Prefiltering and Causality Tests

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Abstract

If data series are not filtered properly prior to the construction of a test of causality, the resulting test statistics are invalid This article describes a general approach to data filtering based on the estimation of autoregressive-moving-average models and on specific tests for the identification of white noise processes For selected examples, traditional approaches to filtering do not perform as well as the general method proposed

Keywords

Causality tests, data filtering, econometric exogeneity

Statistical techniques developed for testing whether the behavior of one variable causes a subsequent change in the value of another variable have been widely used by economists in recent years The tests are often used to determine whether one variable can be treated as exogenous with respect to another The tests are also used as a form of pretest estimation in determining whether a regressor makes a significant contribution to the explanation of the variation in a dependent variable

Although causality tests have become more widely used in recent years, many practitioners disagree over the validity of the results of these techniques [1] This article reviews some empirical issues relevant to the use of causality tests and the necessary documentation of the procedures employed Because the type of test employed in much applied research depends crucially on proper filtering of the data prior to testing, we will focus on problems that are likely to occur if economic data are transformed by the filter suggested by Sims, but the results are not checked against some white noise test

We first outline the intuition supporting causality tests and discuss criticisms raised by Feige and Pearce regarding the testing procedures used in much of the applied literature (*4*) We then illustrate the potential problems associated with applying the Sims filter to economic data with examples using economic time series frequently employed in studies of inflation and price change We discuss an alternative approach to data filtering and diagnostic checks for white noise that uses an autoregressive moving-average (ARMA) transformation Finally, we make suggestions regarding the future use of causality tests

Causality Tests: An Overview

Granger (*6*) defines econometric causality as follows "Y_t is causing X_t if we are better able to predict X_t using all available information than if information apart from Y_t has been used " Or more simply, Y_t causes X_t in the econometric sense if and only if one can predict X_t better by using past values of Y_t and X_t rather than by basing the prediction on the past history of X_t alone Sources other than the original papers by Granger and Sims provide details on the mechanics of applying such a test (see (*2*)) The general idea is to estimate regressions with and without the additional information contained in Y From these regressions one can construct a joint F-test on the significance of the coefficients associated with future values of Y A significant F value would then suggest the presence of a causal relationship between X and Y To check for feedback—or whether causation also runs from Y to X—one can repeat the test by regressing Y on past and future values of X If neither joint F-test on the coefficients associated with future values of X or Y is significant, one can conclude that the two variables are unrelated

The importance of filtering the data prior to estimating the regression models and calculating the joint F-statistic is related to the spurious regression problem described by

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[1] The problem of detecting causal relations can be especially acute in bivariate models if the variables are likely to share a common relationship with a third variable, this problem is discussed at length in (*8*), (*9*), and several other papers (Note Italicized numbers in parentheses refer to items in the References at the end of this article) Schwert (*11*) has argued that Box-Jenkins models may not be causal-preserving so that the use of autoregressive-moving average (ARMA) model residuals in causality tests makes those tests subject to a potential errors-in-variables problem That is, "if the original variables are measured with random errors, causality tests based on the estimated innovations series could fail to detect relationships that would be detected using the untransformed data " A recent review of alternative testing procedures and their limitations is summarized in (*1*)

Granger and Newbold Data filtering is intended to remove the serial correlation present in most time series If filtered properly, each resulting time series used in a test of causality will be a white noise process so that any significant relationships represented by the joint F-test will be based on actual, systematic relationships between the two series instead of on a spurious relationship caused by the common serial correlation

Adequate data filtering is essential to the validity of causality tests because the failure to remove serial correlation from the data will bias the estimates of coefficient variances Because most time series share a similar pattern of serial correlation, the variances are likely to be biased downward This downward bias will result in artificially large t statistics associated with individual coefficients and in a correspondingly large joint F-statistic for any causality test Failure to filter the data adequately may leave some common serial correlation in the data that will bias the test statistics upward and possibly suggest a significant causal relationship where, in fact, none exists

Data Filtering

The problem of serial correlation might be turned into a benefit if a common pattern among time series makes it possible for one filter to transform successfully most economic series to the white noise processes required by the testing procedures Such a filter would standardize the mechanics of testing procedures and let researchers conduct their tests of interest after a routine data transformation Although no universal filter has been found, some applied researchers apparently believe that such a filter exists This belief creates a problem for those who apply and interpret the results of causality tests

Belief in a universal data filter is probably the result of a statement that Sims made in his original article [2] In a study which investigated the causal relationships between gross national product (GNP) and different measures of the money supply, Sims advocated filtering the data by the following transformation

$$Z = \ln X_t - 1\ 5 \ln X_{t-1} + 0\ 5625 \ln X_{t-2}$$

which is an expansion of $(1 - KL)^2$ where L is the lag operator and K = 0 75 He said this filter "approximately flattens the spectral density function of most economic time series, and the hope was that regression residuals would be very nearly white noise with this prefiltering" (*12*) As we shall see later, the spectrum of a white noise process will be flat and its plot can be used as one diagnostic check for the adequate filtering of data

The (unintended) result of Sims' statement has been for researchers to apply his filter to a wide variety of economic time series *without* subsequent checking for whether this transformation actually has created a new white noise process As the following examples will illustrate, many common economic time series are not transformed to white noise by Sims' filter This result is not wholly unexpected in view of the numerous and volatile shocks represented in the economic data since 1972 when his article was published But, unless the data are transformed to white noise processes, the results of a causality test are invalid

Sims' Filter Applied to Some Common Economic Series

Prior to the description of an alternative approach to data filtering, it may be helpful to illustrate the potential problems associated with not testing filtered data to determine whether the transformation has reduced a series to a white noise process For this purpose, the following variables have been chosen the narrowly defined money stock (Ml), average wage rates for the manufacturing sector (W), and the GNP deflator (DEF) [3] Each series is monthly from January 1961 through December 1977 Table 1 presents descriptive statistics for each series—prior to transformation and after transformation by the Sims filter

The spectra for these series are plotted in figures 1-3 The area under a spectral plot is the variance of the data series Because we have moved from the time domain to the frequency domain, the frequencies represented on the horizontal axis are measured from $-\Pi$ to Π radians, however, because the plot is symmetric about zero, only the area from 0 to Π is shown [4]

Visually, the spectrum identifies any spikes in the plot associated with particular frequencies between 0 and Π The presence of a spike in the spectral density at a particular frequency suggests that a relatively larger share of the series' variance is explained by that frequency If the series is a white noise process, the spectrum should not contain any spikes because no one frequency would contribute more than any other to the explanation of variance A visual check of the spectrum can be supported by the Kolmogorov-Smirnov and Fisher tests for white noise, these tests are described in several texts (see (*5*))

[2] A similar problem results if the data are expressed as first differences, a data transformation suggested by Box and Jenkins as a means of detrending a time series (*3*)

[3] The monthly GNP deflator series was provided by Data Resources, Inc

[4] The spectra for these series were estimated with triangular weights of the form 1-2-3-2 1 and 1 2 3-4-3-2-1, the results did not vary with the choice of weighting scheme Issues associated with the choice of lag window and the problem of leakage are discussed in most time-series texts

Table 1—Descnptive statistics for vanables[1]

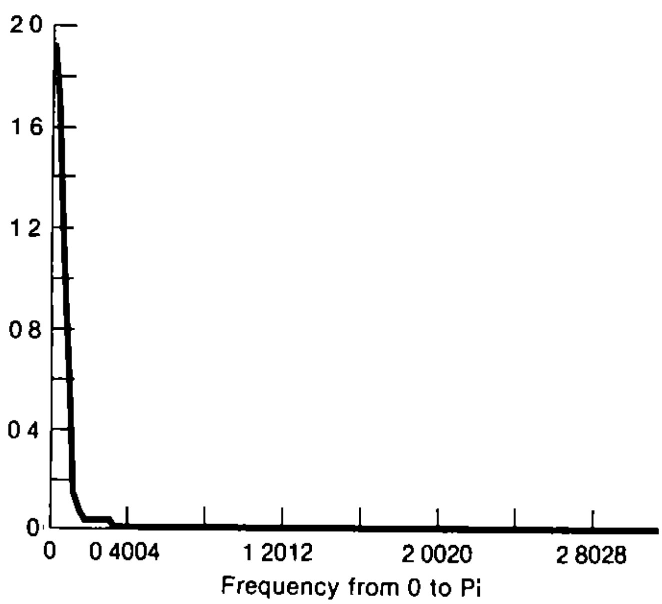
Vanable	Mean	Standard deviation	Minimum	Maximum
		In levels		
DEF	0 938	0 230	0 688	1 453
MI	216 918	57 168	144 000	348 200
W	3 472	1 022	2·280	5 880
e_t	000	001	- 004	003
		Transformed by Sims' filter		
DEF	- 005	015	- 025	026
MI	335	024	284	390
W	364	019	333	404

[1] Number of observations = 204

The Sims filter did not transform any of the three senes to white noise The spectral plots display a result common to most economic senes—that is, a large spike in the spectrum at low frequencies near the ongin A spectrum of this shape suggests that much of the vanance of the senes can be explained by a strong trend in the data However, the intention of the filtenng was to remove elements of trend so that the transformed senes would be a white noise process The plots in figures 1-3, which result from filtenng common aggregate senes by Sims' method, show clearly that this method is not appropnate for these data The conclusions suggested by the spectral plots are supported further by the white noise tests reported in table 2 For each senes, the test statistic rejects the null hypothesis that the chosen filtenng technique produced a white noise process Causality tests based on these data could yield invalid test statistics

Figure 1

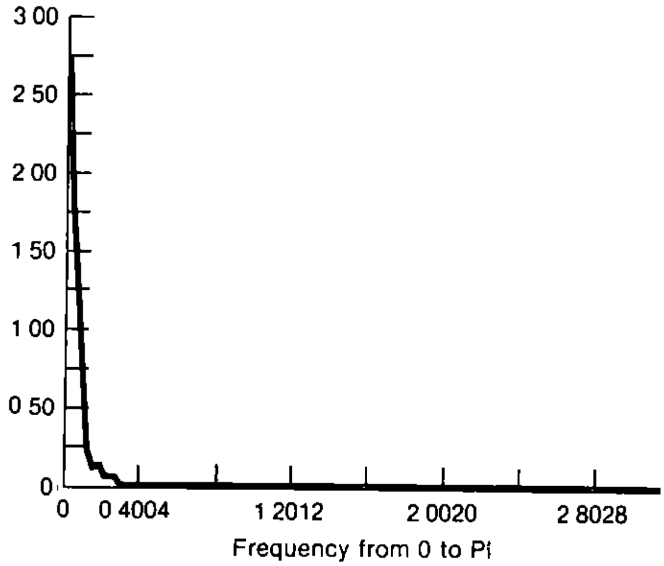
Spectral Density for GNP Deflator (DEF)



Vertical scale entries are multiplied by 10^3

Figure 2

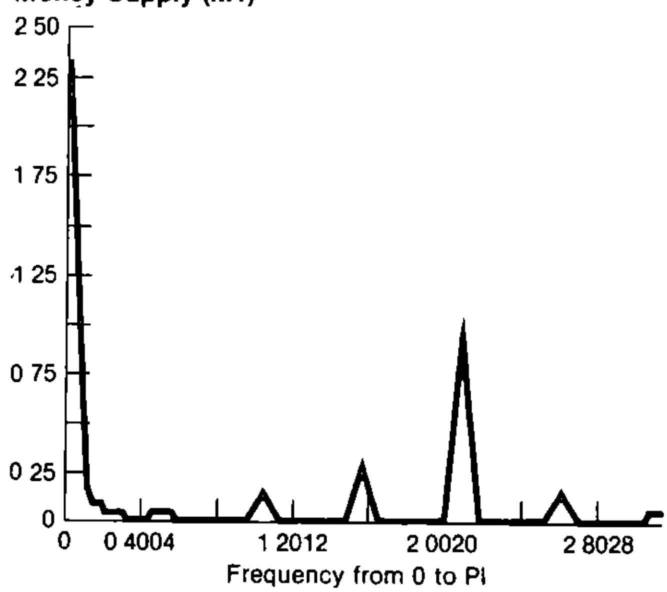
Spectral Density for Wage Rates (W)



Vertical scale entries are multiplied by 10^3

Figure 3

Spectral Density for Narrowly-Defined Money Supply (M1)



Vertical scale entries are multiplied by 10^3

Table 2—Estimated values for the Fisher Kappa statistic

Variable	Estimated Fisher Kappa[1]
DEF	64 31
W	59 89
MI	30 76
e_t	5 89

[1] All estimated values are to be compared with a critical value of 7 38 Critical values are provided by (*5*, p 284)

An Alternative Approach to Filtering

One may search for an appropriate filter by changing the value of K in Sims' transformation or by attempting similar *ad hoc* data manipulations We will now present an alternative approach to filter selection and use one of the previous series to illustrate its practical application Although this technique involves some preliminary data analysis, it can provide a reasonable guide to the identification of an appropriate data transformation

The suggested alternative to filtering uses the estimated coefficients of an ARMA model to transform each data series This approach requires identifying each series based on an analysis of its autocorrelation and partial autocorrelation functions, estimating the identified model, and finally, getting the model's estimated residuals If the fitted model is the appropriate time series representation of the data, its residuals will be white noise However, identification of the most appropriate time series representation of a variable is not always a simple task "It is important to realize the specification of an ARMA model is an art, rather than a science" (*10*)

The residuals from each model can be tested against a null hypothesis of white noise in the same manner already described Once a vector of white noise residuals is created for each series, the actual causality tests can be run by use of these residual vectors The causality test will regress one vector of residuals on past and future values of the other residual vector A joint F-test on the significance of the coefficients associated with the future values will then indicate if, after proper filtering, one series still contributes to the explanation of the variation in the other

To illustrate, the GNP deflator (DEF) will be identified and then estimated by an ARMA model with the residuals from the estimated model subsequently tested for white noise If we were to test for a causal relationship between DEF and another variable, the same steps would be followed, thereby creating a residual vector for that series We could then perform the actual causality tests by regressing the residual vectors on each other as described earlier However, our purpose here is only to illustrate an alternative approach to data filtering

The first step involves the identification of an ARMA model which will represent the process that generates values for the series Procedures described by Box and Jenkins and found in a variety of time series texts suggest that one can identify a model by analyzing the autocorrelation and partial correlation functions of the series The plots of these functions indicate how many autoregressive and moving average terms to include in the model For DEF, these plots suggest that a third-order autoregressive model will adequately represent the process which generates values for DEF[5] That is, we have identified a model of the form

$$DEF_t = \alpha + \beta_1 DEF_{t-1} + \beta_2 DEF_{t-2} + \beta_3 DEF_{t-3} + e_t$$

to represent the DEF series

With estimated values for the α and β_i terms, a residual vector can be created by simple manipulation

$$e_t = DEF_t - \alpha - \beta_1 DEF_{t-1} - \beta_2 DEF_{t-2} - \beta_3 DEF_{t-3}$$

This estimated residual vector is the filtered series which would be used in a causality test If the estimated ARMA model is the correct model for the DEF series, the e_t vector should be white noise

To test the residuals as a white noise process, one can employ plots of the series' spectral density and white noise tests A flat spectral density indicates a white noise series because no particular frequency between 0 and Π radians makes a relatively larger contribution to the series' variance than any other This visual check can be supported by a white noise test provided by Fisher (see (*5*))

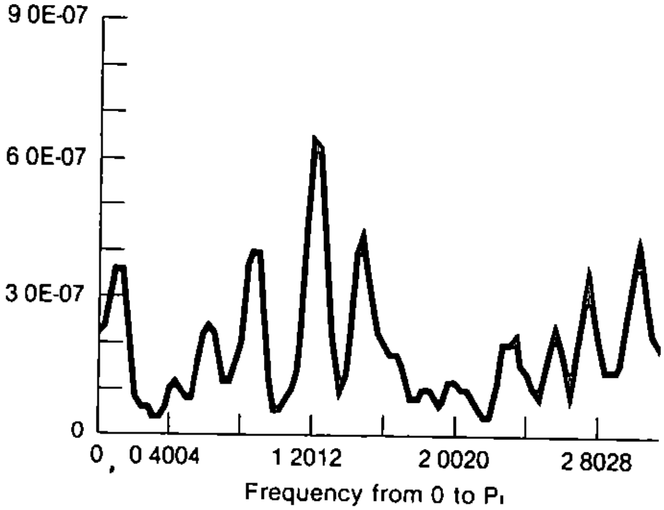
Figure 4 shows the spectral density for e_t Table 2 shows the Fisher Kappa statistics for all variables The plot reveals no particular pattern in the relationship between frequency and the height of the spectral density This flat spectrum would suggest that e_t is a white noise process This result is supported by a test statistic of 5 89, which is less than the critical value of 7 38 for 100 degrees of freedom[6] From these test results, one can conclude that the residual vector from the estimated ARMA model is a white noise series Thus, the e_t vector is an appropriately filtered representation of DEF that could be used in a causality test

[5] One should note that, although a third-order auto regressive model was found to be appropriate for the DEF series, this same model may not appropriately represent other series In fact, the DEF series could most likely be represented and transformed to white noise by something other than an AR(3) model, a possibility discussed in most time series texts However, the point remains that filtering data by using the coefficients of an ARMA model requires that each time series be analyzed individually rather than be transformed by some common manipulation

[6] The Fisher Kappa does not follow a standard F distribution Fuller provides the correct critical values against which the estimated test statistic should be compared (*5*, p 284)

Figure 4

Spectral Density for Residuals From the AR(3) Model Estimated for the GNP Deflator



Conclusions

One of the requirements of causality tests is that the data series be filtered to create white noise vectors from the original series values Sims suggested a filter which he apparently believed would adequately transform most economic series—at least prior to 1972 We have demonstrated, however, that this filter does not properly filter a variety of common economic series, thus invalidating their use in causality tests

A suggested alternative to filtering involves estimating an ARMA model The residuals from the ARMA model are the filtered version of the data series The spectral plot for the residual vector and tests for white noise can be used to indicate whether the results are, in fact, a properly filtered white noise process Results based on the GNP deflator (DEF) indicate that Sims' filter does not produce a white noise series but that the residuals from an ARMA model are white noise and can, therefore, be used correctly as one variable in a causality test

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