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Testing for causality among paired economic time series

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by

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I. CAUSALITY AND FEEDBACK IN ECONOMIC TIME SERIES

A. Introduction

The purpose of this study is twofold. One purpose is to test the direction and degree of causality and feedback between certain economic time series. The second purpose is to display a methodology for handling autocorrelation in time series data in a way that assures more accurate results of the typical causality and feedback tests. The proposed method is, in many ways, less burdensome and restrictive than most that are now generally in use.

More specifically, causality and feedback between the following three sets of time series[1] are tested:

1. seasonally adjusted nominal personal income (PI^s) and seasonally adjusted nominal currency and demand deposits ($M1^s$),
2. seasonally adjusted nominal personal income (PI^s) and nonseasonally adjusted nominal currency and demand deposits ($M1^{ns}$), and
3. seasonally adjusted nominal personal consumption expenditures (C^s) and seasonally adjusted nominal personal disposable income (DI^s).

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[1]The data for the PI^s, $M1^s$, $M1^{ns}$ variables were collected on a monthly basis for the years from 1947 through 1974. The C^s and DI^s variables were quarterly data collected for the same time period. See Appendix A for a detailed summary of the data sources.

In order to test for causality, noncausality, feedback, and nonfeedback, the PI^s, $M1^s$, and $M1^{ns}$ data were converted to natural logs (the C^s and DI^s data were not converted), and then analyzed by an iterative process which estimated both the regression parameters and error structure of each model. The main methodological novelty of this iterative approach lies in its immediate removal of the error autocorrelation that is known to exist in the model. Secondly, the iterative approach is fairly simple to carry out and requires no prior restrictions as to the rationality and shape of the lag distributions.[1]

Once an adequate[2] estimate model was obtained, the appropriate test was undertaken to test for the direction and degree of causality and feedback between the variates involved.

In the remainder of this chapter, (1) the rationale for this study is presented, (2) the money-income nexus is discussed, and (3) the more recent and relevant theoretical and empirical work regarding causality and feedback are discussed.

B. Rationale

The building and testing of economic models is an integral part of the body of science referred to as Economics. If one accepts Kane's

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[1]See Kmenta (1971, pp. 473-495) or Johnston (1972, pp. 292-320) for an excellent survey of distributed lag models. See also the excellent survey article on distributed lags by Zvi Griliches (1967, pp. 16-49).

[2]An estimate model was judged adequate for proceeding to test causality and feedback if the serial correlation that was known to exist in the original model had been removed. The entire testing process is outlined in Chapter II.

definition (1968, p. 12) of an economic model as "...a logical representation of whatever a priori or theoretical knowledge economic analysis suggest is most relevant for treating a particular problem," then it becomes apparent that the results of economic modeling must be relevant and make sense. Jacob Marschak has pointed out there are two particular properties that are peculiar (in degree, not essence) to econometric methods:

1. First, the standards of the economist's profession require that his empirical results be useful for practical policy, at least over the short horizons.
2. Second, many of his prior assumptions are based on vague "common sense" and introspection, rarely amenable to controlled experiment, (Christ, 1966, p. viii).

These two points provide a first reason for this study. That is, how might a policy maker utilize information as to the degree and direction of causality and feedback between monthly nominal $M1^s$, $M1^{ns}$, and PI^s and quarterly C^s and DI^s? Hopefully such studies as the current one help broaden the understanding and perception of the policy maker as to the impact of varying policy moves. For example, if there is unidirectional causality between monthly money stock and monthly personal income, but no causality between monthly personal income and money stock, then the case for monetary policy is strengthened. Alternatively, if there is bidirectional causality (feedback) between these two variates, the case for monetary policy is weakened. Likewise, if there is no causal or feedback link between money stock and personal income, the Friedman case for monetary policy is decidedly weakened. (Let us hasten to add, however, that it is not the purpose of this study to argue the merits of one policy prescription over another for economic ills.) Marschak's second peculiar property calls for common sense results. Many of the recently reported results of similar studies are not consistent and in some cases the results seem contrary to common sense. Though this work does not purport to be the final say on the money-income nexus, the results of this study are at least consistent with what many economists would expect to be the case.

A second general purpose of this study is to present a procedure for handling serial correlation in economic time series data. The iterative methodology employed in this study provides the researcher a method for handling autocorrelation in error in a fairly straightforward manner. Once the error serial correlation has been corrected for, then the appropriate tests for detecting causality and feedback may be made. Of the more popular methods currently being employed for handling error autocorrelation, particularly the Box-Jenkins approach and the cross-spectral analysis approach, the iterative method employed in this study appears equally as efficient, yet less cumbersome with which to deal. Further, it is suspected the iterative approach helps reduce the degree of multicollinearity that is known (or suspected) to exist between the "specified independent" variables. One drawback to the iterative approach, however, is that it is costly to carry out if many iterations are needed for the adequate solution.

A final rationale for this study is found in the fact that all recent studies seeking to determine causality and/or feedback between economic activity and money time series have used quarterly data. In this study monthly data are chosen, based on the suspicion that quarterly data do not appear frequently enough to accurately reflect the causal and/or feedback relationship, if it exists. Personal income, though not generally regarded as an overall indicator of economic activity, was chosen because it was the most meaningful economic variable available on a monthly basis for the time period in question.[1] Though quarterly data were used for the C^S and DI^S variables, one reason for their inclusion was to provide another example of the value of the methodology being presented in this study for determining causality, feedback, and explanatory models. Another reason for their inclusion was to test the Keynesian hypothesized causal relationship between income and consumption. With respect to reason two, to our knowledge this type of analysis has not been undertaken to date.

C. Money and Economic Activity

As a large portion of this study deals with the testing of money and economic activity models, a discussion of the main points of the relationships hypothesized to exist follows.

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[1]Most researchers would agree that monthly data would be superior to quarterly data. Friedman (1969, pp. 130-131) argued in his original paper, "The Demand for Money: Some Theoretical and Empirical Results," that annual data are unduly crude for studying timing relationships and that monthly data should be used instead. However, most authors also argue that GNP is the best proxy for economic activity and GNP data are not available on a monthly basis. Hence some tradeoffs must occur between data frequency and proxy adequacy.

1. The Friedman argument

Professor Friedman is generally credited with reawakening interest in the role of money and its relationship to economic activity in a 1959 article, "The Demand for Money: Some Theoretical and Empirical Results." Though the import of this classic article is to set forth an explanation of the demand for money, a careful reading persuades one to conclude the "money-income nexus" was, at a minimum, in an embryonic stage.

> It will then follow that, given a stable demand function for money, measured income will be highly sensitive in short periods to changes in the nominal stock of money--the short-run money multiplier will be large and decidedly higher than the long-run money multiplier, (Friedman, 1969, p. 138).

In 1963 Professor Friedman and Anna Jacobson Schwartz analyzed monetary history between 1867-1960 for the United States. Some of their major conclusions include:

1. Changes in the behavior of the money stock have been closely associated with changes in economic activity, money income, and prices.

2. The interrelation between monetary and economic change has been highly stable.

3. Monetary changes have often had an independent origin; they have not been simply a reflection of changes in economic activity, (Friedman and Schwartz, 1963, p. 676).

Some critics of the monetarist views of Friedman accuse him of believing "money is all that matters," and that the causal link between money and economic activity is only one way; i.e., money to income. However a closer reading of Friedman's works reveal the inaccuracy of this type of criticism. For example, Friedman and Schwartz (1963, p. 686) realize "The close relation between changes in the stock of money and changes in other economic variables, alone, tells nothing about the origin of either or the direction of influence." Further, even though in the final chapter of Monetary History, the authors point out numerous examples and case studies of times when monetary changes have been independent (in the sense they have not been an immediate or necessary consequence of contemporaneous changes in business conditions) of economic activity, they are careful to note:

> While the influence running from money to economic activity has been predominant, there have clearly also been influences running the other way, particularly during the shorter-run movements associated with the business cycle, (Friedman and Schwartz, 1963, p. 695).

In all fairness to the critics of Friedman and his followers, the statements of the "monetarists" have become less guarded over time. That is, Friedman's statements concerning the money-income relationships would be more positively phrased today than in 1959. Case in point might be the following statement, made in an interchange between Walter Heller and Milton Friedman in 1969:

> What I and those who share my views have emphasized is that the quantity of money is extremely important for nominal magnitudes, for nominal income for the level of income in dollars--important for what happens to prices. ...We have always stressed that money matters a great deal for the development of nominal magnitudes..., (Friedman and Heller, 1969, pp. 46-47).

2. The Cagan contribution

Utilizing a detailed analysis of the determination of the money supply, Cagan (1965) has argued that the long-run relationship between the price level and the money supply cannot be totally due to feedback from prices to money. His analysis as to the short-run relationship between income and money measures does not yield such firm conclusions, however. Of course, there will be a long-run relationship between almost any two sets of economic time series and much of their observed smoothness over time is due to the serial correlation of error. Or, as J.S. Cramer notes:

> The fact that several economic variables react to some or all of their determinants with a definite time lag, coupled with the existence of many causal relations among all macro-economic variables, makes all aggregate time series move smoothly and in unison. Hence almost any pair of economic time series will show a sizeable correlation, whether they are directly causally related or not, ...here we merely wish to quote their smooth movement in time as an explanation of the serial correlation of disturbances in time series analyses, (1971, pp. 87-88).

With respect to the money-income relationship, the question of feedback and the long-run relationship between these two variables has not been answered by Cagan. His conclusions regarding feedback between the money supply and the price level, however, do tend to support the view that the long-run relationship between money and income measures could not be entirely due to feedback.

Cagan (1972) briefly touched on the question of lags in the monetary effects of the changing monetary growth rate on percentage changes in GNP between 1953 and 1969 for quarterly data.[1] His results lead him to conclude:

> 1. The estimated pattern indicates that the initial monetary effect on aggregate expenditures is quite rapid; indeed, within six months the initial monetary effect takes place, (pp. 110-111).

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[1]It is important to remember that Cagan regressed percentage change in quarterly GNP on lagged monetary growth rate between 1953 and 1969.

2. There is overshooting, however, in the total effect, and it takes about 18 months for this overshooting to be offset by a policy change, and the total long-run effect to return to unity, (pp. 111-112).

The most recent work of Cagan (1972) leads one to question the length of the lag between monetary changes and monetary effects on income. Though it is not the stated purpose of this study to define the size of lags in monetary policy impact, the following conclusions of past studies raise some interesting questions regarding lags in monetary action and their economic effect.

1. Friedman (1961) has argued that "...monetary actions affect economic conditions only after a lag that is both long and variable," (p. 238). The length of the lag generally varies between 6 and 29 months, with 16 months being the average.
2. Culbertson (1960, 1961), on the other hand, has argued that the lag is somewhere between 3 and 6 months.
3. Gibson (1970) comments that Culbertson "...later agreed that his conclusions were based on 'causal empiricism,'" (p. 299). Gibson then proceeds to show that "...when the data are organized in a more systematic way, ..., they show that anticyclical monetary policy can have a rather quick effect on national income," (p. 299).
4. Mason (1976) qualified Gibson's (1970) conclusion by noting that there is an oscillatory nature to the effect of monetary policy. That is, if monetary authorities choose stop and go policies, they will overshoot their income growth targets and have to counteract. This oscillatory action of stop and go type monetary policy is used to argue for stable monetary policy for the meeting of long run goals, not fine tuning the economy.

The import of the above papers may be summarized as follows:

1. The distributed lag effect of monetary policy, particularly stable (as contrasted with stop and go type) monetary policy, is of an intermediate time structure, i.e., probably less than a year.

2. "The most acceptable way to avoid such erratic behavior of monetary policy is to have some idea of the long-run relationship between money and income," (Mason, 1976, p. 497)[1].

In this section we have attempted to summarize the basic arguments and empirical results of studies analyzing the income-money relationship. Our discussion has centered on (a) whether or not a relationship does exist, (b) whether or not causality or feedback exists, and (c) the length of distributed lag one should use to test for causality and feedback.

With these thoughts in mind, we now turn to a discussion of the more recent theoretical works regarding money and income causality and feedback.

D. Recent Theoretical Work

Though it is difficult to distinguish between theoretical and empirical work (as most studies include both), we will confine our discussion to the theoretical constructs that have recently been published in various forms. The presentation is in logical, not chronological, order.

1. Granger (1969)

Arguing that previous papers concerned with causality in economic systems (in a simultaneous equation framework) have, in general, only defined instantaneous causality and not discussed feedback, Granger sets forth four sophisticated post hoc, ergo propter

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[1]Of course, this is one stated purpose of this study, i.e., to more adequately determine the long relationship between money and income.

<u>hoc</u> definitions of causality, feedback, instantaneous causality, and causality lag. Most of the analysis is carried out in terms of a two-variable model, though generalization to a three-variable model is briefly discussed. Granger (1969, p. 424) argues that "Causality and feedback are here defined in an explicit and testable fashion." Then after a short discussion of spectral methods and feedback models, causality and feedback for the stationary time series process are defined as follows.[1]

<u>Causality</u> is said to exist between two economic time series if the optimum, unbiased, least squares minimum predictive error variance of X, when utilizing all germane information, is less than the optimum, unbiased, least squares minimum predictive error variance of X, when utilizing a subset of all germane information. <u>Feedback</u> is said to occur if causality (as defined above) is observed to exist between the two time series in question such that X causes Y and Y causes X when utilizing only past values of each time series.

<u>Instantaneous causality</u> is said to exist between the same two economic time series if the optimum, unbiased, least squares minimum predictive error variance of X, when utilizing past values of all germane information, is greater than the optimum, unbiased, least squares minimum predictive error variance of X when both past and present values of all germane information are used. The nicety

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[1]The verbal discussions are herein given. The mathematical definitions are more rigorously set forth in Chapters II and III.

of the Granger definitions is that they can be tested by carrying out the appropriate OLSE regressions.

The Granger definitions of causality and feedback are generally accepted today.[1] The central theme of the Granger definition of causality (as contrasted to earlier works) has to do with the importance of time. As an example of an earlier work, we might quote Simon (1953, p. 51) as showing that his definition of causation "...does not imply time sequence, nor does time sequence imply causation." Granger on the other hand, finds time essential to his definitions.

2. Feige and Pearce (1974)

Accepting Granger's definitions of causality, Feige and Pearce argue that the specification of a dynamic regression model for testing income and money relationships is only appropriate when causality is unidirectional from money to income or from income to money. That is, the authors set out to determine whether or not the purported exogenous variables in an income-money model are truly exogenous.[2] The approach taken by the authors is primarily that of Box and Jenkins

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[1]See, for example, Feige and Pierce, 1974 mimeo, pp. 3-4); (Pierce, 1975 mimeo, pp. 1-2); and (Pierce and Haugh, 1975 mimeo, pp. 1-2).

[2]This is an extremely important point as has now been shown. That is, the estimation and interpretation of the famous St. Louis reduced form models (particularly of Andersen and Jordan) critically depend on the degree to which the policy variables are truly exogenous. See a good discussion of this point in Goldfeld and Blinder, (1972, pp. 585-640). Particularly note pp. 632-635, where a good, but terse, summary of existing empirical work is given and a discussion of how each author has attempted to reconcile the reduced form model approach with that of the more structural approach.

(1970). The authors first set forth an explicit type of Granger's definition of causality specifying that the endogenous variable is now treated as an exogenous variable. That is, X is now said to cause Y if the minimum least squares error variance of a regression of Y on past Y and all past and present X is less than that of Y on past Y only. Incorporating this specification, the feedback definition of Granger is accepted. The authors also define "independence" as occurring when the minimum, estimated, least squares error variances are the same for Y on past Y and past and current X as they are for Y on past and current X only. (The opposite case for X on Y must hold also.)

Armed with these definitions, the authors suggest the following procedure (which they note was outlined by Haugh (1972) in his doctoral dissertation):

1. Express the X and Y variates as deviations from their respective means,

2. determine the linear filters that "prewhiten" the X and Y series,[1] and

3. calculate the cross correlation function for the two series of white noise residuals in order to test for causality, feedback, and/or independence.

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[1]Prewhitening X and Y, the authors argue, is "... tantamount to finding forecasting models for X and Y which yield minimum expected mean square forecast errors for future value of the series," (Feige and Pearce, 1974 mimeo, p. 4). The prewhitening linear filters are chosen according to the ARIMA (p, d, q) methodology set forth by Box and Jenkins (1970). ARIMA (p,d,q) conveniently defines a class of time series models known as autoregressive, integrated, and moving average. The parameters p, d, and q, refer to the order of the autoregressiveness in the model, the type of difference taken in the time series, and the order of the moving average in the model.

Feige and Pearce next discuss the conditions under which a dynamically specified regression model is the appropriate specification, concluding that a dynamic regression model of Y on X is only appropriate if the X (exogenous) variables are truly independent of the error series. The authors argue that such independence or nonindependence can be empirically tested for by examining the cross correlation function of the two residual series.

The remainder of the Feige and Pearce paper is devoted to an investigation of various paired quarterly GNP, M1, and MB (monetary base) time series data, both seasonally and unseasonally adjusted.

As the purpose of this section is restricted to a discussion of theoretical work,[2] we will conclude by noting that the main feature of the Feige and Pearce study is to set forth a Box and Jenkins (1970) type methodology for preparing and testing any two time series (in which it is known error autocorrelation exists) for causation, feedback, and/or independence.

3. Pierce and Haugh (1975)

Utilizing an analogy of events in a sample space, Pierce and Haugh classify the 256 possible causality events that can occur relating a time series X to another time series Y, if one is interested in whether "X causes Y," "Y causes X," or "does instantaneous causality exist between X and Y?" In this work, the authors accept and utilize the Granger definitions of causality,

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[1]The empirical results of Feige and Pearce are found in this chapter in the Recent Empirical Work section.

because "... it appears difficult to present an alternative definition for causality which can be tested empirically, " (p. 2). After carefully defining the bivariate time series model framework in which they are operating, the authors set forth some important conditions for practical modeling problems in order to accurately test for the type and direction of causality. (The discussion of these conditions is in terms of cross correlation functions and their shape.) The authors conclude the theoretical portion of their study by equivalently redefining the Granger (a) causality and (b) instantaneous causality constructs in cross spectral terminology.

4. Pierce (1975)

Utilizing the Box and Jenkins (1970) general procedure, Pierce examines causality between various economic time series. Arguing that the differences between the conclusions of varying studies were a result of the failure of most authors to satisfactorily account for autocorrelation, Pierce sets out a step by step approach for (a) transforming raw data (prior to testing for causality) in order to broaden their usage, and (b) assessing causal relationships among variables.

Pierce argues that past values of the endogenous variable must be used in the right hand side of the model or the relationships of causality, etc. will be overstated. That is, Pierce would agree with the Feige and Pearce (1974) definitions of causality, and all the empirical work in his study utilizes the past history of the endogenous variables as a right hand variable. Pierce, on the other hand, suggests transformations be directly applied to the raw data; whereas Feige and Pearce choose to transform data that has been re-expressed as "differences from the mean."

Pierce suggests an entire theoretical time series modeling process (as consisting of five steps) which moves from the detection of causality in a univariate model to the detection of causality in multivariate models; however, the empirical work that follows is all done in the simpler univariate model. The concluding comment of Pierce is that "The economy is a miserable experimental design," (p. 37). Caines and Chan (1975) would go even further than this, and to their study we now turn.

5. <u>Caines and Chan (1975)</u>

Caines and Chan doubt the ability for a researcher to isolate "causality" in the Granger (1969) sense and offer an alternative method for viewing and studying stochastic processes. The authors note that, "...we believe the concept of causality belongs properly to the realm of experimental science," (p. 498). The authors therefore present a theoretical process (it should be noted, however, that two examples of the canonical representation of two joint processes, one simulated and the other involving unemployment and gross domestic production for the United Kingdom, are briefly presented in the study) by which the researcher in the nonexperimental sciences might go about detecting feedback in various stationary stochastic processes. This process is mainly one of analyzing any ordered pair of multivariate processes, in terms of the canonical representation of the joint process with respect to its innovations, for feedback. The definition for detecting this feedback is in terms of canonical representations and Wiener filters.

One of the operational procedures that follows from this study is that feedback may be detected by utilizing OLSE and regressing the Y process on the past X process. Then regress Y on all past and future X values and determine if the mean square estimation error of each regression is significantly different. This test for feedback is similar to the one utilized in this study to detect causality between any two processes.[1]

One important point raised by Caines and Chan is whether or not identification techniques for feedback (causality in this study) depend on the assumption that the observed independent variables and the error must be independent of one another. Caines and Chan would argue that their approach for detecting feedback does not require this restriction.

6. Sims (1972)

Accepting Granger's (1969) definitions and utilizing the Hilbert space argument, Sims proceeds to set forth two important

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[1]Of course, Caines and Chan (1975) have already indicated they do not feel "causality" (instead they say feedback) can be detected in nonexperimental sciences. Whether or not this is true is, of course, an interesting point, and one that the authors recognized at the outset; i.e., "Of course, despite our disclaimer, the reader is free to decide in the end that we may have merely introduced yet another notion of causality," (p. 498).

theorems.[1] Theorem 1 states that "...causality runs only from X to Y if past Y does not influence current X," (p. 544). Theorem 2 describes an autoregressive representation of Y on X as causality testable only if Y does not cause X. Inherent in this theorem is the restriction that the X variables must be independent of the residual series. Sims sets forth the generally accepted tests for causality in terms of expected mean square variances. In addition, he discusses and applies several tests for serial correlation in residuals. Though the bulk of this study is devoted to empirical analysis, Sims makes several points that are germane to this study and these are summarized below.

1. Sims argues that his testing procedure for causality of X to Y requires there be no feedback between X and Y, in order for it to be reasonable to interpret a distributed lag regression of Y on current and past X. That is, if causality from X to Y is found but not from Y to X, then there must be no feedback between X and Y or the X to Y causality is questionable.

2. The test for causality would also fail if there were any relation at all between the causal structure and the property of the error terms. In practice, however, this would rarely be the case.

3. The method of detecting causal relationships between time series "...is not easily fooled,"[2] (p. 543).

4. The absolute size of the regression coefficients is important regardless of the outcome of the t tests.

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[1]The proofs of these two theorems are given in the appendix to the study. See pp. 550-551.

[2]For example, Sims states that the simple linear structures proposed by Tobin (1970) to compare Keynesian and Friedman models in terms of causality cannot be constructed to give "apparent" money-to-GNP causality, (p. 543).

5. Seasonal adjustments of data vary with the time series in question, hence the researcher should use undeseasonalized data whenever possible.

In this section, we have surveyed and discussed the more mainstream theoretical works concerning notions of causality, feedback, etc. We have found that most work utilizes the Granger definitions, though some authors have used the Hilbert space (or sample space) type framework for defining causality. Some authors have argued that the exogenously specified variables must be independent of the error series in any model in order for the causality tests to be valid. All authors have recognized the cruciality of correcting for serial correlation in the observed residual series; however, the method for correction has been considerably varied. We now turn to a discussion of the more predominant empirical works regarding causality detection between economic time series, paying particular respect to those involving money-income type models.

E. Recent Empirical Work

It is a well accepted fact that simple correlation techniques applied to money and income data are not conclusive evidence as to causality. Likewise a comparison of leading, lagging, and roughly coincidental cyclical movements in two time series data would be shaky ground upon which to purport such a theory.[1] Because of these

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[1]A classic example of the length to which such studies might be taken is found in an article entitled "Of the Relationship Among Red Squirrels, Butter Prices, Steel," (<u>WSJ</u> 12 Jan 1972). In this article the cyclical properties of red squirrels, butter prices, and steel are analyzed and a causal relationship implied.

considerations and others, many researchers have undertaken studies to determine if causality and feedback exist between money and income. As is the case with many studies involving such complex relationships, the results of most studies are not in concert. In Table 1.1 the partial results of some of the more major and recent studies are summarized to amplify this nonagreement.

Sims' (1972) article represents a major effort to analyze money, income, and causality. Subsequent to this 1972 piece, numerous other studies have been forthcoming. Among the more recent works since Sims, those of Dy Reyes (1974), Feige and Pearce (1974), and Pierce (1974) will be discussed, as they are most relevant to this study.

1. Sims (1972)

Sims investigates both quarterly monetary base (MB) and money stock (M1) data as well as quarterly gross national product (GNP) data for the United States between 1947 and 1969. He utilizes the ordinary least squares estimation technique on distributed lag models having applied no prior restrictions on the shape of the distribution. His data were converted to natural logs and prefiltered by $1 - 1.5L + .5625L^2$. The filter chosen by Sims (1972, p. 545) is justified as a filter which "...approximately flattens the spectral density of most economic time series..." with the hope "...that regression residuals would be very nearly white noise with this prefiltering." The author then runs a series of regressions treating first money, and then GNP, as the exogenous variable. Several variants of each model are presented, some including four future and eight past lags of the

TABLE 1.1

PARTIAL RECENT RESULTS OF MONEY AND INCOME TYPE CAUSALITY MODELS FOR THREE MAJOR STUDIES UTILIZING UNITED STATES DATA

Study	Data Type	Measure of		Lag Type[b]	Causality[a]		Feedback	Time Period
		Money	Income		$M \rightarrow Y$	$Y \rightarrow M$		
Sims (1972)	Quarterly (Seasonally adjusted)	M1	GNP	4F, 8L	Yes	No	Not testable	1947-69
		MB	GNP	4F, 8L				
Dy Reyes (1974)	Quarterly (Raw)	M1	GNP	4F	Inconclusive	Inconclusive	NA	1951-70
		M1	GNP	8L				
Feige and Pearce (1974)	Quarterly (Seasonally adjusted)	M1	GNP	12F, 12L	No	No	NA	1947-69
		MB	GNP	12F, 12L	No	No		
	Quarterly (Seasonally unadjusted)	M1	GNP	12F, 12L	Yes	No		
		MB	GNP	12F, 12L	No	No		

[a] $M \rightarrow Y$ means money causes income, whereas $Y \rightarrow M$ means the reverse is true.

[b] F is for future, L is for lag.

"independent" variable and other models just including eight past lags and no future values. The data are also divided into two subperiods and tested for sample consistency. Sims is careful to apply both first-order[1] and second-order tests on each model so as to test the accuracy of each model's estimated structure as well as its residual structure. At the same time, Granger's rules for testing the degree and direction of causality are invoked.

Sims concludes the following regarding money-income causality:

> These results allow firm rejection of the hypothesis that money is purely passive, responding to GNP without influencing it. They are consistent with the hypothesis that GNP is purely passive, responding to M according to a stable distributed lag, but not influencing it, (1972, p. 547).

However, the above results are tempered by the following statement regarding the questionable outcome of the second-order tests regarding residual normality, independence, and nonautocorrelation.

> The conclusion from this list of approximate and inconclusive tests can only be that there is room to doubt about the accuracy of the F tests on regression coefficients, (Sims, 1972, p. 549).

2. Dy Reyes (1974)

Dy Reyes (1974) set out to determine if causality existed between money and economic activity for the United States, Canada, and Japan. The time period over which each nation's data were collected varied according to availability, but in every case three different

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[1]As noted earlier, Sims argues that in such distributed lag models, estimated coefficient size as well as significance should be considered. Therefore, information as to the estimated coefficient sign and size is all that is given in the paper.

methodologies were applied to each nation's data. Dy Reyes applied (a) Sims' "pre-determined, pre-filtered" methodology, (b) a "two-stage regression" procedure, and (c) a "first difference iterative estimation" procedure to raw (uncorrected for trend and seasonality) quarterly nominal gross national product and money stock for each nation. Though each model type was an unrestricted distributed lag model, the methodology employed varied, hence a terse discussion of each follows.[1]

The first method has been discussed above in the section dealing with Sims' paper. Method two consists of pre-determining the "appropriate" lag structure as determined by t tests on the parameter estimates found in an initial OLSE model on a four quarter, logged and lagged, seasonal, and trend variable model. After estimating the type of autoregressiveness that exists in the initial estimate model error, a series of regressions are run on the transformed data whose error structure is now (hopefully) free of serial correlation. Sims' testfor causality is then utilized to determine whether or not causality exists in each case. The third method utilized by Dy Reyes is a more standard type approach. After being converted to natural logs, each data set is first-differenced, then the various initial models are fit. Appropriate linear filters are determined (from the initial model's lagged residual results) and utilized to transform the original data. The transformed data are

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[1]Both the second and third methods of Dy Reyes are, in some respects, similar to the methodology employed in this study.

then analyzed via the OLSE methodology. Once again, Sims' test is utilized to test for causality.

The results of Dy Reyes' work are varied. No relationships between money and income could be inferred for the Canadian data. In the case of Japan, only one model type showed any causality and then the causality direction was from GNP to M1.[1] Finally, in the United States, two model types indicated causality from M1 to GNP.

3. Feige and Pearce (1974)

Following the Box and Jenkins approach for estimating and identifying an ARIMA (p, d, q) model which correctly specifies[2] the time series under consideration, Feige and Pearce proceed to define a procedure by which causality between both seasonally adjusted and nonseasonally adjusted variables MB, M1, and GNP might be tested. Much of the Feige and Pearce procedure for testing causality revolves around the two stage empirical procedure that was originally suggested by Haugh (1972). The procedure involved the following two steps:

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[1]Given that the Dy Reyes models are correctly specified, it might be reasonable to find varying causality results for a less developed or developing economy as contrasted to a more developed economy. That is, Starleaf and Floyd (1972) have argued that monetary policy (as contrasted with fiscal policy) may be expected to have a greater influence on economic activity in a more developed country as compared to a less developed country. Rousseas (1972) notes "There is much reason to suspect that Friedman's demand function is more applicable to underdeveloped countries, and Keynes to advanced economies," (p. 178). This is due to the conjectured absence of a money illusion in a less developed country.

[2]A model is correctly identified if the residuals of both time series are white noise.

Step One - The identification and estimation of the appropriate linear filters that will eliminate serial correlation in the two time series in question are first found. This is accomplished by explaining each series' deviation from its mean in terms of a polynomial lag structure of serially uncorrelated (white noise) values.

Step Two - The cross correlation function of both series is now examined and causality, feedback, and independence are determined. The Granger (1969) definitions are utilized in this step.

Employing quarterly data for the United States between 1947 and 1969, as does Sims (1972), the authors find,

> We could, however, also characterize our findings as allowing 'firm rejection of the hypothesis that money is purely passive' and that 'causality does not run one way from GNP to money,' (1974, p. 19).

In an attempt to reconcile Sims' results with their own, the authors next show that much of the difference between the two studies has to do with the different filtering procedures used by both and the asymmetrical treatment of lags in Sims' approach. The authors conclude that the filter chosen by Sims does not flatten the spectral density of the series, consequently the residual series was not white noise. Further, it is argued that Sims erred in not maintaining symmetricity in his future and past lagged variables.

In conclusion, the results of most recent empirical work regarding the money and income relationship have been varied. Possible explanations for the inconsistency might be found in (a) the choice of nonappropriate filters, (b) the failure to adequately pre-whiten the time series in question, or (c) the incorrect model specification. A final possibility, but one we choose to ignore, is that econometric and time series modeling procedures simply cannot aid the researcher in determining causality.[1]

F. Overview

In Chapter I, a terse review of the most relevant theoretical work regarding causality has been presented. A discussion of the more germane empirical work testing for money and income causality was also given. Also, the rationale for, and the importance of, such studies were briefly discussed. Chapter II presents a detailed analysis of the methodology employed in this study and the justification for its usage. Chapter III summarizes the results of the full time period and subperiod $M1^s$, $M1^{ns}$, and PI^s models. Then in Chapter IV the C^s and DI^s models are treated. The conclusions and areas for further research are discussed in Chapter V.

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[1]We invoke the Ostrich Lemma on this point. "Just because the methods and results are not thoroughly consistent, the researcher need not throw up his hands and quit, i.e., hide his head in the sand." Instead the search for improved methods should go on.

II. METHODOLOGY

In this chapter a discussion and proof of the methodology employed in this study is given. The first section is devoted to the laying out of the OLSE model and its underlying assumptions. Next, the problem of serial correlation is discussed. The second section is devoted to a discussion of numerous historical methodologies that have been presented to handle the problem of autoregressive errors. In the third section a concise proof of the methodology employed in this study is given. The final section briefly sets forth some fundamental definitions of terms peculiar to this study.

A. The Ordinary Least Squares Model and Assumptions

1. Relationships

Consider the following simple functional model

$$Y = f\,(X_1,\ e) \qquad (2.1)$$

where Y is a dependent random variable, whose movements may be explained by both the independent variable X_1 and the error term e. Suppose the true model that explains this relationship is given as

$$Y_t = B_0 + B_1\ X_{t,1} + e_t \qquad (2.2)$$

and the ordinary least squares estimate relationship is given as

$$\hat{Y}_t = \hat{B}_0 + \hat{B}_1\ X_{t,1} \qquad (2.3)$$

where

1. Y_t and e_t are random variables,
2. $X_{t,1}$ is normally considered an exogenously determined variable, though it may be considered a random variable,[1]
3. Y_t is a dependent variable whose probability density function (PDF) depends, at least partially, on the probability density function of e_t,
4. $\hat{B}_0$ and $\hat{B}_1$ are random variables whose PDF depends at least partially on the PDF of Y_t and, by transitivity, on the PDF of e_t, and
5. $\hat{Y}_t$ represents the estimate of the dependent variable Y_t.

The ordinary least squares estimation (OLSE) methodology yields two normal equations that are simultaneously solved to obtain B_0 and B_1 estimates ($\hat{B}_0$ and $\hat{B}_1$ respectively) according to the "minimize the sum of the squared residuals" criterion. Careful observation leads one to conclude that not only are the parameter estimates $\hat{B}_0$ and $\hat{B}_1$ dependent upon the PDF's of Y_t and e_t, but any interactions <u>between</u> the PDF's of Y_t and e_t, and $X_{t,1}$ will affect the sample statistics $\hat{B}_0$, $\hat{B}_1$, $SE_{\hat{B}_0}$, $SE_{\hat{B}_1}$, R^2, etc. The import of these past few sentences is twofold:

1. The unbiasedness, consistency, efficiency, and accuracy of any OLSE model directly depends on the fulfillment of all the OLSE assumptions, and further

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[1]If $X_{t,1}$ is a random variable then the ordinary least squares estimation methodology and assumptions must be altered to reflect this possibility. However in this study $X_{t,1}$ is considered a nonstochastic variable and the standard assumptions for the ordinary least squares estimation methodology are acceptable.

2. If one knows[1] that one, some, or all the OLSE assumptions are not being met because of the relationship between the PDF's of the dependent and independent variable as well as the error term, then the original data may usually be transformed so that the OLSE assumptions can then be fulfilled.[2]

Now, let us more specifically set forth the ordinary least squares estimation assumptions regarding the dependent, independent, and error terms.

2. The OLSE assumptions

All versions of the OLSE assumptions standardize to the following set.[3]

1. Normality $e_t \sim N$

   The error terms are random variables, normally distributed.

2. Zero Expectation $E\,(e_t) = 0.0$

   The expected value of the error terms is zero.

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[1]In reality, one really never "knows" the actual relationships between the dependent, independent, and error terms in any model. These relationships are merely estimated by ordinary least squares, best linear unbiased, generalized least squares, maximum likelihood, etc. solution methods based on the researcher's a priori assumptions or past empirical analyses of the data.

[2]This is certainly not a trivial point. A tremendous amount of theoretical and empirical work has been undertaken to test OLSE assumption validity and the transformations that need to be made in order for these assumptions to be met. Indeed, one primary purpose of this study is to elucidate one such transformation procedure that might be used when all the OLSE assumptions are not met.

[3]For example, see (Christ, 1966, pp. 350-357); (Johnston, 1972, pp. 121-123); (Kane, 1968, pp. 355-356); (Kmenta, 1971, pp. 202-205); etc.

3. Homoskedasticity $E(\sigma_{et}^2) = \sigma^2$ for all t

   The effects of the external causes of the error terms remain unchanged throughout the observations in a sample and in repeated samples.

4. Nonautoregression $\text{Cov}(e_i, e_j) = 0$ when $i \neq j$

   The effects of the external causes of the error terms act independently on the current observation irrespective of their effect on previous or subsequent observations.

5. Nonstochastic

   Each explanatory variable in the model must be a nonstochastic variable having values fixed in repeated samples and having a finite mean and variance.

In addition, some authors may add the following two assumptions to ensure a nontrivial solution exists.

6. Degrees of Freedom

   Each sample must have more observations than parameters to be estimated.

7. Rank

   The rank of the (X'X) matrix must be one less than the number of parameters being estimated.

As equally well known as the OLSE assumptions, is the fact that if all the OLSE assumptions hold, then the ordinary least squares estimation (OLSE) estimators are also the Best Linear Unbiased Estimation (BLUE) estimators and the Maximum Likelihood Estimation

(MLE) estimators.[1] Though both the BLUE method and MLE method yield slightly more information regarding the estimate model in question, most often the OLSE methodology is used because of computational ease. Such is the case in this study.

A second point to be made is that economic data, in particular, do not always exhibit properties consistent with the OLSE assumptions. For this reason, a researcher has to be certain, when undertaking econometric work, that the OLSE assumptions have been met.

Numerous tests have been devised to test for model efficacy and assumption fulfillment. These tests may be divided into two types:

(a) First-order tests: These tests assume no assumption violation and are the normal t, F, R^2, etc. tests.

(b) Second-order tests: These tests are for determining the degree to which the OLSE assumptions appear to have been met.

Kane has put the importance of both the first- and second-order tests being fulfilled into proper perspective:

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[1]Though no specific discussion of the Best Linear Unbiased Estimation or Maximum Likelihood Estimation techniques are discussed in this study, the interested reader will find discussions of each of these methods in any standard econometrics textbook, such as Christ (1966); Dhrymes (1970); Goldberger (1964); Johnston (1972); Kane (1968); Kmenta (1971); Murphy (1973); Tintner (1952); etc. For proof of the statement that the estimators of OLSE are the BLUE and MLE estimators, one might particularly note Kane (1968, pp. 355-356); Kmenta (1971, pp. 206-215); and Murphy (1973, pp. 186-187). More specifically, the BLUE estimators equal the OLSE estimators if there is independence between the error term and the independent variables. In addition, if the error terms are also normally and independently distributed, then the BLUE estimators = OLSE estimators = MLE estimators. Further, even if the error terms are autocorrelated, Aitken (1934-35) has shown that if this lack of independence is taken into account, the OLSE estimators are the same as the generalized least squares estimation (GLSE) estimators.

> When it seems safe to certify these residuals as random and conforming to the various assumptions on which the first-order tests are predicated, we can pronounce a theory properly and adequately tested. But when the distribution of residuals belies one or more of these assumptions, we have to take corrective action. This will be seen to involve both respecification (of either the systematic or the random elements of the model) and re-estimation, with the process coming to a halt only when the residuals of the new model pass the second-order tests, (1968, pp. 352-353).

It is now less common to find econometric models presented without second-order tests having been conducted to ensure accurate modeling; nonetheless, many estimate models of earlier econometric studies and their implications are suspect because of basic assumption violation. For example, Granger and Newbold (1974a, p. 1) in an earlier version of their Journal of Econometrics article (1974b), cite at least six published works wherein assumption 4 (nonautoregression) appears to have been violated, at least in the first-order.

With reference to the study at hand, the initial violation of assumption 4 (nonautoregression) is recognized and hopefully corrected. That is, the methodology herein presented is one way to iteratively (a) reduce the observed residual structure to one exhibiting the "appropriate qualities,"[1] and then (b) determine the regression coefficients. It is also suspected (after close study of the least squares

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[1]Most authors refer to a residual structure possessing the "appropriate qualities" as a "white noise." A white noise series, by definition, need possess only one quality, that is successive terms must not be correlated. If the only problem with a model is autocorrelated residuals, then this statement on "appropriate qualities" could be reworded to say "... reduce the observed residual structure to white noise."

output) that the methodology employed in this study not only adequately solves the problem of error autocorrelation, but that it also mitigates the problem of possible multicollinearity. We now turn to a brief discussion of the causes and consequences of autocorrelated error structures.

3. Autocorrelation

Autocorrelation, sometimes referred to as serial correlation, exists in most economic time series, particularly if the time interval between successive observations is small. With respect to the error term in time series data, autocorrelation may be observed for several reasons.

(1) An important exogenous variable may have been omitted from the regression, thus causing the residual term to absorb the influence of the omitted variable.

(2) There may exist serial correlation in the specified exogenous variable, which may cause the residual term to exhibit serially correlated properties. Johnston (1972, p. 244) calls this situation a special case of omitted variables.

(3) The residual term may also exhibit serial correlation due to a measurement error in the endogenous variable or exogenous variables.

The above list, though not all inclusive, is representative of the most common reasons for observed serial correlation in residuals. In this study it is assumed that the observed autocorrelation in the residuals might be due to any one, two, or all three of the above list.

The consequences of serial correlated error in an OLSE model may be summarized below.

(1) The sampling variance of the model parameter estimates will be unduly large (hence inefficient) compared with those

achievable by a slightly different method of estimation, (Johnston, 1963, p. 179).

(2) The normal OLSE formulas for the sampling variances of the model parameter estimates will likely yield underestimated variances, (Johnston, 1972, p. 246).

(3) The standard error of estimate is a biased estimate of the true variance of the error terms. In this case, it's value will be underestimated because of positive autocorrelation. Likewise, an overoptimistic R^2 will be given, (Wallis, 1972, p. 91).

The above consequences distill to a single statement. Autocorrelation of the error in a model means the variance estimators for the regression coefficients, the model, and the residuals are inefficient; hence, the usual t and F tests are no longer valid.

The practical result of error autocorrelation, as observed in the residual structure, is that the normal first-order tests of the model are no longer proper; and therefore, if nothing is done to solve the problem, the results of such a model are suspect (at the least), and most likely false. For this reason great care has been exercised in this study to assure that no serial correlation exists in the residual series of each of the final models in which causality and feedback are tested.

With the above thought in mind, we now turn to a discussion of the historical development of the methodology being employed in this paper for handling error autocorrelation and other alternative methods that have been proposed. The reader should note that only the <u>mainstream historical</u> methods are discussed. The more recent theoretical and empirical work was already discussed in Chapter I.

B. Correcting for Autocorrelation, Historically Speaking

In this section several earlier discussions of various ways to handle autocorrelated errors are summarized. We begin by discussing what appears to be the earliest work on error autocorrelation correction procedures, and end with a brief summary of the various methods and their approaches. The emphasis in this section is to set forth some of the earliest methods used to deal with serially correlated errors, particularly those that are similar to the one we choose to use in this study.

1. Cochrane and Orcutt (1949)

One of the best known and earliest works discussing two-stage (or what we choose to call iterative) methods of dealing with serial correlation in error terms appeared in 1949. This 1949 paper by Cochrane and Orcutt provided much of the ground work for the current state of the art. After a short discussion of major complications that arise in economic time series, the authors suggest two methods by which the autocorrelated error in the original model can be transformed to an error structure exhibiting all the necessary characteristics in residual form. Though two methodologies are presented in the paper, the first is discarded because of the results of some earlier work of the authors. That is, earlier work of the authors when employing sampling experiments on "generated data," (data constructed by the authors so both the explanatory variables and error terms possessed the same autoregressive structure) tended to show a large degree to biasedness toward residual normality. As these early tests exhibited a bias toward randomness when it was felt autocorrelation still existed, the authors suggest an alternative method for handling models in which the error was autocorrelated.[1]

Method One, which is what we have chosen to call the "iterative method" in this study, is outlined by Cochrane and Orcutt as follows:

> First, estimate the desired regression coefficients by ordinary least squares and obtain the resulting series of residuals. Then estimate from those residuals by least squares the autoregressive parameters of a one or two lag difference equation. Use these autoregressive parameters to make an autoregressive transformation of the observed series aimed at randomizing the error term, and re-estimate the desired regression coefficients. Put these revised estimates back into the original equation, obtain the resulting series of residuals and estimate their autoregressive parameters. Use these to make a new autoregressive transformation of the original series and so on until estimates of the desired regression coefficients are obtained which are consistent with the estimates of the autoregressive parameters of the residuals in the sense that no further adjustments are necessary, (1949, pp. 53-54).

For reasons listed earlier, the authors chose to discard this method. Instead, they suggest "... selecting an autoregressive transformation of the series involved such that the autocorrelation of the series of residuals are approximately equal to the expected values of autocorrelations of random series of the same length," (1949, p. 54). However, as there is no apparent procedure for selecting a

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[1]As this article appears to be among the first suggesting procedures by which to handle models having autocorrelation, we will discuss it in greater depth than later works.

commensurate autocorrelation series,[1] an approximation must be made. In suggesting the first- or second-difference approximation, the authors conclude, "If we prove to be right about the nature of most error terms in current formulations of economic relations, then the residuals of the first difference transformation will turn out to be sufficiently random and no further steps will be necessary," (1949, p. 54).

The choice of the first-difference approximation as the method to apply to models possessing autoregressive error structure is partially based on the fact "...that nearly optimum results can be achieved if the error term is only a rough approximation to a random series...," (1949, p. 53). However, it would seem that if rough approximations appear adequate, the iterative method might also be utilized as long as the researcher was careful to check for the "randomization bias."[2]

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[1]It would appear that the selection of an "error series that is equal in all respects to the autocorrelated series, except that it is random" would be a difficult task. If the true error variance-covariance matrix is known, which is what must be known in order to match various error structures, then the obvious question is: why not use the Generalized Least Squares Estimation (GLSE) technique as proposed by Aitken (1934-35) and forget the transformation procedures? After all, the asymptotic efficiency of the GLSE and OLSE techniques is the same if both of the error variance-covariance matrices are the same. See for example, Fuller, (1975 mimeo, Chapter 9, p. 9).

[2]A valid question to ask regarding this point is, how detrimental is randomization bias? Fuller (1975, mimeo, Chapter 9, p. 22) notes that in estimating the autocorrelation structure from the OLSE residuals, the bias in estimated autocorrelations is small in large samples and can therefore be ignored.

In summary then, Cochrane and Orcutt prefer to handle autocorrelated error in a model by the first-difference approach. The approach which the authors choose <u>not</u> to use (and which we have herein called the iterative methodology) has generally been credited to them, however.[1]

3. Kadiyala (1968)[2]

Kadiyala questioned the transformation approach of Cochrane and Orcutt in terms of efficiency and consistency. In this short paper Kadiyala showed that in a simple first-order autoregressive process, a difference transformation (such as was proposed by Cochrane and Orcutt) on all the original data may not yield OLSE results that are as efficient as the OLSE results on the original untransformed data, particularly if positive autocorrelation of the errors is present and the

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[1]This is a curious point. Most authors credit Cochrane and Orcutt with the two-stage iterative procedure, rather than the first difference procedure. See, for example, (Johnston 1972, p. 262); Kmenta, 1971, pp. 287-289); (Murphy, 1973, pp. 315-322); etc. Rao and Griliches do note, however, "Actually Cochrane and Orcutt do not recommend the use of this estimator because of the downward bias in ρ_0. They also suggest the possibility of iterating several times more. Nevertheless, since they seem to be the first to mention such an estimator, we associate their names with it," (1969, p. 255). Obviously, even though Cochrane and Orcutt do suggest the iterative methodology, they use the first-difference approach in their paper.

[2]The reader should note that it appears the point of the Kadiyala article was recognized in an earlier, unpublished piece by Prais and Winsten (1954).

degree of interdependence (generally denoted by ρ) between two successive errors is thought to be close to unity.[1]

Kadiyala proceeds to show that if the first row of data is lost by a differencing transformation from the original T X T data matrix, then the resultant transformed T-1 X T data matrix does not always yield the most efficient OLSE results. The author closes his article by suggesting "On the other hand, the addition of one weighted observation to the Cochrane-Orcutt procedure yields the best linear unbiased estimator--at practically no extra cost," (1968, p. 96).

3. Prais and Winsten (1954)[2]

Prais and Winsten, in an unpublished (and generally unavailable!) Cowles Foundation Discussion Paper, have pointed out that the Cochrane and Orcutt method is inefficient unless the correct diagonalizing transformation matrix has the same row and column dimension as the original data matrix. The loss in efficiency, the authors argue, is critically dependent upon the magnitude of variation between the first observation of the independent variable and its mean. This is so because the differencing transformation leads to a loss of one row of data, and this lost row could be extremely critical in defining a changing economic structure.

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[1]Interestingly enough, most authors still argue <u>for</u> using first-difference procedures when the value of ρ (a measure of the degree of interdependence between successive error terms) is unity. See, e.g. (Goldberger, 1964, p. 238); (Granger and Newbold, 1974b, p. 118); (Kmenta, 1971, p. 292); etc.

[2]Most of the following discussion has been gleaned from the Rao and Griliches paper (1969, p. 257) and Johnston (1972, pp. 264-265).

The authors argue, as does Kadiyala, that if ρ were unity, the top row of the transformed data matrix would now be a row of zeros. The importance of the Prais and Winsten piece lies in the authors' recognition of the measurement of efficiency loss as a function of the first observation's difference(s) between its mean(s).

The Kadiyala (1968) and Prais and Winsten (1954) arguments are now generally accepted as valid.[1] In practice, if sample size is small, the appropriate transformation to re-estimate lost data is crucial. But in large sample sizes the potential gain in efficiency is offset by the tedium of replacing lost data by the appropriate re-estimation process, particularly if the autoregressiveness is greater than second-order. In this study, given the large sample size, no effort was made to re-estimate lost data.

4. Durbin (1960a)[2]

This two step procedure basically involves the treatment of a simple autoregressive model (where the usual definitions hold)

$$Y_t = f\,(X_t,\ e) \qquad (2.4)$$

in the following manner

$$Y_t = f\,(Y_{t-1},\ X_t,\ X_{t-1},\ e) \qquad (2.5)$$

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[1]See, for example, (Johnston, 1972, pp. 259-261).

[2](Durbin, 1960a, pp. 139-153) The discussion of the suggested method of handling an autoregressive model in which there are no lagged dependent variables on the right hand side is found between pages 150-153.

Model (2.5) is fit by OLSE techniques and an estimate of the degree of autocorrelation between successive residuals is given by the estimated regression coefficient for Y_{t-1}. This estimate is used to transform all of the original variables and the OLSE methodology is re-applied to the transformed data in order to obtain estimates of the true parameters of (2.4). Durbin has shown that the regression coefficients thus obtained from (2.4) are asymptotically more efficient than the original OLSE estimators of (2.4) and equally efficient (and possessing the same asymptotic properties) as the MLE estimators.

J. Durbin has essentially suggested another type of first-difference approach to estimate ρ.

5. Maximum Likelihood Estimation

A method not generally in use, because of the complexity of solution, is the MLE method for regression parameter estimation. Though the MLE method is widely used for correctly specified models that meet all the necessary assumptions,[1] its usage for models exhibiting autocorrelated error terms is limited because of cost and time constraints.[2]

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[1]Christ (1966) notes, "The maximum likelihood method is widely used and is important because in many applications it yields estimators that are consistent, asymptotically normal, and asymptotically efficient," (p. 372).

[2]Rao and Griliches, in comparing small sample properties of this method, note that since it is not assured that the sample likelihood function has only one local maximum that the entire range of ρ from 1.0 to -1.0 should be taken to assure a global maximum of the likelihood function. Obviously this can be very time consuming and costly, (1969, p. 2).

The method only requires that the normality assumption (assumption 1) be met, and then estimates of the regression coefficients and the correlation coefficient between successive residuals (measured by ρ) are simultaneously determined. The procedure is carried out under a nonlinear restriction and the estimates thus determined are those that are at least as likely to generate the observes sample as in any other set of estimators. As this method appears to be expensive, time consuming, and tedious, it is not generally a popular method for treating error autocorrelated models. Furthermore, in small samples, Rao and Griliches have shown this method to be "...somewhat inferior to the two-stage estimators...," (1969, p. 260).

6. Conclusion

The presence of autocorrelated error in any model presents a problem. Granger and Newbold (1974b, p.111) categorize three well known consequences of error autocorrelation as:

1. Estimates of the regression coefficients are inefficient.
2. Forecasts based on the regression equations are sub-optimal.
3. The usual significance tests on the coefficients are invalid.

However, it has been shown elsewhere (in terms of an OLSE procedure) that once the proper correction for error autocorrelation has been made the OLSE results are consistent, unbiased, and asymptotically efficient.[1] Of the various methods suggested for handling error serial correlation in time series data, the differencing approach appears to be remarkedly popular. Of the two stage iterative approaches, the decision as to which to use generally distills to one of personal preference. It is known that for large samples, the second-stage estimators of all the methods discussed herein are asymptotically efficient, unbiased, and consistent if the first-stage estimators of the error variance-covariance matrix are consistent. In the case of small samples, some question arises as to the most efficient two-stage method to be used.

Of the three methods we have discussed in this section, all vary as to the procedure for estimating the degree of error autocorrelation that exists in the model. The basic difference in each case is between an empirical or a priori estimation of the type of error correlation that exists in the model. As past studies have shown all the methods we have discussed to be identical for large samples, we choose to use the iterative process. We now turn to a short proof of this iterative process.

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[1]See Kmenta (1971, pp. 270-282) for a detailed discussion of the implications of autocorrelated errors on the OLSE estimators. Also see Kmenta (1971, pp. 282-292) for a good brief review of the most commonly employed methods of dealing with autoregressive error.

C. The Iterative Methodology

The results of a violation of the OLSE nonautoregression assumption have been set forth earlier. In our examples (wherein positive residual autocorrelation is observed), the effect on the OLSE estimation may be summarized as follows:

1. The regression coefficients are unbiased and consistent.
2. The variances of the regression coefficients are not minimal, hence the regression coefficients are not efficient.
3. The estimated variances of the regression coefficients are biased low.
4. The sample t and F values are too large.
5. The standard error of the estimate is biased low.
6. The R^2 value is biased high.

In this section we show the OLSE methodology is applicable and accurate if the error autocorrelation is properly detected and the appropriate steps are taken. We will also delineate the rules and guidelines utilized in this study to assure the OLSE assumptions were all met in the final analysis.[1]

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[1]After all, we wish to ascertain the causal and feedback relationships that may exist between the economic time series in question. To assume the problem of error autocorrelation away or to assume it nonsolvable would be reverting to the ostrich lemma. Dhrymes (1971, p. 55) has put it rather well, "On the other hand, we should bear in mind that it is the economic theoretic content of a model and behavior characteristics that are of crucial significance, and thus we should not turn to a theoretically deficient model simply because the estimation problem it presents cannot be easily tackled."

1. Correcting for error autocorrelation using an estimated variance-covariance matrix

Given the following simple[1] model (2.6), let us examine how one may effectively correct for known error autocorrelation:

$$Y_t = B_0 + B_1 X_{t,1} + u_t \qquad (2.6)$$

where Y_t is the endogenous variable, $X_{t,1}$ the exogenous variable, B_0 and B_1 are the regression parameters, and u_t is the first-order autocorrelated error. Two points of departure are possible; i.e., (1) if the true variance-covariance matrix of the error terms of (2.6) is known, then one simply proceeds with the GLSE procedure; (2) on the other hand, when the error variance-covariance matrix is not known, it must be estimated. After estimation and the appropriate transformation to correct for autocorrelation, one proceeds with the OLSE process.

As the error variance-covariance structure is rarely known in practice, the normal procedure is to estimate this structure by analyzing the residual output. Once the estimated autoregressiveness has been determined, the researcher proceeds to transform all the data, to correct for error autocorrelation, and then continues with the OLSE process. Does this transformation yield results commensurate to those of treating the autoregressiveness in the actual

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[1]For the sake of simplicity, all the discussion in this section will take place in terms of a first-order error autocorrelation series of a linear bivariate model.

model as per the autoregressive structure? The answer to that question is yes, as we now show.

Suppose the error autocorrelation structure is known to be of the following form:

$$u_t = \rho u_{t-1} + e_t \tag{2.7}$$

where u_t and u_{t-1} have been defined earlier as first-order serially correlated error terms, and ρ is the first-order autoregressive coefficient. Of course, e_t represents an error series that meets all the relevant OLSE assumptions, i.e. $e_t \sim \text{NID}(0, \sigma_t^2)$. In addition, we specify $\rho < |1.0|$.

In this study we argue that knowledge of the error autocorrelation allows the researcher to transform all the original variables and thereby reduce the residual series of the model to white noise. We wish now to compare the results of such a transformation to those obtained by treating the autoregressiveness of the error in the model.

Invoking expectations algebra, the actual relationship of Y_t regressed on $X_{t,1}$ would be

$$E(Y_t/X_{t,1}) = B_0 + B_1 X_{t,1} + u_t \tag{2.8}$$

combining (2.8) and (2.7), we obtain (2.9)

$$Y_t = B_0 + B_1 X_{t,1} + \rho u_{t-1} + e_t \tag{2.9}$$

Knowing that

$$u_{t-1} = Y_{t-1} - (B_0 + B_1 X_{t-1,1}) \tag{2.10}$$

means that by substitution of (2.10) into (2.9), collecting like terms, and simplifying, we obtain

$$(Y_t - \rho Y_{t-1}) = B_0(1-\rho) + B_1(X_{t,1} - \rho X_{t,1,1}) + e_t \qquad (2.11)$$

Equation (2.11) compares to that one would obtain by transforming (2.6) by the estimated first-order autoregressiveness of (2.7). This estimate would be

$$\hat{u}_t = r\,\hat{u}_{t-1} \qquad (2.12)$$

and the appropriate transformation[1] of each variable in (2.6) would be

$$\tilde{Y}_t = (Y_t - rY_{t-1}) \qquad (2.13)$$

$$\tilde{X}_{t,0} = (X_{t,0} - rX_{t-1,0}) \qquad (2.14)$$

$$\tilde{X}_{t,1} = (X_{t,1} - rX_{t-1,1}) \qquad (2.15)$$

The model of such transformed variables would be shown as

$$\tilde{Y}_t = B_0\,\tilde{X}_{t,0} + B_1\,\tilde{X}_{t,1} + e_t \qquad (2.16)$$

or

$$(Y_t - rY_{t-1}) = B_0(1-r) + B_1(X_{t,1} - rX_{t-1,1}) + e_t \qquad (2.17)$$

comparison of (2.17) and (2.11) will indicate the similarity of the two equations. The appropriate question is, how accurate is the estimate

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[1]The symbol " $\sim$ " indicates a transformed variable.

r of ρ ? This is a question to which Amemiya (1973) has addressed himself.

Amemiya (1973) has shown that for the fairly complex case of a mixed ARIMA (Arithmetic, Integrated, Moving Average) residual process (as determined by regressing the OLSE residual on itself, lagged L times), provides GLSE estimators that are equal to the BLUE estimators. Further, both processes are asymptotically normal. As the detail and depth of the proof goes beyond the scope of this study, we will not discuss the Amemiya (1973) work in detail. An interesting question posed, but not answered by the author, is how to choose L, the number of past period residuals to utilize in estimating the error variance-covariance structure. Another question posed by Amemiya (but not answered) involves sample size. That is, how large must sample size be to ensure the best estimate (as determined by the residual structure analysis) of the error autoregressiveness. The general guidelines given by the author lead one to conclude that (1) L should be increased until independence between the current residual process and lagged residual processes occurs, and (2) sample size should be kept large. The asymptotic properties are best fulfilled under these two conditions. In general these guidelines have been followed in this study.

The final remaining question is, to what degree, if any, does autocorrelated error (if corrected for) conflict with the validity of the remaining OLSE assumptions? Kmenta (1971, pp. 270-273) has shown that if the error series is autoregressive, as specified in (2.7), and

ρ is not equal to 1.0 or -1.0,[1] then by recognition of the generating process of estimated errors as a function of e_t and u_0, it can be shown that the first-order autoregressive process (2.7) does not in any way conflict with the remaining basic OLSE assumptions concerning the error term in the model. This is, of course, the essence of our argument.

We have shown that the OLSE methodology is not harmed by the presence of autocorrelated errors, if the appropriate correction for this autoregressiveness is carried out. We now discuss the guidelines by which one estimates the variance-covariance structure.

2. Rules and guidelines for selecting the estimated variance-covariance matrix

Though it is generally accepted that the researcher may utilize the estimated variance-covariance matrix, the problem of what guidelines to employ in order to decide the best estimate variance-covariance structure to use have not been determined.[2]

The following guidelines were utilized in this study to determine the most appropriate autoregressive representation of the residual

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[1]If the autoregressive nature of the error is specified as follows, Cov $(e_t, e_{t-s}) = \rho^s \sigma^2$; then Kmenta (1971, p. 270) notes that if $|\rho| = 1$, then the covariances do not diminish as "s" increases and the variance of the residual would grow infinitely large.

[2]As stated earlier, most authors assume that Cov $(e_t, e_{t-s}) = \rho^s \sigma^2$ and that the residual structure is adequate to describe this relationship. However, the decision rules for determining the best residual series variance-covariance structure are not clearly defined in the literature and subjectivity on the part of the researcher is ultimately involved.

structure of a model, and hence specify the estimated variance-covariance structure.

a. Significance The order of the autoregressiveness was partially determined by the significance or non-significance (at the five per cent level and for a two-tailed t test) of successive r_i values. As an alternative rule (whenever successive r values were not all significant), the first r value and the last, or next to last, r value had to be significant (at the five per cent level and for a two-tailed t test).

The explanatory value of successively lagged $\hat{u}_t$'s in accounting for movements in $\hat{u}_t$ is being tested. As the explanatory value of successively further removed $\hat{u}_t$'s should generally decrease (but not necessarily geometrically), the alternative rule was needed.

b. Magnitude The absolute magnitude of successive r values should be generally decreasing. That is, the longer the observed autoregressive structure length, the smaller (in absolute terms) should be the value of succeeding r_i's.

The rationale for this rule is obvious. As one would expect the explanatory value of successively further removed $\hat{u}_t$'s to decrease, then this rule when coupled with that of significance[1] should adequately

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[1]In this type of modeling the absolute size of regression coefficients is most important, particularly if they are significant. However, insignificance does not warrant immediate dropping from further consideration. Sims (1972, p. 545) makes a point similarly related, "It is a truism too often ignored that coefficients which are 'large' from the economic point of view should not be casually set to zero no matter now 'insignificant' they are."

provide a reasonable estimate of the autoregressive structure of the residuals.

c. Durbin-Watson d statistic The value of this calculated statistic should be approximately 2.0. Though it is known that the d statistic becomes less powerful for higher-order schemes (because autoregressive residual models include lagged endogenous variables by definition), the d statistic still provides a good hint as to the possibility of higher-order schemes.[2] Durbin (1970) has set forth an improved statistic if endogenous variables are explicitly included in the regression. However, in this study, no effort was made to employ this improved test.

The significance, magnitude, and Durbin-Watson d statistic tests collectively should define the autoregressive scheme of each original model's residual series. If this scheme has been correctly identified then the appropriate transformations should be carried out. As a double check on the adequacy of the first three checks described above, two more incidental tests might be mentioned.

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[1]Naturally it is known that the D-W d tests for absence or presence of first-order autoregressiveness, but there is not reason to suspect that if first-order autoregressiveness is present, there is no second-order serial correlation. In fact, just the opposite would most likely be the case. Murphy (1973, p. 316) makes a similar point, "If these residuals are autocorrelated according to the d test, then a second order autoregressive scheme may be indicated. Similarly, the residuals from a second order pattern could be examined to indicate if a third order scheme is suggested, and so forth."

d. Signs The signs of contiguous r values should generally alternate, beginning with a positive value.

e. Unity The roots of the polynomial chosen to describe the autoregressive error structure should all fall within the unit circle. If this were not the case, an explosive, and nonstable, situation could occur. The common sense nature of both of the above two rules is apparent and has been alluded to earlier.

Once the appropriate autoregressive scheme estimate had been chosen, as outlined above, then the appropriate transformations were made and a second OLSE regression determined. As a test of the adequacy of this appropriate autoregressive scheme estimate, the residuals of the second OLSE regression were analyzed. This was done to test the residual adequacy as per the OLSE assumptions. The basic tests that were applied are next briefly set forth.

3. Testing for residual normality and independence

Though many statistical and plotting tests for the examination and analysis of residuals[1] have been set forth in the literature, the

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[1]See, as an example of some of the statistical tests that have been set forth, Anscombe and Tukey (1963, pp. 141-160). For some of the standard plotting tests, see some standard econometric tests, such as (Kane, 1968, pp. 360-361); (Murphy, 1973, pp. 301-304); etc.

following tests were undertaken to test the adequacy of the residual structure of the estimate model[1] in question.

a. Normality The basic test utilized in this study for ascertaining residual normality was to plot the empirical cumulative distribution function (e.c.d.f.) of the observed residuals for the transformed variable regression. The plot is actually determined by plotting the residual frequency against the ordered residuals. If the plot appears normal, then normality is assumed.[2]

b. Independence There are two tests for independence that were conducted. The Durbin-Watson d statistic was calculated and an OLSE fit of the lagged residuals of the estimate model in question was carried out. If the D-W d was close to 2.0, then first-order (and higher-order) autoregressiveness was assumed to be nonexistent. If the t tests conducted on the regression coefficients of the lagged OLSE were not significant, it was assumed that no autocorrelation remained in the residual structure.

As the basic constructs of the above three tests are well known and have generally been discussed earlier in this paper, no further discussion ensues. With these thoughts in mind, we close this general chapter by providing definitions of three terms peculiar to this study.

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[1]If the appropriate autoregressive scheme has been utilized to transform the original data, then the estimate model should yield a residual structure of $\hat{e}_t$ that is NID $(0, \sigma_t^2)$.

[2]For a proof of the expected shape of an e.c.d.f. of any normally distributed array, refer to selected standard statistics textbooks.

D. Definitions

1. White noise

A white noise series is one in which the observations are not correlated, and repeated samples from the series would yield equal variances. The concept of a "white" noise is analogous to the concept of "white" light wherein no subinterval of the visible spectrum predominates. The "noise" portion of the term refers to the observations being unsystematic. A "pure white noise series" is a white noise series in which the observations are also independent.

In this study the residual series we observe and test must meet more than the white noise or pure white noise restriction. That is, they must be both normally and independently distributed.

2. Causality and feedback

Causality is herein defined for temporal systems. The definitions herein set forth, though based on sophisticated *post hoc, ergo propter hoc* type of reasoning, are generally accepted in the literature, mostly because of the difficulty of finding feasible and testable alternatives.

Let the following definitions be given at the outset.[1]

1. X is a stationary stochastic process.
2. Y is a stationary stochastic process.
3. $\bar{X}$ represents a subset of *past* values of X.
4. $\bar{Y}$ represents a subset of *past* values of Y.

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[1]Granger (1969) sets forth definitions similar to this in an explanatory section following his general definitions. See pp. 429-430.

5. $\bar{\bar{X}}$ represents a subset of past and present values of set X.
6. $\bar{\bar{Y}}$ represents a subset of past and present values of set Y.
7. $(\bar{\bar{X}} - \bar{X})$ represents a subset of present values of set X.
8. $(\bar{\bar{Y}} - \bar{Y})$ represents a subset of present values of set Y.
9. σ^2 is the minimum predictive error estimate from an OLSE fit.
10. $\sigma^2(Y/X)$ represents the minimum predictive error estimate of the OLSE regression of Y on X.

With the above definitions in mind, causality between X and Y (Y_t is said to be causing X_t and is denoted $Y_t \longrightarrow X_t$) is defined as

$$\sigma^2(X/\bar{\bar{Y}}) < \sigma^2(X/\bar{\bar{Y}}-\bar{Y}) \tag{2.18}$$

Of course, X_t is said to be causing Y_t ($X_t \longrightarrow Y_t$) if

$$\sigma^2(Y/\bar{\bar{X}}) < \sigma^2(Y/\bar{\bar{X}}-\bar{X}) \tag{2.19}$$

Feedback is defined to exist between X and Y ($X \longleftrightarrow Y$) if both (2.18) and (2.19) occur. That is, feedback means bidirectional causality between the two series X_t and Y_t.

The testing of the above relationships becomes one of testing the predictive power of the lagged exogenous variables. The test is carried out in terms of F tests on the separate regressions. For example, if causality exists of the form $X_t \longrightarrow Y_t$ then the regression coefficients of the lagged X_t, as a group, should be significantly different from zero. The appropriate F calculation compares the two estimated mean square error of both regressions of Y_t on past and present X_t and Y_t on only present X_t.

In Chapter II we have discussed and presented the methodology employed in this study. We now proceed to present and discuss the results of the study.

III. THE MONEY AND INCOME MODELS

In this chapter the results of the money-income (and income-money) models will be presented and discussed. A specific example of the methodology being employed is first given for one of the money-income models. The empirical results of the four basic models are then given and evaluated. The subperiod models are next presented and discussed.

A. A Methodological Application

1. The methodological model

In order to aid the reader in visualizing the iterative procedure utilized in this study for handling the problem of autocorrelated error, the following example of the methodology, as applied to one variation of the money-income models, is presented. Where possible, reference is made to the corresponding empirical results; however, the discussion is primarily one of symbolic representation. The following symbols and representations are used throughout this section.

1. A hat " ^ " is used to signify an estimate of a parameter.
2. A tilda "~" is used to represent transformed variables.
3. An underlining bar "___" is representative of a matrix.
4. Elements of any matrix will be represented by the lower case of the matrix symbol. For example, any single element of $\underline{U}$ is specified as u.

Consider the following functional money-income relationship

$$M1^S = f\,(PI^S,\ S,\ Time,\ u) \tag{3.1}$$

where $M1^S$ represents nominal money stock seasonally adjusted, PI^S is nominal personal income seasonally adjusted, S represents seasonal dummies, Time represents the trend, and u represents the error term. In more specific terms, let this relationship imply that this month's money stock is dependent on previous levels of personal income, seasonal variation, and trend, as represented in (3.2).

$$M1_t^S = f\,(PI_t^S,\ PI_{t-1}^S,\ \ldots,\ PI_{t-12}^S;\ S_2,\ \ldots,\ S_{12};\ \text{Time},\ \text{Time}^2;\ u) \qquad (3.2)$$

where $M1_t^S$ represents today's nominal seasonally adjusted money stock, PI_t^S through PI_{t-12}^S represents today's and twelve lagged nominal seasonally adjusted personal income levels, S_2 through S_{12} are dummy variables chosen to represent monthly seasonal variations in $M1_t^S$.[1] Time represents the linear trend and Time^2 represents the quadratic trend. The seasonal dummies have been chosen to remove any seasonal variation that may occur in the time series. Time was chosen to remove any spurious correlation between the two time series in question due to the long run, coincidental, secular movements between money stock and personal income. Finally, u is representative of the error term.[2] Model (3.2) implies that today's level of seasonally adjusted, nominal money stock is dependent on the last

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[1] S_1 has been dropped to avoid a possible dummy trap and is now estimated with the intercept term. See Johnston (1972, pp. 178-180).

[2] As it is known the error structure of this model is autocorrelated, the symbol u is used to represent it rather than e, an error series fulfilling all the OLSE assumption requirements.

thirteen time period's level of nominal and seasonally adjusted personal income, seasonal variation, linear and quadratic trend, and error.

Given the above hypothesized relationship, the $M1^S$ and PI_t^S data were collected on a monthly basis between January, 1947 and through December 1974. Seasonality (S) was treated by building a dummy variable utilizing the code 1 for the month for which the data was collected and a 0 for the other eleven months. Time was symmetrically constructed by numbering each datum set from -162.0 to +161.0, including zero. Time and its square were thus constructed to reduce the degree of correlation between the two time series. Once the data were collected, coded, and adjusted, the $M1^S$ and PI^S variables were converted to natural logs.

In the matrix form, the hypothesized model may be represented as follows:

$$\underline{M1}^S = \underline{X}\,\underline{B} + \underline{U} \qquad (3.3)$$

where $\underline{M1}^S$ is a 324 x 1 vector.[1] $\underline{X}$ is a 324 x 28 matrix of independent variable, $\underline{B}$ is a 28 x 1 vector of regression parameters, and $\underline{U}$ is the 324 x 1 matrix of autocorrelated error terms. Under the OLSE procedure, the estimate model of (3.3) would be found as

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[1]Twelve observations were sacrificed because of the twelve month lag structure of the model. Given the sample size, and the difficulty of estimating lost observations, the sample size remained at 324 for model (3.3).

$$\underline{\hat{M1}}^{s} = \underline{X}\,\underline{\hat{B}} \qquad (3.4)$$

where $\underline{\hat{B}}$ now represents the regression coefficients, or a 28 x 1 vector of regression parameter estimates. We now turn to investigate the residual series of (3.4) as found by the OLSE fit of (3.3).

2. Correcting for autocorrelation

Let $\underline{U}$ represent the residual vector of (3.4). We desire to determine the autoregressive nature of this residual series by fitting a series of OLSE regressions of the general form

$$\hat{u}_t = \sum_{i=1}^{n} r_i\, \hat{u}_{t-i} + e_t \qquad (3.5)$$

where $\hat{u}_t$ represent the autocorrelated errors of $\underline{U}$, n represents the order of the autoregressive process, and e_t represents a residual series that is white noise. More specifically, five separate regressions of form (3.5) were fit,[1] i.e.

(1) $\hat{u}_t$ on $\hat{u}_{t-1}$ (3.6.1)

(2) $\hat{u}_t$ on $\hat{u}_{t-1}$, $\hat{u}_{t-2}$ (3.6.2)

$\vdots$ $\vdots$ $\vdots$

(5) $\hat{u}_t$ on $\hat{u}_{t-1}$, ..., $\hat{u}_{t-5}$ (3.6.5)

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[1]All five regressions were fit on a $\underline{U}$ of dimension 319 x 1. Though slightly wasteful of a few more degrees of freedom, it allowed the five fits to be accomplished in a single computer run.

Each equation thus fit by the OLSE technique yielded a vector of regression coefficients that described the autoregressive structure of each equation. This vector may be described as $\underline{R}$, whose estimate elements are r_t.

Each of the five regressions (3.6.1) to (3.6.5) were then analyzed in order to determine the degree and magnitude of the residual autoregressiveness of (3.4). Though there is an element of subjectivity in determining the equation that best describes the type of autoregressiveness, the decision guidelines outlined in Chapter II were utilized as best possible.

In the particular money-income model variant in question, the five equations (3.6.1) through (3.6.5) are presented in tabular form in Table 3.1 below. Utilizing the decision guidelines set forth in Chapter II, equation (3.6.3) was chosen as the most adequate equation describing the type of autoregressiveness found in (3.4),[1] and the coefficients, r_1, r_2, and r_3 are collectively referred to as the "autoregressive filters."

The next step in the iterative process is to transform all of the original independent and dependent variables as found in (3.2). This transformation is carried out in the following manner. Given the following empirical form of (3.6.3)

$$\hat{\hat{u}}_t = 0.952\,\hat{u}_{t-1} + 0.076\,\hat{u}_{t-2} - 0.103\,\hat{u}_{t-3} \tag{3.7}$$

[1]Equation (3.6.3) best met the <u>significance</u>, <u>signs</u>, <u>magnitude</u>, <u>unity</u>, and <u>Durbin-Watson</u> decision guidelines.

TABLE 3.1

THE REGRESSION COEFFICIENTS, DURBIN-WATSON VALUE, AND R^2 VALUE FOR THE FIVE LAGGED RESIDUAL MODELS OF THE SEASONAL MONEY-INCOME MODEL (3.2)

Equation	r_1	r_2	r_3	r_4	r_5	D-W	R^2
(3.6.1)	.933[a]					1.96	.93
(3.6.2)	.955[a]	-.023				2.01	.93
(3.6.3)	.952[a]	.076	-.103[d]			2.00	.93
(3.6.4)	.954[a]	.074	-.123	.021[e]		2.00	.93
(3.6.5)	.954[a]	.070	-.121	.051	-.031[e]	2.00	.93

[a]Significantly different from zero at .5 per cent.
[b]Significantly different from zero at 1 per cent.
[c]Significantly different from zero at 2.5 per cent.
[d]Significantly different from zero at 5 per cent.
[e]Significantly different from zero at 10 per cent.

let $\tilde{A}_t$ represent the variable to be transformed where $t = 1, 2, \ldots,$ 324. Let $\tilde{A}_t$ represent the transformed variable A_t, and let e_t represent the white noise error series. The specific transformation on any variable in model (3.2) is shown as

$$\tilde{A}_t = A_t - 0.952\, A_{t-1} - 0.076\, A_{t-2} + 0.103\, A_{t-3} \tag{3.8}$$

Once this transformation has been carried out on all the variables in (3.2), the OLSE fit of the autoregressively filtered (transformed) variables now yields a second stage estimate model as

$$\underline{\hat{\tilde{M1}}}^{s} = \underline{\tilde{X}}\,\underline{\hat{B}}' \tag{3.9}$$

where $\underline{\hat{B}}'$ represents the regression coefficient vector for the transformed variables. The differences between estimate equations (3.4) and (3.9) may be given as follows:

1. The sample size of (3.4) is 324, whereas in (3.9) it is only 321.
2. Estimate equation (3.9) is a more asymptotically efficient estimate of the hypothesized relationships of (3.2) than estimate equation (3.4).[1]

If the correct autoregressive filters have been chosen, then estimate

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[1]The improvement in efficiency of such two stage processes has been clearly shown by Rao and Griliches (1969, pp. 253-272). However, the degree to which the relationship is true still depends on such considerations as whether (a) the model is correctly specified, (b) there are any errors in variables, (c) the autoregressive filters are appropriate, (d) etc.

model (3.9) may be analyzed according to the first-order tests set out in Chapter II. In addition the residual structure of (3.9) may be tested for normality and nonautoregressiveness. (If the transformations carried out above did reduce the residual structure to white noise, the second-order tests should so indicate.) If it was felt the estimate model was adequate according to the criteria outlined in Chapter II, then tests for both causality and feedback were conducted. If, on the other hand, the estimate model was judged lacking,[1] then the above process was repeated after making the following calculation.

Utilizing the following relationship,

$$\underline{U}' = \underline{M1}^s - \underline{X}\,\hat{\underline{B}}' \tag{3.10}$$

As $\underline{X}\,\hat{\underline{B}}'$ is equal to $\hat{\tilde{\underline{M1}}}^s$, a new transformed residual series $\underline{U}'$ was determined by calculating the transformed dependent variable estimate ($\tilde{\underline{M1}}^s$) according to the relationship specified in (3.9)[2]. That is, the transformed $\hat{b}'$ estimates of matrix $\hat{\underline{B}}'$ of (3.9) were multiplied times each original independent variable with which they were associated.

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[1]Generally speaking, an estimate model was judge lacking if the D-W d statistic indicated serial correlation (at least in the first-order) still existed in the residuals of (3.9) and the residuals still appeared to be nonrandom as per a plot. The entire criteria by which an estimate model were judged is outlined in Chapter II.

[2]Note, the residual series of (3.10) is not the same as the residual series of (3.9). The residual series of (3.10) need not be calculated, however, if the residual series of (3.9) possessed the white noise properties.

Then, by subtracting the resultant matrix of above from the original independent variable matrix, the new estimated residual series was determined.

The steps discussed between equation (3.6.1) and estimate model (3.9) were then carried out until more positive test results are obtained. Once a white noise residual structure was obtained for a model like (3.9), however, the following two tests were conducted to test for causality and feedback.

3. Testing for causality

The tests for causality were set out in Chapter II. Given the specific money-income model under consideration, the causality test is conducted on the following two variants of that model:

$$\underline{\hat{\widetilde{M1}}}^{s}_{tx1} = \underline{\widetilde{X}}_{tx28}\,\underline{\hat{B}}'_{28x1} \tag{3.12}$$

and

$$\underline{\hat{\widetilde{M1}}}^{s}_{tx1} = \underline{\widetilde{X}}_{tx16}\,\underline{\hat{B}}'_{16x1} \tag{3.13}$$

(3.12) is the full model having current and lagged PI^{s} variables, eleven seasonal dummy variables, two time variables, and an intercept term. Model (3.13), on the other hand, consists of only current PI^{s}, eleven seasonal dummy variables, two time variables, and an intercept term. The test for causality is conducted by comparing the sum of squares for deviation (or error) in each model variant. The test is basically one of comparing the degree to which the lagged exogenous variables reduce the residual mean square error.

If we let SSDEV (28) and MSDEV (28) represent the sum of squares for error and mean squares for error in the full model and SSDEV (16) represents the nonlagged model sum of squares for error, then it has been shown that the following F test is appropriate for testing causality.[1]

$$F\,(n, d) \;=\; \frac{\dfrac{\text{SSDEV (16)} - \text{SSDEV (28)}}{12}}{\text{MSDEV (28)}}$$

If the calculated F value is significant as compared to the tables F value[2], then causality is said to exist between PI^S and $M1^S$ and the direction of causality is from PI^S to $M1^S$. The next important question revolved around feedback.

4. Testing for feedback

The tests for feedback have been set out and defined in Chapter II. Basically, however, in order to test for feedback the causality test must be applied in two variants of both the money-income and the income-money model. Recall that the two variants of the money-income model were set out in (3.12) and (3.13). Assume as before that SSDEV (28) represents the error sum of squares for the full money-income model and SSDEV (28)' the error sum of squares for

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[1]See Granger (1969, pp. 428-429).

[2]The degrees of freedom, 'n' for the numerator will be 12. However, the degrees of freedom, 'd', for the denominator MSDEV (28) will vary according to the number of linear filters used to "pre-whiten" the time series in question.

the full income-money model. Therefore MSDEV (28) and MSDEV (28)' follow in definition for the full model of money-income and income-money respectively. It should be obvious then that SSDEV (16) and SSDEV (16)' are the error sum of squares for the money-income model and the income-money model in turn. So in addition to (3.12) and (3.13), the money-income model variants, we have (3.14) and (3.15), the income-money variants

$$\hat{\tilde{\underline{PI}}}^{s}_{tx1} = \tilde{\underline{X}}_{tx28}\,\hat{\underline{B}}'_{28x1} \tag{3.14}$$

$$\hat{\tilde{\underline{PI}}}^{s}_{tx1} = \tilde{\underline{X}}_{tx16}\,\hat{\underline{B}}'_{16x1} \tag{3.15}$$

The independent variable matrix of (3.14) is composed of thirteen current and lagged $M1^{s}$ variables, eleven seasonal dummies, and two time variables. In (3.15) the twelve lagged $M1^{s}$ variables are dropped and all else remains the same.

The F test for causality in the income-money model then becomes

$$F\,(n, d) = \frac{\dfrac{SSDEV\,(16)' - SSDEV\,(28)'}{12}}{MSDEV\,(28)'}$$

Reverting to the Granger definition of feedback as set forth in Chapter II, feedback is said to occur between two economic time series if both relevant F tests are significant. That is, if the F calculated values are greater than the F table values in both the money-income model and the income-model, then feedback is said to occur.

We next discuss the empirical results of the money-income and income-money models for the full time period between 1947 and through 1974 and the subperiod models between 1947 and 1968, and between 1969 and through 1974.

B. Empirical Results for the Money and Income Models

The results for the income-money and money-income models for the entire time period utilizing $M1^s$, $M1^{ns}$, and PI^s are herein presented and discussed. Then the results of the two subperiod (1947-1968 and 1969-1974) income-money and money-income models are given for the $M1^s$ and PI^s variables. The decision to drop $M1^{ns}$ in the subperiod models was two fold:

1. cost and time constraints, and the
2. suspicion that deseasonalization of the PI^s variable as contrasted to nondeseasonalization of the $M1^s$ could spuriously bias the results.[1]

The results of our analysis lead us to conclude the following: A strong relationship exists between economic activity and money. More specifically, if economic activity is adequately proxied by monthly, nominal personal income, and if money stock is an adequate representation of money, and if our model representations do meet the necessary assumptions, then it is our finding that seasonally adjusted money and economic activity are causally related in a

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[1]Sims (1972, p. 546) makes a similar point regarding two time series that have been deseasonalized by varying procedural assumptions. The better situation would be to have two raw data sets and proceed with the analysis. However, as monthly raw data were not available for our chosen variables, we kept our lag structures long enough and free enough in form (as suggests Sims) to avoid possible bias.

bidirectional manner. Alternatively, we might state that feedback exists between seasonally adjusted money and economic activity. We now proceed to show our results in more detail.

1. Money and income models, 1947-1974

In Tables 3.2 and 3.3 the full period regression coefficients and standard deviations for the current and lagged PI^s and $M1^s$ (or $M1^{ns}$) variables as well as the linear and quadratic trend variables are shown for the original autocorrelated error model and the final nonautocorrelated error model. The results of the final models in each case are those to which we will mostly devote our discussion.

a. $M1^s$ on PI^s The regression coefficients of this regression equation suggest that there is a generally decreasing lag structure in the impact of personal income on money stock. Further, the standard deviations of these regression coefficients vary in a consistently decreasing fashion and possess an extremely small range of variation. The range of the largest and smallest standard deviations of the current and twelve lagged PI^s regression coefficients is between .027 and .035. No economic reason can be given for the statistical significance of the PI^s_{t-8} regression coefficient, but when all twelve lagged regression coefficients are collectively tested as a group (see Table 3.4), we find that they vary significantly from zero at the 5 per cent level. The test for causality between PI^s and $M1^s$ leaves us to conclude that causality, as defined earlier in this study, does exist from PI^s to $M1^s$; that is, $PI^s \longrightarrow M1^s$.

TABLE 3.2

LAG DISTRIBUTIONS FROM TIME DOMAIN REGRESSIONS OF MONTHLY MONEY STOCK AND PERSONAL INCOME, SEASONALLY ADJUSTED, 1947-1974[a]

Coefficient[d] on[e]	Original $M1^s$ on PI^s	Final[b] $M1^s$ on PI^s	Original PI^s on $M1^s$	Final[c] PI^s on $M1^s$
t	.667[e]	.089[e]	.810[e]	.199[e]
	(.157)	(.034)	(.328)	(.096)
t-1	.050	.093	.095	.163
	(.227)	(.034)	(.502)	(.097)
t-2	-.109	.006	-.256	-.063
	(.226)	(.034)	(.499)	(.097)
t-3	-.004	.057	.100	.066
	(.225)	(.035)	(.491)	(.100)
t-4	-.064	.057	-.072	-.063
	(.182)	(.034)	(.490)	(.098)
t-5	-.010	.010	-.095	.029
	(.168)	(.034)	(.489)	(.099)
t-6	-.165	-.034	.256	.273[e]
	(.167)	(.034)	(.489)	(.099)
t-7	.033	.013	.035	-.142
	(.166)	(.034)	(.490)	(.099)
t-8	.023	.083[e]	.113	.114
	(.164)	(.031)	(.491)	(.098)
t-9	-.102	.009	.133	.141
	(.167)	(.029)	(.492)	(.100)

[a]Regressions were run using natural logs of the $M1^s$ and PI^s variables. After the "original" regression was run, all the variables were filtered by the appropriate linear filters, as shown in this table. The "final" regression was on the filtered variables. Each final regression shown in the table includes the current and lagged values of the independent variable of $M1^s$ or PI^s, a constant term, eleven seasonal dummies, and a linear and quadratic trend term.

[b]Seasonal dummies S_5, S_6, S_7, and S_{12} were significantly different from zero for the final regression $M1^s$ on PI^s.

[c]No seasonal dummies were significantly different from zero for the final regression PI^s on $M1^s$.

[d]The subscripts t, t-1, t-2, ..., t-12 represent the relevant current and lagged $M1^s$ or PI^s variable time periods.

[e]Significantly different from zero, 5 per cent level.

TABLE 3.2--Continued

Coefficient[d] on[e]	Original $M1^s$ on PI^s	Final[b] $M1^s$ on PI^s	Original PI^s on $M1^s$	Final[c] PI^s on $M1^s$
t-10	-.082	-.007	.338	.186
	(.167)	(.028)	(.500)	(.096)
t-11	.026	.006	.171	.020
	(.166)	(.028)	(.501)	(.097)
t-12	.486[e]	.011	-.742[e]	-.001
	(.123)	(.027)	(.328)	(.095)
Time	-.002[e]	.001	.003[e]	.003[e]
	(.0001)	(.001)	(.001)	(.0004)
$Time^2$	.000003[e]	.000006[e]	-.000001[e]	-.000001
	(.0000002)	(.000001)	(.0000003)	(.000002)
Linear Filters				
r_1		1.108[e]		1.000[e]
r_2		.003		.099
r_3		.025		-.279[e]
r_4		-.135[e]		.235[e]
r_5		-.029		-.004
r_6		-		.015
r_7		-		-.153[e]
r_8		-		.028

TABLE 3.3

LAG DISTRIBUTIONS FROM TIME DOMAIN REGRESSIONS OF MONTHLY MONEY STOCK, NOT SEASONALLY ADJUSTED AND PERSONAL INCOME, SEASONALLY ADJUSTED, 1947-1974[a]

Coefficient[d] on[e]	Original $M1^{ns}$ on PI^{s}	Final[b] $M1^{ns}$ on PI^{s}	Original PI^{s} on $M1^{ns}$	Final[c] PI^{s} on $M1^{ns}$
t	.724[e]	.162[e]	.707[e]	.181[e]
	(.161)	(.059)	(.203)	(.073)
t-1	-.028	.040	.108	.125[e]
	(.233)	(.060)	(.266)	(.064)
t-2	-.120	-.038	-.090	-.014
	(.231)	(.064)	(.265)	(.063)
t-3	.046	.085	.059	.085
	(.230)	(.069)	(.260)	(.063)
t-4	.019	.067	-.109	-.062
	(.186)	(.069)	(.260)	(.063)
t-5	.041	-.026	.066	.112
	(.172)	(.069)	(.260)	(.064)
t-6	-.130	-.030	.062	.076
	(.171)	(.069)	(.260)	(.064)
t-7	-.044	.041	.096	.090
	(.170)	(.066)	(.260)	(.064)
t-8	.028	-.001	.109	.075
	(.167)	(.055)	(.260)	(.063)
t-9	-.097	-.027	.157	.098
	(.170)	(.055)	(.258)	(.064)

[a]Regressions were run using natural logs of the $M1^{ns}$ and PI^{s} variables. After the "original" regression was run, all the variables were filtered by the appropriate linear filters, as shown in this table. The "final" regression was on the filtered variables. Each final regression shown in the table includes the current and lagged values of the independent variable of $M1^{ns}$ or PI^{s}, a constant term, eleven seasonal dummies, and a linear and quadratic trend term.

[b]All seasonal dummies were significantly different from zero for the final regression $M1^{ns}$ on PI^{s}.

[c]All seasonal dummies but S_{12} were significantly different from zero for the final regression PI^{s} on $M1^{ns}$.

[d]The subscripts t, t-1, t-2, ..., t-12 represent the relevant current and lagged $M1^{ns}$ or PI^{s} variable time periods.

[e]Significantly different from zero, 5 per cent level.

TABLE 3.3--Continued

Coefficient[d] on	Original $M1^{ns}$ on PI^{s}	Final[b] $M1^{ns}$ on PI^{s}	Original PI^{s} on $M1^{ns}$	Final[c] PI^{s} on $M1^{ns}$
t-10	-.103	.001	.224	.098
	(.171)	(.052)	(.265)	(.064)
t-11	.047	-.009	.081	.051
	(.169)	(.048)	(.266)	(.064)
t-12	.499[e]	.056	-.582[e]	-.036
	(.125)	(.047)	(.203)	(.072)
Time	-.002[e]	.001	.003[e]	.003[e]
	(.0002)	(.001)	(.0001)	(.000)
$Time^2$	.000003[e]	.000007[e]	-.0000008[e]	-.0000003
	(.0000002)	(.0000002)	(.0000003)	(.0000002)
Linear Filters				
r_1		.824[e]		1.023[e]
r_2		-.047		.090
r_3		.438[e]		-.278[e]
r_4		-.251[e]		.238[e]
r_5		-		-.124[e]
r_6		-		-
r_7		-		-
r_8		-		-

TABLE 3.4

F-TESTS OF THE FULL PERIOD (1947-1974) REGRESSIONS OF MONTHLY MONEY STOCK, SEASONALLY ADJUSTED AND NONSEASONALLY ADJUSTED AND PERSONAL INCOME, SEASONALLY ADJUSTED[a]

Regression	df	F Value
$M1^{s}$ on PI^{s}	12; 292	1.837[b]
$M1^{ns}$ on PI^{s}	12; 293	.676
PI^{s} on $M1^{s}$	12; 289	3.015[c]
PI^{s} on $M1^{ns}$	12; 292	2.306[c]

[a]The F test was made on the Mean Square Error Difference of (a) the full model of one current and twelve lagged independent variables ($M1^{s}$, $M1^{ns}$, or PI^{s}), eleven seasonal dummies, linear and quadratic trend, and a constant term and (b) the partial model consisting of all the same variables as above with the exception of the relevant twelve lagged independent variables ($M1^{s}$, $M1^{ns}$, or PI^{s}).

[b]Significantly different from zero, 5 per cent level.

[c]Significantly different from zero, 1 per cent level.

<u>b. PI^s on $M1^s$</u> The standard deviations of the current and lagged $M1^s$ variables (as shown in Table 3.2) are even better behaved in terms of their variability; that is, they range between .095 and .100. The same cannot be said of the regression coefficients, however, as they vary between -.142 and .273. The algebraic sum of these regression coefficients, however, is .922, suggesting that in total, the elasticity of PI^s with respect to the money stock is close to unity over the thirteen month time period. The test for causality of PI^s on $M1^s$ shows causality does exist of the type $M1^s \longrightarrow PI^s$. This result is significant at the 5 per cent level and is shown in Table 3.4.

For the two final regressions reported in Tables 3.2 and 3.3, the residual structures appeared to meet both the normality and independence restrictions. The results suggest that feedback (or bidirectional causality) exists between monthly seasonally adjusted personal income and money stock. The causality between $M1^s \longrightarrow PI^s$ does appear to be a stronger relationship than causality of the form $PI^s \longrightarrow M1^s$.

We now discuss the monthly nonseasonal money stock and seasonal personal income regression results. Reference to Tables 3.3 and 3.4 is made at this point.

<u>c. $M1^{ns}$ on PI^s</u> The results of this final regression suggests that no causality of the form $PI^s \longrightarrow M1^{ns}$ exists in the total sample period between 1947 to 1974. The reason for this apparent

result has been alluded to in the introduction to this section.[1] The sum of the regression coefficients is .779 and the range of the standard deviations of these regression coefficients for personal income (current and lagged) was between .047 and .069. The regression coefficients ranged between -.038 and .162 with the PI_t^s variable being the only one of the current and lagged personal income variables whose regression coefficient was significantly different from zero.

<u>d. PI^s on $M1^{ns}$</u> The regression coefficients of this final regression showed more variability than the $M1^{ns}$ on PI^s, having a range of -.062 to .181. The standard deviations of these regression coefficients of the current and lagged money stock, nonseasonally adjusted possessed range between .063 to .073, a smaller range than the $M1^{ns}$ on PI^s regression. The $M1_t^{ns}$ and $M1_{t-1}^{ns}$ regression coefficients differed significantly from zero in this final model and a linear trend significance was noted. When it came to testing causality, a $M1^{ns} \longrightarrow PI^s$ causality was found to exist. However, the hypothesis of feedback or bidirectional causality was rejected as $PI^s \longrightarrow M1^{ns}$ did not exist.

In summary, for the full time period models, the seasonally adjusted data seemed to behave as expected and, for the most part, the seasonal dummies were not important variables in these regressions. The nonseasonally adjusted money stock data did not provide results consistent to those found for the seasonally adjusted money stock. However, the seasonal dummies were generally significant in the

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[1]It is curious, however, that the reverse causality of $M1^s \longrightarrow PI^s$ is found to exist at the 1 per cent level of significance (see Table 3.4).

nonseasonal money stock data regressions as would be expected. The $M1^s \rightarrow PI^s$ causality does seem to be a slightly stronger observed relationship than the $PI^s \rightarrow M1^s$ causality. In all cases, the residual structure, when subjected to the normality and independence tests, did appear to be normally and independently distributed. Even if one did not accept the e.c.d.f. results as adequate proof of residual normality, there could be no doubt as to the white noise characteristic of the residual structures in each case. We will now discuss the subperiod models of income-money and money-income for the seasonally adjusted data.

2. Money and income models, 1947-1968 and 1969-1974

Tables 3.5, 3.6, and 3.7 are relevant to the following discussion. The subperiod models were only conducted on the seasonally adjusted data, due to money and time constraints and the suspicion of the spurious relationship that might occur when utilizing data treated for seasonality and nonseasonality respectively.

The choice of subperiod division was based on the generally accepted fact that prior to 1968 the monetary authorities were considering the market rate of interest the target variable. Thus, as income changed in response to the authorities' moves to maintain a stable market rate of interest, the money stock generally moved in tandem with income. However, after 1969 more emphasis was placed on money stock as the target variable, hence one would suspect a more adequate test of causality between money and income during the later subperiod if causality did exist. That is, when the market rate of interest is stable,

TABLE 3.5

LAG DISTRIBUTIONS FROM TIME DOMAIN REGRESSIONS OF MONTHLY MONEY STOCK AND PERSONAL INCOME, SEASONALLY ADJUSTED, SUBPERIOD 1947-1968[a]

Coefficient[d] on[e]	Original $M1^s$ on PI^s	Final[b] $M1^s$ on PI^s	Original PI^s on $M1^s$	Final[c] PI^s on $M1^s$
t	.524 (.136)	.083[e] (.031)	1.431 (.425)	.258 (.142)
t-1	.072 (.201)	.098[e] (.031)	-.257 (.659)	.024 (.143)
t-2	-.075 (.199)	.020 (.031)	-.401 (.657)	.117 (.144)
t-3	-.020 (.197)	.081[e] (.033)	.090 (.643)	.032 (.155)
t-4	.121 (.154)	.087[e] (.032)	.029 (.650)	-.080 (.154)
t-5	-.006 (.141)	.004 (.032)	-.026 (.651)	.135 (.154)
t-6	-.143 (.140)	.015 (.032)	.148 (.650)	.171 (.154)
t-7	.049 (.137)	.080[e] (.029)	.223 (.650)	.059 (.155)
t-8	-.017 (.134)	.031 (.025)	-.095 (.649)	.075 (.154)
t-9	-.077 (.138)	.032 (.026)	.180 (.643)	.330[e] (.156)

[a]The subperiod regressions were run using natural logs of the $M1^s$ and PI^s variables. After the "original" regression was run, all the variables were filtered by the appropriate linear filters, as shown in this table. The "final" regression was on the filtered variables. Each final regression shown in the table includes the current and lagged values of the independent variable of $M1^s$ or PI^s, a constant term, eleven seasonal dummies, and a linear and quadratic trend term.

[b]Only seasonal dummy S_{11} was significantly different from zero for the final regression $M1^s$ and PI^s.

[c]No seasonal dummies were significantly different from zero for the final regression PI^s and $M1^s$.

[d]The subscripts t, t-1, t-2, ..., t-12 represent the relevant current and lagged $M1^s$ or PI^s variable time periods.

[e]Significantly different from zero, 5 per cent level.

TABLE 3.5--Continued

Coefficient[d] on[e]	Original M1[s] on PI[s]	Final[b] M1[s] on PI[s]	Original PI[s] on M1[s]	Final[c] PI[s] on M1[s]
t-10	-.075	.022	.619	.260
	(.138)	(.025)	(.657)	(.148)
t-11	.013	.028	.457	.041
	(.137)	(.024)	(.655)	(.147)
t-12	.352[e]	.041	-1.283[e]	-.242
	(.101)	(.024)	(.428)	(.161)
Time	-.001[e]	-.001	.002[e]	.002[e]
	(.0001)	(.0005)	(.0001)	(.001)
Time^2	.000002[e]	.000002[e]	-.0000009[e]	.0000004
	(.0000002)	(.000001)	(.0000003)	(.000002)
Linear Filters				
r_1		1.116[e]		1.025[e]
r_2		.052		.087
r_3		-.010		-.329[e]
r_4		-.231[e]		.321[e]
r_5		-		-.167[e]
r_6		-		-
r_7		-		-
r_8		-		-

TABLE 3.6

LAG DISTRIBUTIONS FROM TIME DOMAIN REGRESSIONS OF MONTHLY MONEY STOCK AND PERSONAL INCOME SEASONALLY ADJUSTED, SUBPERIOD 1969-1974[a]

Coefficient[d] on[e]	Original $M1^s$ on PI^s	Final[b] $M1^s$ on PI^s	Original PI^s on $M1^s$	Final[c] PI^s on $M1^s$
t	.193	-.166	.415	.075
	(.264)	(.162)	(.321)	(.208)
t-1	.006	.121	.279	.334
	(.302)	(.162)	(.400)	(.182)
t-2	.035	.117	-.146	-.313
	(.295)	(.124)	(.393)	(.188)
t-3	-.137	.016	.268	.258
	(.294)	(.128)	(.386)	(.177)
t-4	.068	-.007	-.115	-.084
	(.280)	(.126)	(.387)	(.175)
t-5	-.045	.071	.001	.020
	(.289)	(.134)	(.387)	(.172)
t-6	-.060	-.203	.405	.451[e]
	(.312)	(.133)	(.387)	(.169)
t-7	-.245	-.145	-.475	-.418[e]
	(.293)	(.127)	(.387)	(.170)
t-8	.347	.353[e]	.017	.112
	(.284)	(.123)	(.388)	(.168)
t-9	-.048	.238	-.015	.032
	(.305)	(.145)	(.387)	(.165)

[a]The subperiod regressions were run using natural logs of the $M1^s$ and PI^s variables. After the "original" regression was run, all the variables were filtered by the appropriate linear filters, as shown in this table. The "final" regression was on the filtered variables. Each final regression shown in the table includes the current and lagged values of the independent variable of $M1^s$ or PI^s, a constant term, eleven seasonal dummies, and a linear and quadratic trend term.

[b]No seasonal dummies were significantly different from zero for the final regression PI^s on $M1^s$.

[c]No seasonal dummies were significantly different from zero for the final regression $M1^s$ on PI^s.

[d]The subscripts t, t-1, t-2, ..., t-12 represent the relevant current and lagged $M1^s$ or PI^s variable time periods.

[e]Significantly different from zero, 5 per cent level.

TABLE 3.6--Continued

Coefficient[d] on[e]	Original $M1^s$ on PI^s	Final[b] $M1^s$ on PI^s	Original PI^s on $M1^s$	Final[c] PI^s on $M1^s$
t-10	-.045 (.304)	-.017 (.149)	.079 (.394)	.027 (.173)
t-11	-.238 (.308)	-.096 (.154)	-.028 (.400)	.047 (.169)
t-12	.164 (.284)	-.101 (.157)	.543 (.302)	.158 (.185)
Time	.006[e] (.002)	.004 (.004)	.001 (.002)	.003 (.006)
$Time^2$	-.000025 (.000013)	-.00004 (.00003)	.00039[e] (.000007)	.00003 (.00004)
Linear Filters				
r_1		.924[e]		1.156[e]
r_2		-.091		-.287[e]
r_3		-.053		-
r_4		.158		-
r_5		-.243[e]		-
r_6		-		-
r_7		-		-
r_8		-		-

TABLE 3.7

F-TESTS OF SUBPERIOD (1947-1968 AND 1969-1974) REGRESSIONS OF MONTHLY MONEY STOCK AND PERSONAL INCOME, SEASONALLY ADJUSTED[a]

Time Period	Regression	df	F Value
1947-1968	$M1^s$ on PI^s	12; 221	3.941[c]
1969-1974	$M1^s$ on PI^s	12; 28	1.425
1947-1968	PI^s on $M1^s$	12; 220	1.995[b]
1969-1974	PI^s on $M1^s$	12; 31	4.727[c]

[a]The F test was made on the mean square error differences of (a) the full model of one current and twelve lagged independent variables ($M1^s$ or PI^s), eleven seasonal dummies, linear and quadratic trend, and a constant term and (b) the partial model consisting of all the same variables as above with the exception of the relevant twelve lagged independent variables ($M1^s$ or PI^s).

[b]Significantly different from zero, 5 per cent level.

[c]Significantly different from zero, 1 per cent level.

the money stock must move in concert with income, whereas when money stock varies, the movement of income would reflect possible causality.

a. $M1^S$ on PI^S Comparing the two subperiod models for causality of the form $PI^S \longrightarrow M1^S$, we find that between 1947 through 1968 and between 1969 through 1974 such causality did and then did not exist. Interestingly, although the causality significance was at the 1 per cent level in the earlier subperiod (whereas the null hypothesis of no causality is accepted in the later subperiod), the 1947-1968 subperiod model exhibited greater stability than the 1969-1974 subperiod model. That is, the regression coefficients in the earlier subperiod were all positive and were more generally decreasing than the later subperiod model. Further, the regression coefficient's standard deviations were much better behaved (in terms of the range between the largest and smallest and the general decreasing nature) in the earlier subperiod models than the later subperiod models. The general crisscrossing nature of the algebraic signs of the later subperiod model was puzzling but might be indicative of the "overshooting" phenomenon referred to by Mason (1976). In both cases the seasonal dummies, with one exception, were significantly different from zero, at the five per cent level. The regression coefficients of the earlier subperiod PI^S variables were significant at time period t, t-1, t-3, t-4, and t-7. In the later subperiod models the PI^S variables were not significantly different from zero except for the PI^S_{t-8} variable. Time was not significant in either the linear or quadratic case in the later subperiod, but was significant in the quadratic case for the later time period. For the 1947-1968 subperiod, feedback was found to exist between money stock and personal income. This was not the case for the later subperiod when causality was found to be unidirectional of type $M1^S \rightarrow PI^S$.

b. PI^S on $M1^S$ The final regressions for testing $M1^S \rightarrow PI^S$ causality showed that causality did exist in both subperiod regressions. As has been found earlier, the significance of the causality appears to be greatest for the case of $M1^S \rightarrow PI^S$. As was the case for the $M1^S$ on PI^S regressions, the earlier subperiod regression exhibited greater characteristics of stability than the 1969-1974 regression. That is, the range of the regression coefficients and their standard deviations are more narrow in the earlier subperiod as compared to the later subperiod. Not much can be said about the coefficient significance in each case. As would be expected, none of the seasonal dummies were significantly different from zero. Further, though not expected, the linear and quadratic trends were not significant in the 1969-1974 regression, though the linear trend was significantly different from zero in the earlier 1947-1968 subperiod.

In conclusion, the causal relationship between money and income appears to be more clearly apparent in the earlier subperiod regressions. There appears to exist feedback during this same time period, whereas this was not the case for the later subperiod regressions. If monetary policy has been deliberately chosen to have an impact on income (as measured by nominal, monthly, seasonally adjusted, personal income), since 1969 and through 1974, we might conclude that either overshooting or nondeciseiveness on the part of the policy makers has occurred.

In any case, the case for bidirectional causality (or feedback) is certainly more strong in this study than most recent studies have found. Several reasons might be given for this disparity in findings:

1. The usage of personal income as a measure of income in this study.
2. The usage of monthly data in this study.
3. The usage of more recent data in this study.
4. The degree and type of variable prefiltering in this study.

We repeat our earlier statement. The results of this study lead us to conclude that feedback exists between nominal monthly money stock and personal income, both seasonally adjusted, for the time period between 1947 to 1974.

In Chapter IV we discuss and present the consumption and disposable income models.

IV. CONSUMPTION AND DISPOSABLE INCOME MODELS

In this chapter the results of the quarterly, seasonally adjusted consumption-income and income-consumption models are presented and discussed. Both the consumption (C^S) and disposable income (DI^S) variables were collected on a quarterly basis between 1947 and through 1974.[1]

The purpose for including the consumption and disposable income regression results was twofold, i.e., they were included

1. as a further example of the usefulness of the iterative methodology for handling known error serial correlation in functional models, and
2. to provide an example of the importance of testing for causality and/or feedback prior to model building and testing.

That is, the consumption and disposable income models provide another example of the broad application of the iterative methodology. Further, however, they allow one to test hypothesized unidirectional causality relationships prior to regression analysis on such models.

In the particular case of consumption and disposable income, one way causality has always been implied. Though all economists now agree that consumption is not adequately explained as just a simple function of income, most all empirical models utilized for estimating consumption functions have included income as an exogenous variable. Haavelmo (1953) is credited with originally discussing the problem of

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[1]See Appendix A for data sources.

error autocorrelation in consumption functions having income as an independent variable. However, to solve the problem of error autocorrelation most empirical work (estimating consumption functions) has been carried out by including the one time period lagged endogenous variable on the right hand side of the relationship. This method is, of course, the method suggested by Durbin (1960a) and is sometimes called two stage least squares (TSLS). In our analysis, however, we have not included the endogenous variable as an "exogenous" variable, but have proceeded to correct for error autocorrelation and then test for causality and/or feedback.

A. Empirical Results for the Consumption and Income Models

In Tables 4.1 and 4.2 are found the summary of the complete original and final regressions of the consumption-income and income-consumption regression models. In each case the independent variable (whether C^S or DI^S) was lagged eight time periods, coupled with its current value. There were also three dummies, a linear and quadratic term, as well as the intercept term. In the four regressions shown in Table 4.1, the intercept term has been left out. The seasonal dummies and trend variables were coded in a like manner as the money and income models. Further, as in the money and income models, the seasonal dummies were included to test for significant seasonal variations in the dependent variable and Time and Time^2 were chosen and coded in such a manner as to remove any spurious correlation between the two time series (i.e. consumption and disposable income), due to their coincidental long run secular movements.

TABLE 4.1

REGRESSION RESULTS OF THE QUARTERLY CONSUMPTION AND DISPOSABLE INCOME MODELS, SEASONALLY ADJUSTED, 1946-1974[a]

Coefficient[b] on[c]	Original DI^s on C^s	Final DI^s on C^s	Original C^s on DI^s	Final C^s on DI^s
t	.034	.449[d]	-.049	.588[d]
	(.109)	(.085)	(.093)	(.077)
t-1	.108	.364[d]	.052	-.105
	(.168)	(.089)	(.154)	(.096)
t-2	.252	.061	.077	.291[d]
	(.210)	(.106)	(.161)	(.096)
t-3	-.171	.236[d]	.045	-.300[d]
	(.207)	(.108)	(.166)	(.091)
t-4	.033	.015	.020	.332[d]
	(.219)	(.113)	(.175)	(.092)
t-5	-.280	-.097	.103	-.213[d]
	(.220)	(.119)	(.176)	(.090)
t-6	-.064	.198	-.025	.113
	(.228)	(.117)	(.171)	(.090)
t-7	.245	.103	.207	.063
	(.224)	(.101)	(.163)	(.089)
t-8	.962[d]	-.183	.364[d]	.104
	(.168)	(.101)	(.102)	(.083)

[a]Each regression consisted of a constant term, one current and eight lagged values of the relevant independent variable C^s or DI^s, three seasonal dummies, and a linear and quadratic trend term. All variables were quarterly, seasonally adjusted data. The original regressions were on the data as collected, and the final regressions were on the filtered variables.

[b]Values in parentheses under each regression coefficient represent the regression coefficient standard deviation.

[c]The subscripts t, t-1, ..., t-8 represent the relevant current and lagged independent C^s or DI^s variable.

[d]Significantly different from zero, 5 per cent level.

TABLE 4.1--Continued

Coefficient[b] on[c]	Original DI^s on C^s	Final DI^s on C^s	Original C^s on DI^s	Final C^s on DI^s
S2	.836	-.187	-.312	.831
	(1.42)	(.577)	(.910)	(2.56)
S3	.651	-.226	-.074	3.98
	(1.34)	(.741)	(.908)	(2.93)
S4	1.119	-.365	-.838	1.94
	(.143)	(.577)	(.932)	(1.77)
Time	-.379[d]	-.225	.595[d]	.608[d]
	(.163)	(.223)	(.104)	(.215)
$Time^2$	-.003	.003	.003[d]	.005[d]
	(.002)	(.003)	(.001)	(.003)
r_1		-.986[d]		-.679[d]
r_2		.437[d]		.135
r_3		-.257[d]		-.012
r_4		.293[d]		-.396[d]
r_5		-		.205
r_6		-		.497[d]
r_7		-		-.254

TABLE 4.2

F TEST RESULTS OF MEAN SQUARE ERROR DIFFERENCE AS ATTRIBUTED TO LAGGED INDEPENDENT VARIABLES FOR THE QUARTERLY, SEASONALLY ADJUSTED CONSUMPTION AND DISPOSABLE INCOME REGRESSIONS, 1946-1974[a]

Final regression	df	F value
DI^s on C^s	8; 99	13.084[b]
C^s on DI^s	8; 94	6.124[b]

[a]Each regression consisted of either (a) a full model of a constant term, one current and eight lagged relevant independent variable C^s or DI^s, three seasonal dummies, and a linear and quadratic trend, or (b) a partial model of a constant term, one current relevant independent variable C^s or DI^s, three seasonal dummies, and a linear and quadratic trend.

[b]Significantly different from zero, 1 per cent level.

1. DI^S on C^S

The final regression of DI^S on C^S (see Table 4.1) shows a fairly stable decaying lag structure between the contiguous lagged consumption variables. Of the current and eight lagged consumption variables, only C^S_t, C^S_{t-1}, and C^S_{t-3} were significantly different from zero. None of the seasonal dummies or secular trend variables were significant. The test for causality indicated a strong causality between consumption and disposable income of the form $C^S \rightarrow DI^S$. The residual structure of the final model appeared to meet the independence and normality tests adequately. As a side note, the DI^S on C^S models only required two cycles to arrive at the final regression and the linear filters were, for the most part, fairly similar in each cycle. Such was not the case for the C^S on DI^S models, however. We now discuss the results of the C^S on DI^S models.

2. C^S on DI^S

The estimated autoregressive structure of the error of the C^S on DI^S model appeared to be fairly complex. The final filters (as shown in Table 4.1) indicated a seventh-order autoregressiveness. When lesser-order filters were applied, the model regression coefficients did not appear to be converging very quickly. Though the final results did not vary to a great degree from the intermediate results, the residual structure of the intermediate cycle regressions did not appear to meet the independence and normality assumptions. Perhaps, the causal relationship between consumption and disposable income ($DI^S \rightarrow C^S$) is intricately related to the level of the past two years disposable income. The size and placement of the final linear filters seemed to be indicating a lengthier lag structure than would be expected. The significance of the final model regression coefficients seemed to confirm this suspicion. That is, the regression coefficients of the variables DI^s_t, DI^s_{t-1}, and DI^s_{t-3} through DI^s_{t-6} were all significantly different from zero at the 5 per cent level. Both Time and Time^2 were also significantly different from zero, although the seasonal dummies were not significant. The F test results of causality testing indicated that $DI^s \longrightarrow C^s$ causality did exist in the consumption and income models. When considered in light of the $C^s \longrightarrow DI^s$ causality, the conclusion was that feedback (or bidirectional causality) existed between quarterly consumption and disposable income, seasonally adjusted between the time period beginning in 1947 and ending in 1974. This did not seem unreasonable. The only puzzling occurrence in the consumption and income models was in the C^s on DI^s final regression, wherein the crisscrossing of regression coefficient signs was observed. Some further analysis will be necessary to explain this occurrence.

B. Conclusion

The results of the consumption and income models certainly warrant some further research. Perhaps the time periods should be equally divided to test for sample consistency. Perhaps years of unusual consumption levels, such as the 'scare buying'[1] of the outset of the Korean conflict should be isolated and their bias to the sample taken into account. Whatever the case, there remains much to be done in studying consumption and income relationships and in this study we had simply discovered a few interesting facts regarding causality.

[1]Evans (1969) notes this era as a time period when consumption levels were rapidly increasing even though income levels were not rising. Such occurrences, if happening very often, would bias the observed causality relationships.

V. CONCLUSION

A. Overview of the Results of this Study

In this study causality and feedback have been tested for in a series of ordinary least squares estimation regressions. Special care has been exercised to correct for known error autocorrelation in each regression. The iterative methodology employed in this study for correcting for error autocorrelation has been carefully outlined and exemplified in Chapters II and III of this study. This iterative methodology utilized the residual structure of an initial (original) regression to estimate the degree and type of error autoregressiveness that exists in the true error structure. The usage of such an iterative procedure was originally set forth by Cochrane and Orcutt (1949), but only recently has it been suggested as a simpler, yet equally efficient as the more complex methods, process for dealing with error autocorrelation.

The regression models examined in this study have varied according to the time period under consideration and the dependent and independent variable specification in each case. In terms of time period, all data were collected for the years between 1947 and through 1974. The money and income model variable were monthly data and the consumption and income model variables were quarterly data.

The purposes of the study were twofold:

1. to exemplify the usefulness of the iterative methodology, and

2. to test for causality and feedback between some specific economic time series.

Our results have led us to conclude that bidirectional causality (or feedback) exists between monthly, seasonally adjusted money stock and monthly, seasonally adjusted personal income for the time period between 1947 and through 1974. The results of the causality and feedback tests lead us to conclude that causality from money stock to personal income is more significant than that of causality from personal income to money stock. For monthly nonseasonally adjusted money stock and monthly seasonally adjusted personal income for the subperiod between 1947 and through 1974, however, unidirectional causality of the type money stock to personal income is found.[1] For the subperiod between 1947 and through 1968, bidirectional causality is found to exist between personal income and money stock. For the subperiod between 1969 and through 1974, feedback (bidirectional causality) is not found to exist. However, unidirectional causality of the type $M1^S \rightarrow PI^S$ is found to exist. The observation of unidirectional causality of $M1^S \rightarrow PI^S$ is consistent with the conjecture that monetary policy makers were concerned with maintaining a stable growth rate in money stock during the subperiod 1969 through 1974 as compared to the desire to maintain a stable market rate of interest in the earlier subperiod between 1947 and through 1968. That is, if policy makers attempt to maintain a stable

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[1]Some doubt as to the validity of this relationship is raised when one recognizes the fact that money stock is nonseasonally adjusted whereas personal income is seasonally adjusted.

market rate of interest, then one would expect to find money stock and personal income movements in concert, and the tests for causality might be expected to show feedback in such cases. On the other hand, if monetary policy makers are controlling the money stock variable, any movement in personal income would not be expected to respond unless some degree of causality between the two did exist. It is, therefore, consistent with the results of the subperiod regression to conclude that monetary policy, as measured by a changing money stock, does have an impact on personal income. For the subperiod 1947 through 1968, the bidirectional causality is less significant for the personal income to money stock causality than for the $M1^S \longrightarrow PI^S$ causality.

The question arises as to why the results of this study are not consistent with other studies. Taking each study discussed in Chapter I, we briefly outline some of the reasons for the differences between the results of each study. Sims (1972) one way causality of type $M1^S \longrightarrow GNP$ is observed after prefiltering all the variables in the regression by a predetermined filter. The difference in results is probably due to three aspects of Sims work: (a) Sims choice of filters must certainly bias the results,[1] (b) the datum used by Sims for economic activity is GNP whereas our proxy was personal income, and (c) in this study we use monthly data whereas Sims used quarterly data. A final area of difference revolves around the Durbin (1960a) type approach of utilizing

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[1]We found in this study that the linear filters used in each model were considerably varied. It is difficult to believe that a single filter could be appropriate for the entire data base.

the endogenous variable on the right hand side of the equation. In this study we do not utilize this approach.

Dy Reyes' (1974) study also utilizes quarterly GNP data to measure economic activity. Of the three methods Dy Reyes sets forth for treating data prior to testing for causality, we find each not consistent with our procedure for some reason. For example, in Method I, as explained by Dy Reyes, insignificant (as determined by t tests) regression coefficients (in the original regression of the given model) led the author to drop the independent variables associated with these nonsignificant regression coefficients and refit the model. The original model, however, is a model possessing error autocorrelation and hence the statistical results obtained from this regression must be judged as not efficient. Therefore a decision to drop variables, as based on t tests of the regression coefficients, is, at best, a doubtful procedure. The same argument might be made against Method II wherein a similar decision is made to drop certain independent variables. In Method III, Dy Reyes utilizes a predetermined filter (as does Sims), and we doubt this approach for reasons we have noted earlier.

Feige and Pearce (1974) subject their original data to such an elaborate filtering technique that it is suspected they actually filter out causality between the two variables.[1] Further, by including twelve

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[1]Feige and Pearce (1974, p. 28) note that "This study has highlighted the fact that tests of causal relations are likely to be quite sensitive to the filtering techniques employed,...."

future and twelve lagged exogenous variables, it is suspected the authors mask the true causal relationship between money and income. Further, as is the case in all previous studies, the authors use quarterly GNP data, whereas in our study we use monthly PI^S as a proxy for economic activity.

In closing this section wherein we have outlined some of the major differences between our results and the results of other studies, we once again note, as does Pierce (1974, p. 37), "The economy is a miserable experimental design." Nonetheless, even given this caveat, the results of our study must be restated: If economic activity is adequately proxied by monthly, nominal personal income, and if money stock is an adequate representation of money, and if our model representations do meet the necessary assumptions, then it is our finding that seasonally adjusted money and economic activity are causally related in a bidirectional manner, i.e., feedback exists between seasonally adjusted money and economic activity.

The results of the consumption and disposable income models led us to conclude that there is also bidirectional causality (or feedback) between quarterly, seasonally adjusted disposable income and quarterly, seasonally adjusted consumption between 1947 and through 1974. The results of the consumption on personal income models (for testing personal income to consumption causality) are somewhat puzzling however.

B. Areas of Further Research

Though many questions have been answered by this study, there are many items of further interest and further research that might be undertaken. In general, the following areas for further research and analysis are suggested.

1. Original, unadjusted monthly gross national product and money stock data should be collected and analyzed in the same manner herein shown.[1]
2. The data base of the more significant and recent empirical works should be obtained and analyzed by the iterative methodology. The results should then be compared and differences accounted for.
3. The data base of this study should be tested according to other current methodologies being proposed for testing causality and/or feedback.
4. The data base of this study should be subjected to the Durbin (1960a) time series methodology for purposes of comparison and checking the validity of the iterative methodology.

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[1]The purpose of collecting Gross National Product (GNP) data ia found in the generally accepted fact that economic activity is better proxied by GNP than personal income. Further, as has been noted earlier, it would be best to utilize raw unadjusted data in any model when testing for causality and/or feedback.

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VII. APPENDIX:

DATA SOURCES

Variable	Time Period	Source
C^s; DI^s	I, 1947 to IV, 1968	Business Statistics, 1973 Edition. p. 197.
	I, 1969 to IV, 1972	Business Statistics, 1973 Edition. p. 7.
	I, 1973 to IV, 1974	Survey of Current Business (Jul, 1975). p. S-2.
PI^s	Jan, 1947 to Dec, 1966	Business Statistics, 1971 Edition. p. 202.
	Jan, 1967 to Dec, 1968	Business Statistics, 1971 Edition. p. 7.
	Jan, 1969 to Dec, 1972	Business Statistics, 1973 Edition. p. 7.
	Jan, 1973 to Dec, 1973	Survey of Current Business (Jul, 1974). p. 23.
	Jan, 1974 to Dec, 1974	Survey of Current Business (Mar, 1975). p. S-3.
$M1^s$; $M1^{ns}$	Jan, 1947 to Dec, 1958	Federal Reserve Bulletin (Dec, 1970). pp. 895-896.
	Jan, 1959 to Dec, 1967	Federal Reserve Bulletin (Feb, 1973). pp. 72-75.
	Jan, 1968 to Sep, 1974	Federal Reserve Bulletin (Dec, 1974). pp. 822-823.
	Oct, 1974 to Dec, 1974	Federal Reserve Bulletin (Aug, 1975). p. A-12.