5] Successful construction of an appropriate ARIMA model often requires a large data set. If the available time series is not large enough the researcher should avoid ARIMA filters. Instead she should follow an iterative procedure similar to that used by Mehra (1977) to devise an appropriate filter.

detection (Odaki (1987)). In a particular situation individual researchers will have to make the decision based on the bias-efficiency trade-offs. Third, use economic theory to determine the important variables to be included in the causality model. If theory can not provide adequate guidance use principal component analysis to identify the relevant variables to be included in the model. Once the variables are identified use a stepwise procedure in the spirit of Hsiao (1982) to include those variables in the model. Finally, use the Box-Cox transformation to determine the appropriate functional form in a particular situation.

Using simulation techniques, Geweke et. al., (1983) and Guilkey and Salami (1982) have shown that the Granger test and the Modified Sims test perform better than the Sims test in finite samples. This finding should also be a point of departure for researchers in the future. Finally, time-series analysis and regression analysis can be combined to create a better analytical tool for causality testing. In fact, Kang (1989) has suggested such a hybrid model, called 'transfer function analysis', for testing causal hypotheses. Although Kang (1989) has shown that this new model is capable of giving better causality results by selecting optimal lag-lengths it remains to be seen how well the model performs with different functional forms.

Table 2: Causality Testing in Economics

Author(s)	Problem Investigated	Nature of Data Used	Nature of Filter Used	Lag Length Selection Criterion	Causality Test Used	Conclusions Drawn
Sims (1972)	Is money really exogenous in money-income relationship?	Seasonally adjusted data of monetary aggregates and current GNP for the U.S. economy over the period 1947-1969.	Quadratic: $(1-kL)^2 = (1-2kL + k^2L^2)$ with $k = 0.75$.	Ad hoc: 4 leads and 8 lags.	Sims Test	Unidirectional causality runs from the stock of money to GNP, hence money can be treated as exogenous.
Mehra (1978)	To examine causal patterns among money, income and interest rate in a multivariate situation.	Seasonally adjusted quarterly data of relevant variables for the U.S. economy from 1952 I to 1972 IV.	Quadratic: $X_t = X_t - 2kX_{t-1} + k^2X_{t-2}$, where the value of k was chosen empirically for each series to remove gross serial correlation in the residuals.	Ad hoc: 4 leads and 4 lags.	Sims Test	In the real money demand equation real income and real interest rates are exogenous, but these results do not hold if the variables are in nominal terms. In fact, in nominal form, no conclusive causal structure between money, income and interest rates emerged.
Goodhart and Gowland (1976)	To examine money-income causality nexus with U.K. data.	Quarterly data of GDP at current prices and money supply for U.K. for the period from 1958 I to 1971 III.	Empirically determined filter of the following form: $(1-B)(1-a_1B-a_2B^2)$ was used to each series.	Estimated the lag profile using OLS.	Sims Test	The direction of causality between money and income in U.K. is unclear. Weak unidirectional causality runs from nominal income to money and from money to prices.
Barth and Bennett (1974)	Causality relationships between stock of money, GNP and industrial production (IP) in Canada.	Seasonally adjusted quarterly data of Canadian GNP, IP and of the stock of money from 1957 I to 1972 II.	Quadratic: $X_t = \ln X_t - 1.5 \ln X_{t-1} + 0.5625 \ln X_{t-2}$.	Ad hoc: 8 past and 4 future lags.	Sims Test	No consistent unidirectional causality running from money to GNP or IP was found. In contrast, test results

						suggest that money supply is determined by IP.
Hsiao (1979)	Money-Income causality relationships using post-war U.S. money and income data.	The seasonally adjusted quarterly money stock and nominal GNP for the U.S. economy from 1947 I to 1977 III.	Empirically determined filter: $(1-L)(1-0.75L)^2$	Used Akaike's FPE criterion to decide the optimum lag length for each series. (2, 7 & 9) and also ad hoc: 4 future and 8 past lags.	Sims Test and Haugh-Pierce Test	While Sims test shows a significant unidirectional causality running from money to income (GNP) the other test shows no discernable pattern of causality relationships.
Layton (1985)	Examine the money-income causal relation with Australian data.	Quarterly data of nominal money supply (M1) and GDP for the period 1959 III to 1978 IV. The period 1976 I to 1978 IV was retained for post-sample validation.	The first differences of natural logs for each variable. Also used ARIMA models to make sure that the residual is white noise.	Ad hoc: 1 to 12 lags were tried.	Granger Test and Haugh-Pierce Test	The bivariate model out performed the ARIMA model. Empirical evidence suggests that there is a feedback relationship between Australian monetary and real income growth.
Silver and Wallace (1980)	Analyze the causality pattern between consumer and wholesale price changes.	Monthly data from January 1952 to April 1977 for the U.S. economy.	Empirically determined autoregressive filter: $F_1(L) = 1.0 - 0.147246L_1 - 0.090223L^2$.	Ad hoc: 12 past and 5 future lags.	Sims Test*	Unidirectional causality runs from wholesale prices to consumer prices.
Colclough and Lange (1982)	Examine the causality relationships between consumer and wholesale price changes.	Percentage changes in monthly urban composite CPI and the composite wholesale price index from January 1945 to December 1979. (seasonally unadjusted data)	Used the following auto-regressive error filter: $F(L) = 1.0 - 0.147246L - 0.090223\ L^2$	Ad hoc: 5 and 12 lags for Granger Test, 5 future and 12 past lags for Sims Test	Granger Test and Sims Test	Both tests suggest bidirectional causality between consumer prices and wholesale prices.

Jones (1986)	To determine the nature of causal relationship between U.S. consumer and wholesale prices.	Percentage changes in monthly consumer and producer prices for the period January 1947 to December 1983.	No prefiltering; time trend and lagged dependent variables are included in the equation.	Ad hoc: 5 and 12 positive lags.	Wald-Granger Test and Sims Test	Bidirectional causality is found to characterize the relationship between consumer and wholesale prices.
Sargent (1976)	Examines the empirical validity of the natural rate of unemployment hypothesis of classical macroeconomics with U.S. data.	Quarterly U.S. data of unemployment rate, money supply, Govt. surplus at constant 1958 dollars, CPI, wage-index in manufacturing (w) and Govt. purchases (current and constant dollar) for the period 1952 II to 1972 III.	Fourier transformation is applied to each series to seasonally adjust the data. Then the data were filtered using the following filter: $F = (1-.75L)^2$.	Ad hoc: 4 and 6 lags for Granger Test and 4 future, and 12 past lags for Sims Test	Granger Test and Sims Test	Test results suggest (i) causal relationship from money wages to unemployment and the long term interest rate; and (ii) that government monetary and fiscal policy variables do not cause unemployment. Essentially the results contradict the natural rate hypothesis.
Mehra (1977)	Examines the causal patterns between industry money wages and consumer prices in the U.S.	Quarterly data on the 18 industry money wages and the consumer price index in the U.S. for the period 1954 I to 1970 IV.	A quadratic filter of the form: $F = 1-2kL + k^2L^2$, where the value of k was determined empirically.	Ad hoc: (i) 4 lags for Granger Test (ii) Three alternative lag-lengths for Sims Test: (4 leads, 8 lags); (8 leads, 8 lags); and (4 leads, 4 lags).	Granger Test and Sims Test	Both tests show strong bidirectional causality between money wages and consumer prices at the aggregate level.
Maki (1985)	Examines the role of trade unions in the wage inflation relationships with Canadian data.	Quarterly wage data for 19 two digit SIC Canadian industries, and CPI from 1961 I to 1979 IV.	First differences.	Ad hoc: 4 and 8 lags.	Granger Test.	There is no causal relationship between money wages and consumer prices at the aggregate level. However, price changes are completely incorporated into wage changes within two years in the unionized sectors.

Barth and Bennett 1975)	Examines the causal relationships among four economic variables: the wholesale and consumer price indices, money supply and the hourly wages of production workers.	Seasonally adjusted quarterly data for money stock (M1), the wholesale and consumer price indices, and the hourly wages of production workers from 1947 I to 1970 IV for the U.S.	Quasi-second differences of natural logarithms of each series: $X(t) = \ln X(t) - 1.5 \ln X(t-1) + .5625 \ln X(t-2)$.	Ad hoc: 4 future and 8 past lags.	Sims Test	Unidirectional causality runs from money supply to wholesale and consumer prices. One way causal chain also runs from consumer prices to wages. So money "is not veil" after all.
Hashemzadeh and Taylor (1988)	Examines the causal relationships between money supply and stock price levels and between the level of interest rates and stock prices.	Weekly data for stock prices, money supply and interest rates for the period from 2nd January 1980 to 4th July, 1986, for the U.S.	Used AR(2) process with the first and second autoregressive parameters set equal to 1.5 and -0.5625 respectively.	Ad hoc: 8 lagged and 4 leading values, and 16 lagged and 8 leading values.	Sim's Test	A feedback system characterizes the causal relationship between money supply and stock prices, but no conclusive causality relationship is found between stock prices and interest rates.
Pierce (1977)	Examines the patterns of causal relationships among 12 monetary and other economic time series with the U.S. data.	Weekly data covering the period from September 18, 1968 to April 10 1974.	Used autoregressive moving-average (ARMA) procedure to prewhiten each series.	Arbitrary: 0, 10, 20 and 30.	Haugh-Pierce Test	No notable causality relationship was found among the selected variables in bivariate models. "The economy is a miserable experimental design", indeed!
Anderson, Wallace and Warner (1986)	Causality patterns between Federal spending and taxation in the U.S.	Annual data of federal spending, federal revenue, GNP and inflation rate for the period 1946-1983, for the U.S.	The first difference of the natural logarithms of all variables used.	Used Akaike's FPE criterion to select the optimum lag lengths.	The Modified Sims Test	Causality runs from expenditures to revenues (real), but not the other way around.
Manage and Marlow (1986)	The causal relationship between Federal expenditures and receipts.	Annual data on Federal budget outlays and budgetary receipts in the U.S. from 1929 - 1982. (excluding data for the period 1941-1946.)	First difference of each of the raw data series.	Ad hoc: four alternative lag-length specifications (2,2); (3,3); (4,4) and (5,5).	The Granger Test	Test results in most cases suggest bidirectional causality; in only a few cases unidirectional causality runs from Government receipts to spending. Not a single case

						is found where causality runs from expenditure to receipts.
Marlow and Manage (1987)	Causality patterns in state and local government finances.	Annual data of nominal state and local expenditures and nominal tax revenues over the period 1952 - 1982 in the U.S.	No prefiltering.	Ad hoc: four different lag length specifications: (2,2); (3,3); (4,4) and (5,5).	The Granger Test	Unidirectional causality runs from tax receipts to expenditures at the state level for all lag structures except the shortest (2,2). For the shortest lag length there is a feedback relationship between receipts and expenditures. At the local level, however, unidirectional causality runs from tax receipts to expenditures only for the shortest lag-length but no evidence is found for expenditures causing tax revenue at the local level.
Ram (1988a)	Causality patterns between government revenues and expenditures at the Federal, state and local levels (U.S.).	Annual data for the period 1929-1983. Quarterly data covering 1947I-1983 IV.	First difference of the logarithms of each series.	Ad hoc: 3, 4, 6, 8 and 12 lags.	The Modified Sims Test	Causality runs mainly from revenue to expenditures at the Federal level. But the causality direction is reversed at the state and local government sectors.
Ram (1988b)	Causality relationships between Government revenues and expenditures in a multicountry setting.	Annual data of Government expenditures and receipts for 22 countries for at least 25 years.	The first difference of the natural logarithm of each variable was used.	Ad hoc: Lag-lengths varying from 2 to 5.	The Modified Sims Test	No consistent pattern of causality exists between Government revenues and Government outlays across countries.

Reid (1985)	Examine the validity of the Ricardian Equivalence Hypothesis with U.S. data.	Annual data of GNP, the market value of privately held outstanding government debt, and stock of money for the 1919-1981 period.	Empirically determined purely autoregressive filters.	Ad hoc: 3 past and 3 future lags.	Sims Test (within-sample and post-sample)	Unidirectional causality appears to flow from nominal debt and nominal money to nominal GNP. Test results indicate the presence of feedback relationships when the variables are defined in real terms. In both cases, the debt neutrality proposition is contradicted.
CeCen(1989)	Examine causal relationships between inflation and productivity to test the empirical validity of one of the implications of X-efficiency theory.	Seasonally adjusted monthly data for U.S. industrial productivity, inflation and the producer price index (WPI) for the 1970-79 period.	First differencing and then Box and Jenkins ARIMA procedure.	Ad hoc: 20 past lags.	Haugh-Pierce Test	Bidirectional causality exists between productivity and inflation. This tends to support the X-efficiency theory at the macro level.

Table 3: Causality Testing in Agricultural Economics

Author(s)	Problem Investigated	Nature of Data Used	Nature of Filter Used	Lag Length Selection Criterion	Causality Test Used	Conclusions Drawn
Heien (1980)	To determine if changes in retail prices are caused by changes in prices at the wholesale level.	Monthly data from 1960-1 to 1976-12 for 23 food items in the U.S.	An ad hoc quadratic: $(1-kL)^2$ with k = 0.75.	Ad hoc: 4 future and 8 past lags.	The Sims Test	For 57 percent of the 23 commodities tested, unidirectional causality runs from wholesale to retail levels. The reverse is true for only 9%, while feedback relationships were found for 13% of the commodities.
Weaver (1980)	To determine if changes in wheat acreage allotments cause changes in wheat acreage planted.	Annual data for the period 1954-1964 for major wheat growing states in the U.S.	No pre-filtering of the data set.	Ad hoc: Only one lead and one lag.	The Sims Test	No generally discernable causal pattern was found and the results suggest that the inter-temporal relationship between acreage allotment and acreage planted varies widely across the states.
Ward (1982)	To determine the direction of price linkage between wholesale and retail levels and between wholesale and shipping points.	Monthly average retail, wholesale and shipping point prices of 8 perishable commodities for four major cities in the U.S.	Empirically determined filters were used.	Ad hoc: 4 leads and 8 lags.	The Sims Test	Wholesale prices are found to lead both retail and shipping point prices.

Bessler and Brandt (1982)	To study the bivariate relationships in the cattle market between cattle on feed, cattle slaughter and income against cattle price, and in the hog market between sow farrowings, hog slaughter and income against hog prices.	Quarterly price and quantity data for 1963-1979 from U.S. cattle and hog markets and quarterly data on consumer disposable income.	No prefilting of the data set.	Used a priori notions to select lag-lengths of 4, 6 and 9 quarters.	The Granger Test	Strong one-way causal relationships were found to run from sow-farrowing to hog prices, income to hog prices, income to hog slaughter, cattle price to cattle on feed and income to cattle prices.
Spreen and Shonkwiler (1981)	Determining the lead-lag relationships between feed costs and feeder and slaughter cattle prices.	Monthly data on cattle feed costs, feeder cattle prices and fed slaughter cattle prices from Jan. 1966 to Dec. 1979 for the U.S.	Ad hoc first differencing and empirically determined filters were used.	Ad hoc approach using prior notion of the cattle production process.	Granger Test, Sims Test and Haugh-Pierce Test	The results of all three test have consistently shown that feed costs lead both slaughter steer and feeder prices. The increased feed costs are found to cause an increase in steer and feeder prices in the first two months, depress them at four, and then an increase eight months later.
Bessler and Schrader (1980 a)	The lead-lag relationships between selected prices and whole bird prices of turkey in the U.S.	Daily price data on several turkey products and the turkey products price index for 1978.	Three-step Box-Jenkins ARIMA procedures to prefilter each series separately.	Ad hoc approach using prior beliefs.	Haugh-Pierce Test	No consistent lead-lag pattern from product prices to whole bird prices to or from whole bird to product prices was found.

Bessler and Shrader (1980 b)	The causal relationships between EMEC and UB price quotes for eggs in the U.S.	Twice weekly price quote data of UB and EMEC for 1977-78.	Empirical filters obtained by using Box and Jenkins procedure. Also used a common filter $L = 1-1.27B + .37B^2$.	Ad hoc approach 0, 9; 10,10 for Haugh-Pierce test, and (3,3) and (9,9) for Sims Test.	Haugh-Pierce Test and Sims Test	Causality running from EMEC price quotes in period t to UB spot market quotes in periods t + 1, t + 2 and t + 3 into the future.
Spriggs, Kaylen and Bessler (1982)	Examine the existence of price leadership between U.S. and Canadian wheat prices.	Daily U.S. and Canadian Wheat prices for 14% and 13.5% proteins wheat for sixteen crop years (1963/64 to 1978/79). (Spring Wheat).	Separate filters were selected for each individual series using Box-Jenkins ARIMA procedure.	Ad hoc approach: 0 to 3 lags.	Haugh-Pierce Test	U.S. wheat prices led Canadian wheat prices over the period 1974-75 to 1975-76. There exists no significant price relationships prior to 1972/73.
Grant et. al. (1983)	How different grain prices affect one another in the U.S.?	Weekly prices of corn, wheat and sorghum at Kansas City; oats, barley and rye at Minneapolis and rice at Houston. The period covered is January 1974 to December 1980.	After first differencing each price series was filtered by appropriate AR models obtained by using Akaike's Information Criterion (AIC).	Ad hoc approach: 20 for all grains and 30 for only rice.	Haugh-Pierce Test	The prices of all feed grains significantly influence each other instantaneously. Changes in rice price cause significant changes in wheat and sorghum prices but not the other way around.
Blank (1985)	Determination of operational market characteristics to assess the price discovery process operating in international markets. (A Case Study of Tobacco)	Annual prices of flue-cured tobacco in Australia and in the U.S. for 1960-1982.	No prefiltering.	Ad hoc approach; only one lag value was used.	Granger Test	Strong one-way causality runs from U.S. to Australian tobacco prices.

Lee and Cramer (1985)	Analyse wheat prices at various locations in the world to determine if there is price leadership on the exporting or importing sides of the world wheat market.	Ten monthly price series and four weekly price series.	Appropriate ARIMA processes are fitted to each of the 10 monthly series using the Box and Jenkins approach. First differencing is used to prewhiten each of the four weekly series.	Ad hoc approach: a zero lag for 10 monthly series and 4 weekly series.	Haugh-Pierce Test	U.S. is found as the price leader over the period 1972 to 1981. This evidence is homogeneous over all varieties of wheat. Over the same period, U.S. and Canada wheat prices display significant instantaneous causality with a lag of less than one month.
Thrueman and Fisher (1988)	Which came first, the chicken or the egg?	Annual U.S. time series of egg production and chicken population for 1930-1983.	No prefiltering.	Ad hoc approach: one to four lags.	Granger Test	Significant unidirectional causality runs from eggs to chickens.

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