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A multivariate time series analysis of commodity, money, and credit markets

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**A multivariate time series analysis of commodity, money, and
credit markets**

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Iowa State University, 1987

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A multivariate time series analysis of
commodity, money, and credit markets

by

Hedayeh Samavati

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CHAPTER I. INTRODUCTION

In 1975, Congress passed House Concurrent Resolution 133 to formalize the "intermediate target strategy" for the conduct of monetary policy. According to this resolution, the Federal Reserve is required to formulate monetary policy in terms of the rate of growth of the money stock and report its monetary policy plans to Congress in advance of their implementation.

With an intermediate target strategy for monetary policy, some financial variable, e.g., the money stock, is used as an indicator for the economic targets at which monetary policy ultimately aims, such as economic growth, price level stability, employment, and international balance. This amounts to having a two-step procedure. The Federal Reserve first determines the rate of growth of the intermediate target that is most likely to lead to the desired ultimate economic outcome. It then chooses some operating instrument over which it can have close control -- for example, a short-term interest rate, like the federal funds rate prior to 1979, the quantity of borrowed reserves from October 1979 to October 1982, or the quantity of nonborrowed reserves since October 1982 -- to achieve that growth rate for the intermediate target itself.

In the 1970s, economists believed that the stability of the nonfinancial sector of the economy relative to that of financial markets was the crucial factor that determined if the focus of monetary policy should be on interest rates or on a monetary aggregate. This was

demonstrated by Poole (1970). Economists also believed that a monetary aggregate was a better choice since financial markets appeared to be more stable than the nonfinancial sector; adopting a monetary aggregate as the intermediate target variable was widely accepted to be the best strategy for the conduct of monetary policy. The basic issues for the policy makers was how to choose the optimum target rate of growth of money as economic situations varied and how to implement this policy.

In the 1980s, however, the issues with regard to monetary stabilization policies and the best way of formulating them are not as settled as they seemed to be in the 1970s.

The appropriateness of attempting to achieve economic stability via changes in the growth rate of the M1 money supply has been questioned. If we were to categorize the issues raised and the debate over the appropriate way of formulating monetary policy into two major groups, the first would be the debate over the appropriate form of the monetary policy rule. Should the monetary authority cause the money supply to grow at K percent per year without exception or, in order to improve the behavior of the goal variables, should the monetary authority attempt to vary the growth rate of the money stock in response to developments in the ultimate goals of policy? The question is how useful and how effective is monetary policy in smoothing the business cycle when monetary policy is determined by a feedback rule.

Economists who are proponents of rational expectation school argue that if the central bank uses a feedback rule which is characterized by the adoption of a "lean against the wind" monetary policy, it cannot

affect real economic variables, either in the long run or in the short run. In other words, if the monetary authority acts in a systematic way in order to affect output or employment, monetary policy will not be effective. This is shown by incorporating both the natural rate and rational expectations hypotheses into structural models of the economy (see Lucas, 1973, and Sargent and Wallace, 1975).

To test these propositions within the context of macroeconomic models, the focus of attention has been on determining whether money is neutral or not. More specifically, the growth rate of the money supply has been decomposed into anticipated and unanticipated components and the effects of these components on real economic variables -- output or unemployment -- have been investigated. It has been argued that anticipated changes in the money supply do not affect real economic variables. For example, see Barro (1978) and Barro and Rush (1980).

However, others (Mishkin, 1982, and Small, 1979) have shown that under a different or a more reasonable setting, and different lag lengths for explanatory variables or redefinition of some of them, anticipated money growth influences real economic variables. Nevertheless, this issue is still not completely resolved since others found results which contradicted Mishkin's.

A second category of issues casts doubt on the usefulness of the M1 money supply as an intermediate target variable of monetary policy.

In the face of deregulation of the financial industry and financial innovations, economists talk about the breakdown of the past relationship between money stock growth and nominal income growth. The reasons cited

as the evidence of this breakdown are: (a) the unpredictable and unusual behavior of M1 money velocity during 1982-1983 and again in 1985 (for example, see Roth, 1984 and 1985) and (b) the systematic prediction errors of St. Louis type reduced form models or standard money demand equations over the 1982-1983 period which have raised questions about the stability of the demand function for money (for example, see Simpson, 1984).

Some economists propose usage of a broad credit aggregate (see B. Friedman, 1981a and 1981b) as the focus of monetary policy. And others argue that although targeting a broad credit aggregate such as total nonfinancial debt proposed by B. Friedman does not seem to be superior to targeting the M1 money supply. Nevertheless, for both macroeconomic modeling and policy making purposes, the credit market should not be ignored since for the determination of output and inflation what matters is the interaction of money and credit markets (see Fackler, 1985).

In this study, we deal directly with the second category and indirectly with the first group of concerns raised over the issue of appropriate formulation of monetary policy. We test conflicting economic theories concerning the relationship among credit market variables, money stock, prices, and income. Specifically, we empirically investigate the dynamic interrelationships of variables of commodity, money, and credit markets in order to see whether the data support the propositions of ineffectiveness of monetary policy and also the breakdown of M1 money

measure and income in a framework where all relevant variables of the above three markets are analyzed simultaneously.

More specifically, in this study efforts are made to determine the causal relationships, as defined by Granger (1969), among five macro-economic variables, three quantities and two relative prices which are supposed to represent the commodity, money, and credit markets. These variables are real GNP, the GNP price deflator, the M1 money stock, total nonfinancial debt, and the 4-6 month commercial paper rate.

The causality results drawn from our model will also enable us to decide whether the credit market variables -- interest rate and stock of credit -- give information or have influence on income determination over and above the information and influence contained in the money stock.

In the past, the question of causality among the named variables or a subset of them has been examined by many authors such as Sims (1972 and 1980), B. Friedman (1981a and 1981b), Fackler (1985), and Litterman and Weiss (1985). All of these authors have used vector autoregression (VAR) techniques in order to fit a multivariate model to the time series data. Different lag lengths have been used in different studies and, to make time series stationary, different differencing schemes have been used. Causality conclusions were then drawn on the basis of the tests of significance of the autoregressive coefficients of one variable explaining the other.

The current study uses a multivariate autoregressive integrated moving average (ARIMA) approach to time series analysis to construct several multivariate forecasting models. This method, which is an

extension of the Box and Jenkins (1970) approach for building univariate forecasting models, was proposed by Tiao and Box (1981). When long lags of each variable are needed, multivariate ARIMA can be a more efficient estimation approach than VAR techniques. The reason is that the ARIMA approach allows for moving average (MA) as well as autoregressive (AR) terms and, most of the time, one single MA term can be substituted for many autoregressive terms and thus degrees of freedom can be saved.

Furthermore, in contrast to prior studies which based their conclusions on tests of significance of model parameters which actually are tests of how good the model fits the data, our Granger causality results are based on comparing "forecasts" of different sets of multivariate models. In other words, in this study, to make inferences about causal relationships, forecast errors of different models are used and a statistical procedure proposed by Ashley et al. (1980) is followed. This approach is explicitly designed to test hypotheses about causalities in a time series context and is more faithful to the definition of Granger causality, i.e., tests of hypothesis are based on the out-of-sample or forecasting performance of the multivariate models.

The outline for the rest of the paper is as follows: In Chapter II a brief review of the relevant literature is presented. Chapter III gives a brief description of the statistical methodology used in the study. Data analysis and empirical results are presented in Chapter IV. Policy and macroeconomic implications of the results are discussed in Chapter V. Finally, Chapter VI includes the summary and conclusions.

CHAPTER II. LITERATURE REVIEW

Several criteria have been discussed by numerous economists with respect to the desirable properties of an intermediate target. Four of the most important are predictability, measurability, reliability in terms of linkage with the goal variables, and controllability.

The M1 money supply measure is based on the medium of exchange role of money which relates to the transaction approach in money measurement. Transaction balances are closely related to the total spending and thus to the ultimate policy goals. The monetary aggregate that is being used for monetary policy purposes then must be the one that most accurately measures the transaction balances. Prior to financial deregulation, M1 was a desirable candidate.

The equation of exchange, $\dot{M} + \dot{V} = \dot{P} + \dot{Y}$, which asserts the rate of growth of money supply (\dot{M}) plus the growth rate of money velocity (\dot{V}) is equal to the rate of growth of nominal income ($\dot{P} + \dot{Y}$), is the theoretical basis for using M1 as an intermediate target variable.

The Depository Institutions Deregulation and Monetary Control Act, passed in March 1980, created a favorable environment for the birth of new types of financial instruments and bank deposits that were both interest bearing and usable for making payments, like negotiable order of withdrawal (NOW) accounts and Super NOW accounts. The inclusion of these types of accounts in the M1 money measure blurred the sharp distinction that had existed between deposits for transaction purposes that were not

interest bearing and could be used for third party transfers and the ones that were interest bearing and could not be used for third party transfers. This, in turn, had a negative impact on the desirable properties that existed in the M1 money supply measure as an intermediate target variable.

From the equation of exchange we also notice that in order for the monetary aggregate targeting policy to be successful, we need the growth rate of money velocity to be predictable. The behavior of M1 velocity during 1982 and the first half of 1983 was most unusual and unpredictable in the sense that its movements were dramatically different from its behavior around the troughs of the past six recessions (see Roth, 1984).

The money-GNP relationship diverged from its historical pattern in 1982 and 1983. In October 1982 the Federal Reserve decided to reduce its emphasis on M1 and rely more on the broader aggregates in policy making. There is also suspicion that financial deregulation¹ may have changed the short-run responsiveness of monetary growth to changes in market interest rates. The argument is that because NOW accounts pay a positive rate of interest, the opportunity cost of holding funds in NOW accounts is less than holding funds in the form of currency or demand deposits which pay no interest. Therefore, the impact of a given change in market interest rates on the opportunity cost of NOW accounts will proportionally be larger and, thus, NOW accounts are more sensitive to market interest

¹In this context, financial deregulation considered by Roth (1985) is referred to deregulation of deposit rate ceilings, the authorization of new deposit accounts by Congress, and the development of new accounts, like MMMF, by nondepository institutions.

rates; this is also true for Super NOWs. The rising proportion of NOWs and Super NOWs may have led to a higher interest sensitivity of M1.

If this is true, the interest rate volatility associated with close, short-run control of M1 has been reduced. The empirical studies supporting these ideas are done by Brayton, Farr, and Porter (1983) and Roth (1985). Given the problems and uncertainties that have arisen due to financial deregulation and focusing on M1 for policy making and implementing, such as the issues discussed above, different economists have tried to find a way to improve the making of monetary policy.

In the search for an alternative monetary target, or an additional financial variable that could be used along with M1 in policy setting, there are a range of possibilities that are supported by several groups of economists.

One group has proposed to supplement the monetary aggregate targets with the real rate of interest target arguing that the high real interest rates since early 1980 have been responsible for the high rate of unemployment.

The other alternative considered and argued for as a candidate for monetary target is a weighted monetary aggregate such as the Monetary Services Indexes (MSI). For example, Barnett (1978, 1980, and 1981), Barnett, Offenbacher and Spindt (1984), and Zupan (1983) argue for MSI.¹

¹These aggregates were originally called "Divisia monetary aggregates" because Barnett used a Divisia index to construct them. Recently, there has been some revisions to construction of these aggregates and the Divisia index is no longer used and, therefore, Divisia monetary indexes are now called "monetary services indexes" (MSI).

MSI are quantity index numbers that correspond to the existing aggregates and are constructed by weighting the component assets growth rates by their corresponding "rental prices" which are supposed to be the indicators of marginal medium-of-exchange (MOE) provided services for each asset.

Historical evidence shows a strong relationship between MOE services of money and economic activity. In this respect, it has been argued that the problem with the simple sum aggregates is that the assets that are being mixed together are nonhomogeneous with regard to the provision of MOE services. It has been claimed that the Monetary Services Indexes provide a superior means for estimating the total flow of MOE services in the economy. Finally, the importance of credit markets has been emphasized by another group of economists.

The importance of monetary policy in the business cycle has been the subject matter of many studies. The high positive correlation between the money stock and the current dollar GNP has been observed. But the existence of this correlation by itself without knowledge of causal orderings between changes in money stock and economic activity is not of substantive value.

Friedman and Schwartz (1963) have documented the tendency for money stock or its rate of change to precede movements in aggregate activity. Tobin (1970) provided explicit examples of the cases where there was no correspondence between causal ordering and temporal ordering of turning points of the economy. Tobin also showed that a model in which money

played a passive role could also explain such timing patterns of the data.

But as explained by Sims (1980): "Friedman and Schwartz did not rely only on statistical timing relationships ... Through detailed analysis of historical episodes, they attempted to document the existence of major swings in the money stock which not only preceded major swings in real activity, but were not themselves reflex responses to developments in real activity" (Sims, 1980, p. 250).

For the post-war period, however, with the acceptance by the government of full employment goals, the feedback relationship between money and income seems more plausible than a unidirectional relationship between them.

Sims (1972) searched for the statistical evidence for exogeneity of money with respect to income in the post-war period (1947-1969). The main finding of his study was that the causality between money and income was unidirectional and it was from money to income. This conclusion therefore strengthened the monetarist position that changes in the money supply have been an important factor in creating post-war U.S. business cycles.

Sims reached this conclusion by testing whether money was causally prior to income in a Granger sense.¹ He developed a statistical testing procedure which he then used in his empirical analysis of the data. The procedure is best described by Sims: "... we have a practical

¹See Appendix A for a definition of Granger causality.

statistical test for unidirectional causality: Regress y on past and future values of x , taking account by generalized least squares or prefiltering of the serial correlation in $w(t)$ [the regression residual]. Then if causality runs from x to y only, future values of x in the regression should have coefficients insignificantly different from zero, as a group" (Sims, 1972, p. 545).

Sims (1980) reexamined the causal relationship of money and income for the inter-war and post-war periods. He used monthly data on M1 money, industrial production, and the wholesale price index. The post-war period referred to 1948-1978 and he used data on 1947 for initial conditions while the inter-war period referred to 1920-1941 and data on 1919 were used for initial conditions. In this study, Sims used VAR methodology for analyzing multivariate time series data. He observed that money stock was strongly causally prior, in a Granger sense, and was responsible for a substantial fraction of variance in production in a system containing money, industrial production, and a price index. After he added a short-term interest rate to his analysis, he found out that money stock lost its central role in explaining income variation. He concluded that in both inter-war and post-war periods "some of the observed comovements of industrial production and money stock are attributed to common responses to surprise changes in the interest rate" (Sims, 1980, p. 253), and, also, that the estimated dynamics are compatible with a nonmonetarist interpretation that money plays a passive role in determining income. B. Friedman (1981b) did the same analysis

except that only he used a credit aggregate instead of an interest rate and he got the same result reached by Sims.

Furthermore, B. Friedman (1981a), using quarterly data for the period 1946-1980, showed that the relationship between aggregate outstanding indebtedness of all nonfinancial borrowers in the United States and nonfinancial economic activity is as stable as the relationship between GNP and asset aggregates such as the money stock and the monetary base. After performing several different statistical tests and establishing that there exists a stable relationship between GNP and total nonfinancial debt, it is of vital importance to find out about the operative chain of causation among money, credit, and income. In modern economies, the behavior of money is much effected by the policy makers' decisions and thus is presumed to be "exogenous." What about exogeneity of credit? If it is the case that money "causes" income and income "causes" credit, then this means that credit is not an exogeneous variable and, from the point of view of monetary policy, of little concern because it is not an independent variable as far as income determination is concerned.

To find out about the causal relationship among price, P , real GNP, X , total nonfinancial debt, C (hereafter called simply "credit"), and M_1 money stock, M (hereafter simply called money), B. Friedman estimated two sets of trivariate vector autoregression systems where the first system's variables were X , P and M and those of the second system were X , P , and

C¹. He also estimated a third system of equations including all four variables, i.e., X, P, M and C.

The causality implications derived from the tests using the above systems are as follows:

From the trivariate systems it is concluded that neither money nor credit incrementally explain income, but from the four variable system which includes both credit and money variables it is inferred that money and credit jointly incrementally explain income. He concluded "... what appears to matter for the explanation of real income is neither money nor credit but, instead, the interrelation between the two."

Furthermore, where in the three-equation systems both credit and money were incrementally explained by income, in the four-equation system income incrementally explains money but not credit. All of this suggests that it does not make sense to say that money causes income and income causes credit, and in a macro economic analysis it is not legitimate to exclude credit and focus on the money stock.

In another study (1983) based on quarterly data for 1959-80, B. Friedman estimated the same three autoregressive systems and performed the same tests but got "partly" conflicting results in the sense that in the trivariate systems both money and credit in the absence of each other marginally explained income but they did not in the presence of each other. On the other hand, they support the findings of the previous

¹Total nonfinancial debt = total credit market liabilities of all U.S. nonfinancial sectors (federal government, households, nonfinancial business corporations, state and local governments, and other nonfinancial businesses).

study that credit is predetermined with respect to income, i.e., that income does not incrementally explain credit.

B. Friedman also suggested that it is more logical to use the information embodied in both sides of the public balance sheet. Focusing on money stock, in monetary policy setting, is using the information contained on the asset side of the public balance sheet only. He proposed an explicit two-target strategy which requires establishing target ranges for both the growth of the M1 money stock and the total domestic non-financial debt. He believes that this framework, as opposed to the current practice which uses two separate definitions of the money supply, is superior in that it draws on a more diverse information base with regard to the signals useful for the design and implementation of monetary policy. This is because, he adds, "money is an asset held by the public, and each monetary aggregate is just a separate way of adding up those assets."

Porter and Offenbacher (1983) are critical of B. Friedman's policy recommendations on the basis of findings implied by vector autoregression (VAR) analysis. They suggested that, first, the VAR model is a reduced-form model and therefore since it is not a structural model it cannot predict effects of a structural change on the economy. And the results of the VAR model may not carry any policy-implications weight. Secondly, in the VAR equation systems, where the ordering of the variables is arbitrary, the conclusions may sometimes differ depending on the chosen ordering of variables. In fact, in a trivariate system containing nominal GNP, interest rates and a financial aggregate, M1 or

domestic nonfinancial debt (DNF), using a different ordering, they found M1 to be significant in both nominal GNP and interest rate equations where domestic nonfinancial debt was significant in neither equation. This is in contrast with B. Friedman's findings.

They also checked the impulse response functions¹ of GNP with respect to monetary aggregates (M1 and M2) and DNF innovations, in order to find out about the stability of these financial aggregates with respect to GNP. They considered two, three, and four variable systems. In the two and three variable systems money, and in the four variable system DNF, displayed a more stable relationship to GNP. Moreover, for each equation which included DNF, they used two measures of DNF. One was in the end of quarter basis (EOQ DNF), and the other as quarterly averages (QA DNF). EOQ DNF, which was also the measure used by B. Friedman, always performed better than the other measure. They concluded, "though the monetary aggregates seem to fare somewhat better than the credit aggregate in the VAR exercises, on balance the results seem to be very sensitive to the methods of measuring the data, the ordering of the variables in the impulse response functions, or variance

¹Vector autoregression is a system of equations. Each equation expresses the current value of a variable as a function of lagged values of that variable and other variables in the system plus an error term. This current error term in each equation is called "innovation" for the left-hand side variable. Instead of writing each variable in terms of lagged values of all variables in the system, it is possible to write the system in the moving average notation, i.e., each variable as a function of its own and other variable's current and past innovations. This representation shows the effect of any given innovation on any given variable through time. The response over time of one variable to one particular innovation is called "impulse response function."

decompositions, and the inclusion of variables in the model. Thus, no reliable inferences may be drawn ... VAR methods are not capable of distinguishing the proper monetary policy target."

Granger causal orderings of the macroeconomic variables -- money, interest rates, inflation, and output -- were also investigated by Litterman and Weiss (1985). The authors reexamined the U.S. post-war data in order to investigate whether the money-to-real interest rate-to-output links implied by most monetary theories of output were compatible with the observed co-movements between money, interest rates, inflation, and output. The observations were for the period 1949:2 to 1983:2. The basic argument of the paper is along the following lines: According to most macroeconomic theories, the ex ante real interest rate is the key variable in determining output. It is also true that nominal interest rate is a poor proxy for theoretically meaningful ex ante real interest rate, as it was shown by Fama (1982) that over the post-war period in the U.S., changes in expected inflation rate can explain a substantial part of the movement in short-term interest rates. Therefore, it is important to emphasize the distinction between movements in expected (ex ante) real interest rates and movements in expected inflation rates.

In order to come up with an estimate of unobservable expected inflation and expected real interest rates, they impose the rational expectation assumption and use the projection of future variables on current and past observable values. An important finding of the paper is that ex ante real rates are exogenous or Granger causally prior, relative to a universe containing money, prices, nominal rates, and output. This

finding is inconsistent with the way both Keynesian and the new equilibrium models believe monetary policy will affect real economic activities.

Litterman and Weiss then formulated an alternative structural model that is consistent with their finding and is capable of explaining the comovements between real and financial variables. The building block of this model is the insight suggested by Fama (1982) and is stated by Litterman and Weiss:

The incremental predictive content of nominal variables for future real variables arises solely because economic agents have some information about future real activity -- beyond that contained in current and lagged variables -- which shows up first in the equilibrium price of financial assets, particularly nominal interest rates. This occurs because expectations of changes in future output induce changes in expected future prices through a neoclassical money demand function and hence affect current inflation rates and current nominal rates. In this context, the comovements between money and future real activity are consistent with a Fed reaction function which attempts to offset, at least partially, the movements in expected inflation rates arising from anticipated output shocks (Litterman and Weiss, 1985, p. 130).

On the neutrality of money, the model is perfectly "classical" in the sense that it assumes that output is independent of current, past, and expected future money whether anticipated or unanticipated.

The conclusion of this paper is that output is structurally exogenous to money and prices, the new information for predicting output will be reflected in expected inflation rate, and nominal interest rates and the expected inflation innovations along with past values of output are sufficient statistics for predicting output. It is also concluded

that monetary instability is not responsible for post-war U.S. business cycles.

Fackler (1985) argued, in a macroeconomic analysis of three markets, (namely markets for goods, credit, and money) we need to have three quantity and two relative price variables in order to have a "complete" model. These variables are: real output, the money stock, the stock of credit, the price of output, and a short-term rate of interest. In addition, he estimated a separate system of equations replacing short-term with a long-term interest rate, reasoning that for income determination, and especially for investment components of income, the relevant rate of interest is a long-term rate. He used quarterly data for the period 1962:1-1980:3 and vector autoregressive methodology.

The causality and economic implications of his five-variable multivariate analysis support B. Friedman's recommendation for having a dual money-credit monetary target since the causality tests suggest that credit is not caused by real income or money. And above all, the causality tests suggest that it is the interest rate that directly causes real GNP, and credit and money only indirectly affects real GNP. His conclusion is:

Changes in the growth of credit neither conditionally cause nor are conditionally caused by changes in monetary growth. However, since money and credit both conditionally cause interest rates, a thorough understanding of the financial markets requires analysis of all three variables. Specifically, credit contains information on interest rate movements over and above that contained in the money stock. Given the importance of interest rate for real output, ignoring credit may provide biased estimates of the linkages between the financial and real sectors (Fackler, 1985, p. 37).

In light of these past studies, it should be clear that researchers have investigated the causal relationships of the key macroeconomic variables in order to find out about interaction of real and financial sectors and the resulting outcome in terms of output, unemployment, and inflation rate.

Is money causally prior to output? Are changes in the money supply responsible for economic fluctuations? Is a more predictable, K-percent, monetary policy more desirable or does it really not matter because money is neutral? How much is the information content of credit market variables? Is a credit aggregate, such as total nonfinancial debt, superior to a monetary aggregate, such as M1, in serving as a target variable for achieving the goal of monetary policy? Given the financial world of today, fast forward moving technology, innovations and creation of new types of accounts that serve as transaction and investment accounts both, and the changing definition of M1, is M1 a reliable short-run policy guide?

In answering the above questions, the last word is not said yet. Different economic theories, according to how they describe the structure of the economic system, provide different answers to the above questions. The final test for competing theories, though, is how their predictions and implications match with the economic realities. This is the task of empirical studies and also, sometimes, the empirical studies gather the stylized facts that are embodied in the economic data which then can be checked for compatibility with different theories.

Sometimes, empirical studies do not provide unique answers to the same question and have conflicting results which is also the case for the empirical studies which have attempted to address some of the above questions. Therefore, when analyzing the data, different conclusions might be reached and this could be due to using different statistical methodologies, difference in frequency of data used, the period covered in the study, the set of variables used, etc. To solve the puzzle, the appropriate approach and specification is needed, but frequently it is not known what is "appropriate."

Under these circumstances, further investigations to check the robustness of conclusions drawn from former studies are always well warranted.

For these reasons, the current study attempts to address the above questions by examining the causal relationships of the relevant variables but using a totally different approach that has not normally been used in the literature in evaluating the causal relationships.

The methodology used is explained in the following chapter.

CHAPTER III. DESCRIPTION OF THE METHODOLOGY

This chapter presents the way hypotheses about causation in a multivariate time series context are tested in this study.

The method is the one proposed by Ashley et al. (1980) and is based on the out-of-sample forecasting performance of multivariate time series models. This chapter is organized as follows: first, the methodology for building multivariate ARIMA models that will be used for forecasting will be presented, and next, the construction of new variables, γ and Σ , using forecasts of multivariate ARIMA models is discussed.

Different γ and Σ variables are used to run regression models; their coefficients will be tested for causal inferences.

Construction of the Multivariate ARIMA Models

The model will be constructed following the multivariate time series model building methodology of Tiao and Box (1981). This methodology is an extension of model building methodology introduced by Box and Jenkins for a single time series. A brief explanation follows.

A multivariate seasonal ARIMA model in its most general form is written as follows:

$$\phi_p(B) \phi_{PS}(B^S) z_t = \theta_q(B) \theta_{QS}(B^S) a_t$$

for the k series in the vector \underline{Z}_t . These series depend on their own past and, also, they may act on each other through a feedback relationship and/or they may be contemporaneously related. $\underline{z}_t = \underline{Z}_t - \underline{\eta}$ is the vector of mean subtracted (for the stationary series), observed time series and $\underline{\eta}$ is the vector of the means of the stationary time series. $\underline{a}_t = [a_{1t}, \dots, a_{kt}]'$, the $k \times 1$ residual vector, is independently and identically distributed as multivariate normal $N(0, \underline{\Sigma})$. The structure of the covariance matrix, $\underline{\Sigma}$, reflects the contemporaneous dependency structure existing in the component series of the model. B is the backward shift operator, for example, $Bz_t = z_{t-1}$ and $(1-B)z_t = z_t - z_{t-1} = \omega_t$. This is called a regular difference, where the working series, ω_t is the difference between two consecutive observations in the original time series.

B^S is the notation for the seasonal backward shift operator, and one can write $B^S z_t = z_{t-S}$. A seasonal difference is written as $W_t = (1 - B^S)z_t = z_t - z_{t-S}$. Here the working series, W_t , is the difference between the value of the observed time series at time t , z_t , and its value at time $(t-S)$. S is the seasonal period. For example, for monthly data the seasonal period, S , is 12. It is usually more convenient to model a stationary series. When the time series to be analyzed is not stationary, we can use regular and seasonal differencing in order to make it stationary. ϕ and Φ are the symbols used for regular and seasonal autoregressive terms, respectively, and θ and Θ are the regular and seasonal moving average terms, respectively. In our general equation

$$\underline{\phi}_p(B) = (\underline{I} - \underline{\phi}_1 B - \underline{\phi}_2 B^2 - \dots - \underline{\phi}_p B^p)$$

is the $k \times k$ matrix of regular autoregressive terms of order p and

$$\underline{\theta}_q(B) = (\underline{I} - \underline{\theta}_1 B - \underline{\theta}_2 B^2 - \dots - \underline{\theta}_q B^q)$$

is regular moving average $k \times k$ matrix of polynomials in B of degree q .

$$\underline{\phi}_{PS}(B^S) = (\underline{I} - \underline{\phi}_S B^S - \underline{\phi}_{2S} B^{2S} - \dots - \underline{\phi}_{PS} B^{PS})$$

and

$$\underline{\theta}_{QS} = (\underline{I} - \underline{\theta}_S B^S - \underline{\theta}_{2S} B^{2S} - \dots - \underline{\theta}_{QS} B^{QS})$$

are $k \times k$ matrices of seasonal autoregressive and moving average of orders PS and QS , respectively (Tiao and Box, 1981).

In addition, for the model to make sense there are mathematical restrictions placed on the parameters of the model. The roots of the determinantal polynomials

$$|\underline{\phi}_p(B)|, |\underline{\phi}_{PS}(B^S)|, |\underline{\theta}_q(B)| \text{ and } |\underline{\theta}_{QS}(B^S)|$$

should be on or outside the unit circle. For the series Z_t to be stationary or to be in statistical equilibrium about a fixed mean, the

zeros of the determinantal polynomials $|\phi_p(B)|$ and $|\phi_{PS}(B^S)|$ should be on or outside the unit circle (Tiao and Box, 1981). In other words, the autoregressive factors lie inside the unit circle. This implies that, given sufficient time, the influence of random shocks, a_t , injected in the system will eventually decay and the system will return to its mean or equilibrium position. For the model to be invertible, the roots of $|\theta_q(B)|$ and $|\theta_{QS}(B^S)|$ should be outside the unit circle (Tiao and Box, 1981). The invertibility restrictions are imposed on the moving average parameters of the ARIMA models in order to make sure that the weights applied to past history of the series die out.

The objective is to find a parsimonious model to uncover the regularities of the data: we seek a model that has as few parameters as possible and at the same time is capable of representing the dynamic and stochastic relationships of the data adequately. This task will be carried out following the Tiao and Box (1981) proposed iterative approach for multivariate ARIMA model building. This method of model building consists of three main steps which may be repeated over and over until the most adequate or desirable model both in an economic and statistical sense is found. These steps are basically the main technical model building stages suggested by Box and Jenkins (1970) and are as follows.

Tentative model identification (or specification)

In building an ARIMA model, the basic assumption is that there is correlation among the values of data at hand; the available data is one

realization of a process that we are trying to model. The process itself is not known. Any univariate ARIMA model representing a process has a theoretical autocorrelation function and partial autocorrelation function. In the multivariate case, ARIMA models have cross correlation matrices and partial autocorrelation (autoregression) matrices which are our main tools in the identification stage of model building. More specifically, we know or expect a certain pattern for theoretical auto, cross, and partial correlation functions underlying each ARIMA model. At the identification stage, we compute the corresponding sample values and then we compare their pattern to that of theoretical ones and decide on the order of autoregressive and moving average terms that we want to include in our model. At this point we only have a "tentative" model that we can estimate. It is tentative because our judgment about the pattern of, for example, autocorrelations is based on the sample values that we have computed using our data which is only one realization of the process that we are trying to model. In other words, the values that we are working with are sample values and they always contain some sampling error, giving us misleading signals when we are determining the pattern of auto, cross, and partial correlations. Another factor that gives rise to a "tentative" model is that it sometimes is hard to decisively decide on the pattern of correlations and, due to this ambiguity, we might consider several tentative models at the identification stage and carry them out to the estimation and diagnostic checking stages and then pick the most desirable one. The question now is what are theoretical and sample cross correlation and partial autoregression matrices.

Cross-covariance and cross-correlation matrices Cross-covariance matrices contain covariances that give us information about the direction and strength of the statistical relationship between ordered pairs of variables at different lags. The covariance between ordered pairs of the same variable is called auto-covariance. The covariance between two different random variables is cross-covariance. Covariances are awkward to use in the sense that their sizes depend on the units in which the variables are measured. We standardize covariances by dividing them by the variances of the variables involved. The new statistic is called auto- or cross-correlation, falls between -1 and +1, and is dimensionless, i.e., measures the same thing as covariance does regardless of units in which variables involved are measured. More specifically, the formulas for theoretical cross-covariance and correlation matrices when the multiple time series $\{Z_t\}$ is stationary,¹ with mean vector μ , at lag l are defined as

$$E[(Z_t - \mu)(Z_{t-l} - \mu)'] = \Gamma(l) = \{\gamma_{ij}(l)\}, \quad l = 0, \pm 1, \pm 2, \dots$$

$$i, j = 1, \dots, k$$

and the corresponding cross-correlation matrix is defined as

¹For a process to be stationary, the joint distribution function describing that process must be invariant with respect to time, i.e., $P(Z_{t+m}, \dots, Z_{t+k+m}) = P(Z_t, \dots, Z_{t+k})$. For a joint normal distribution, the stationarity condition is that mean (first moment) and variance and covariances (second moment) to be constant over time.

$$\underline{\rho}(\lambda) = \{\rho_{ij}(\lambda)\}$$

where

$$\rho_{ij}(\lambda) = \gamma_{ij}(\lambda) / [\gamma_{ii}(0) \gamma_{jj}(0)]^{1/2}$$

or

$$\rho_{ij}(\lambda) = E[(Z_{it} - \mu_i)(Z_{j(t-\lambda)} - \mu_j)] / \{\text{var}(Z_{it})\text{var}(Z_{jt})\}^{1/2}.$$

Note that

$$\underline{\Gamma}(-\lambda) = \underline{\Gamma}'(\lambda) \text{ and } \underline{\rho}(-\lambda) = \underline{\rho}'(\lambda).$$

To come up with an expression for $\underline{\Gamma}(\lambda)$, we can write the ARIMA model as

$$\underline{\phi}_p(B) \underline{z}_t = \underline{\theta}_q(B) \underline{a}_t$$

or

$$(\underline{I} - \underline{\phi}_1 B - \underline{\phi}_2 B^2 - \dots - \underline{\phi}_p B^p) \underline{z}_t = (\underline{I} - \underline{\theta}_1 B - \underline{\theta}_2 B^2 - \dots - \underline{\theta}_q B^q) \underline{a}_t$$

or

$$(\underline{z}_t - \underline{\phi}_1 \underline{z}_{t-1} - \underline{\phi}_2 \underline{z}_{t-2} - \dots - \underline{\phi}_p \underline{z}_{t-p}) = (\underline{a}_t - \underline{\theta}_1 \underline{a}_{t-1} - \underline{\theta}_2 \underline{a}_{t-2} - \dots - \underline{\theta}_q \underline{a}_{t-q}).$$

Post-multiply both sides of the above equation by $\underline{z}'_{t-\lambda}$:

$$(\underline{z}_t - \underline{\phi}_1 \underline{z}_{t-1} - \underline{\phi}_2 \underline{z}_{t-2} - \dots - \underline{\phi}_p \underline{z}_{t-p}) \underline{z}'_{t-\lambda}$$

$$= (a_t - \phi_1 a_{t-1} - \dots - \phi_q a_{t-q}) Z_{t-l}' \quad (3.1)$$

Assuming stationarity, we can write the vector ARIMA model of the form,

$$\phi_p(B) Z_t = \theta_q(B) a_t$$

in a pure moving average form of

$$Z_t = \psi(B) a_t$$

where $\psi(B) = \phi_p^{-1}(B) \theta_q(B)$. Using $Z_t = Y(B) a_t$ and given the assumptions about the distribution of $\{a_t\}$ we can write

$$E(a_{t-j} Z_t') = \begin{cases} \Sigma & j = 0 \\ \Sigma Y_j' & j \geq 1 \\ 0 & j < 0 \end{cases} \quad (3.2)$$

Taking the expected value of both sides of equation (1) using (2) we can write,

$$\Gamma(l) = \begin{cases} \sum_{j=l-r}^{l-1} \phi_{l-j} \Gamma(j) - \sum_{j=0}^{r-l} \theta_{j+l} \sum Y_j' & l = 0, 1, \dots, r \\ \sum_{j=1}^r \phi_j \Gamma(l-j) & l > r \end{cases}$$

where $\theta = -I$ and $r = \max(p, q)$

and if $p < q$, $\phi_{p+1} = \dots = \phi_r = 0$,

if $q < p$, $\theta_{q+1} = \dots = \theta_r = 0$.

For a vector moving average model of order q , i.e., $p=0$ or ARIMA $(0, q)$ we have

$$\Gamma(\lambda) = \begin{cases} \sum_{j=0}^{q-\lambda} \theta_{-j+\lambda} \sum_{-j} \theta_{-j}, & \lambda = 0, \dots, q \\ 0 & \lambda > q \end{cases}$$

This means that, for a vector moving average model of order q , the theoretical auto and cross-correlation matrices (CCM) are nonzero up to lag q and they will be zero after lag q , i.e.,

$$\rho(\lambda) = \begin{cases} \rho(\lambda) \neq 0 & \lambda = 0, 1, \dots, q \\ \rho(\lambda) = 0 & \lambda > q \end{cases}$$

At the identification stage we compute sample CCM as follows:

$$\hat{\rho}(\lambda) = \{\rho_{ij}(\lambda)\} \quad i, j = 1, \dots, k$$

where $\rho_{ij}(\lambda) = \frac{\sum_{t=\lambda+1}^n (Z_{it} - \bar{Z}_i)(Z_{j(t-\lambda)} - \bar{Z}_j)}{\sum_{t=1}^n (Z_{it} - \bar{Z}_i)^2 \sum_{t=1}^n}$

$$(z_{jt} - \bar{z}_j)^2 \quad 1/2 .$$

For a moving average model of order q we expect that $\rho(\ell)$ or cross-correlation matrices to converge to zero after lag q . In other words, if sample CCM is cut off after lag q , we choose q as the moving average order of our model. Therefore, sample cross-correlation matrices are very useful in determining the moving average order of our model.

Partial autoregression (correlation) matrices Partial

autocorrelation is another important tool in the identification stage of ARIMA models. In the univariate case, partial autocorrelation measures the dependence between Z_t and Z_{t+k} taking into account the effects of the intervening Z 's, e.g., finding the relationship between the ordered pair (Z_{t+4}, Z_t) with the effects of $Z_{t+3}, Z_{t+2}, Z_{t+1}$ on Z_{t+4} accounted for. The set of partial autocorrelations of different orders is called partial autocorrelation function. In the multivariate case, we define a generalized partial cross-correlation matrix function and denote it by $\underline{P}(\ell)$. It is shown for a stationary vector AR model of order ρ , with no moving average terms,

$$\underline{P}(\ell) = \underline{\phi}_\ell \quad \ell = 1, 2, \dots, \rho,$$

$$\underline{P}(\ell) = \underline{0} \quad \ell > \rho.$$

In the univariate case we estimate the sample partial auto correlations by a series of least-squares regression coefficients. Specifically, partial autocorrelation at lag k is the regression coefficient of z_t when we regress Z_{t+k} on $Z_{t+k-1}, \dots, Z_{t+2}, Z_{t+1}$ and Z_t . In the multivariate case, if \underline{Z}_t follows an AR(p) model we have

$$\underline{Z}_t = \underline{c} + \underline{\phi}_1 \underline{Z}_{t-1} + \underline{\phi}_2 \underline{Z}_{t-2} + \dots + \underline{\phi}_p \underline{Z}_{t-p} + \underline{a}_t.$$

Vector \underline{c} and matrices $\underline{\phi}_1, \underline{\phi}_2, \dots, \underline{\phi}_p$ can be estimated by multivariate least squares. At the identification stage we don't know p , the autoregressive order of the model. We fit successively higher orders of vector autoregressive models:

$$\underline{Z}_t = \underline{c} + \underline{\phi}_1 \underline{Z}_{t-1} + \dots + \underline{\phi}_\ell \underline{Z}_{t-\ell} + \underline{a}_t.$$

For $\ell = 1, 2, \dots$

The sample partial autoregression matrix at lag ℓ is:

$$\underline{P}(\ell) = \underline{\phi}_\ell \quad \ell = 1, 2, \dots$$

If at lag $\ell > p$ all elements of $\underline{P}(\ell)$ were small or statistically not significant, the tentative order of the vector AR model would be p . There is also a likelihood ratio statistic, $M(\ell)$, to help determine the autoregressive order of the model. Using this statistic, after each fit of AR(ℓ) we can test the null hypothesis $\underline{\phi}_\ell = \underline{0}$ against the alternative

$\phi_l \neq 0$. Let $S(l)$ be the matrix of residual sum of squares and cross products for the AR(l) model. The likelihood ratio statistic is defined as:

$$\frac{|S(l)|}{|S(l-1)|}$$

The $M(l)$ statistic is defined as:

$$M(l) = -(N - 1/2 - l \cdot k) \log_e \frac{|S(l)|}{|S(l-1)|}$$

which under the null hypothesis is asymptotically distributed as χ^2 with k^2 degrees of freedom where $N=n-p-1$ is the effective number of observations when a constant term is included in the model.

Sample residual cross-correlation matrices after AR fit Sample cross-correlation matrices of the residual series \hat{a}_t 's from each fitted autoregressive model are another tool at identification stage. They are of interest because their diagonal elements show how the fit is improving as we increase the autoregressive order of the model. Since we know it is desirable to find a fit which minimizes the residual variances while being parsimonious.

Also, for mixed vector autoregressive moving average models, none of the theoretical cross-correlation matrices $\rho(l)$ and the generalized partial cross-correlation matrices $P(l)$ cut off at any lag; instead they both gradually decay toward 0 and this makes it difficult to determine

any AR or MA order. In this case, patterns in residual cross-correlations after AR fit may help us to determine the orders.

Estimation

After the model is tentatively identified, i.e., the orders (p,q) are specified, its parameters can be estimated. The constant vector \underline{c} and the parameters of the model

$$\underline{\phi} = [\underline{\phi}_1, \underline{\phi}_2, \dots, \underline{\phi}_p], \quad \underline{\theta} = [\underline{\theta}_1, \dots, \underline{\theta}_q] \text{ and } \underline{\Sigma}$$

are estimated by maximizing the corresponding likelihood function. Two approximation methods are available in the estimation procedure of the Scientific Computing Associates (SCA) system, the computer software employed in the computations of this study. The first one forms a "conditional" likelihood function and the second one an "exact" likelihood function. It has been shown (Hillmer and Tiao, 1979) that if the number of observations is not sufficiently large or if the series tends toward noninvertibility, i.e., if one or more zeros of $|\underline{\theta}_q(B)| = 0$ lie on or close to the unit circle, using the conditional likelihood function in the estimation procedure will result in estimates of moving average parameters with large biases. It is advised to use the exact likelihood method in such a case. However, since the exact likelihood method involves more computing time, it is recommended that the exact likelihood method be employed only after the model has been identified.

Diagnostic checking

The criticism of the model, checks for inadequacies in it, and the search for ways to improve the model takes place in this step which basically involves the analysis of residuals. The basic assumption of the model is that the random shocks, a_t 's, are independently distributed. We do not have a_t 's but their estimates, \hat{a}_t 's, the residuals of the model. Therefore, detecting the departures from randomness among residuals is part of residual analysis. One way to check for the randomness of residuals is to plot the individual standardized residual series against time. For an adequate model, one expects a random scatter of the residuals about a fixed horizontal line. Any pattern other than this dictates the need for improvement of the model.

Another way to check for the independence of residuals is to analyze the cross-correlation matrices of the \hat{a}_t at different lags. If the model is adequate, none or very few elements of residual cross-correlation matrices at different lags are statistically significant.

The plot of residuals can also show us the abnormally large or significant residuals which suggests that we need to reconsider our model because there might be other important explanatory variables that our model has not taken into account.

If residuals of the model do not meet these criteria, we need to go back to the identification stage and further improve the model under the guidance of patterns of significant residuals. Otherwise we infer that the model cannot be improved further and the current model is adequate. The adequate model is then used for forecasting.

Testing for Causality

Although the concept of causality is very difficult to define, a generally acceptable definition which is due to Granger (1969) states that y causes x if series y_t has some special information about x_t that is useful in forecasting x_t and is not available elsewhere. How do we know y_t contains some special information about x_t ? If an information set Ω_t that includes all the information relevant to x_t , including y_t , is used to forecast x_t resulted in a superior forecast than the forecast based on the information set Ω'_t which is the set Ω_t excluding y_t , then we conclude that y_t has some special information about future values of x_t that is not found elsewhere. The procedure proposed by Ashley et al. (1980) and followed in this study compares two sets of forecasts of a given variable when the given information set includes and when it excludes another variable. The forecasts that have smaller mean square errors (MSE) are judged to be superior forecasts. The systematic way of testing for superiority of one set of forecasts over the other is as follows: let $e_{k,t}$ be the forecast error of the model with all the variables. In our case, the full information set consists of five variables. And, let $e_{k-1,t}$ be the forecast error of the model with all the variables in the information set excluding one. Then let

$$\gamma_t = e_{k-1,t} - e_{k,t}$$

and

$$\Sigma_t = e_{k-1,t} + e_{k,t}.$$

Using γ_t and Σ_t we can run the following regression:

$$\gamma_t = \beta_1 + \beta_2[\Sigma_t - m(\Sigma_t)] + u_t$$

where $m(\Sigma_t)$ is the sample mean of Σ_t and u_t is the error term with mean zero and assumed to be uncorrelated with Σ_t (see Ashley et al., 1980, p. 1154).

The forecasts of the model with k -variables outperforms the forecasts of the model with $k-1$ variables, if we can reject the null hypothesis, $\beta_1 = \beta_2 = 0$, in favor of the alternative that both are nonnegative and at least one is positive. If both coefficients are positive, an F-test of the null hypothesis that both parameters are zero can be performed. Significance level is equal to half that reported in the F-statistic table. If one of the two least square estimates, $\hat{\beta}_1$ or $\hat{\beta}_2$, is significantly negative, the k -variable model cannot be judged to have given rise to better forecasts. If one coefficient is insignificantly negative, a one-tailed t-test on the other estimated parameter can be used. If the null hypothesis is rejected, we conclude that the forecasts of the k -variable model outperforms the forecasts of the model with $k-1$ variables.

The data analysis and the empirical results are presented in the following chapter.

CHAPTER IV. THE DATA AND THE EMPIRICAL RESULTS

The Data

Quarterly data from the first quarter of 1952 to the fourth quarter of 1985 for real GNP (GNP in 1972 dollars), the implicit price deflator for GNP, and the M1 money supply were obtained from various issues of Business Statistics, the Survey of Current Business, and Economic Indicators. Monthly values of the 4-6 month prime commercial paper rate were obtained from the same sources. Quarterly interest rate data were calculated by averaging the monthly values. The data for total nonfinancial debt were obtained from the Board of Governors of the Federal Reserve System. Total nonfinancial debt is the outstanding credit market debt of the U.S. government, state and local governments, and private nonfinancial sectors. Monthly averages of daily observations were converted into quarterly observations by simple averaging. All the data, except for the interest rates, were seasonally adjusted.

The Data Analysis -- Identification

Examination of plots of data against time reveals that all of the series are nonstationary in that both the levels and variabilities increase with time.

For a single time series, stationarity can be induced by differencing and power transformations where needed. Although in univariate time series modeling one must use a stationary series, in multiple time series modeling, as discussed by Tiao and Box (1981) and

Hillmer and Tiao (1979), simultaneous differencing may neither be necessary nor advisable because when considering several nonstationary series jointly, some linear combinations of them might be stationary and simultaneous differencing may lead to complications in model fitting.

In this study, the data were transformed. However, the intent was not to achieve stationarity. The goal was to transform the data into growth rates for the appropriate series. Therefore, in the first step, natural logarithms of all the five series were taken. Then, first differences of the logarithm data for real GNP, the implicit price deflator, the M1 money supply, and total nonfinancial debt were calculated. The interest rate series was left at the logarithm level since the objective was to investigate the relationship among the growth rate of real GNP, the growth rate of the M1 money supply, the growth rate of the price level or the inflation rate, the growth rate of credit, and the level of the interest rate.¹

Checking the summary statistics provided by SCA, it was observed that some of the eigen values of the sample covariance matrix were zero. Zero eigen values for the sample covariance matrix imply the existence of linear dependency among some of the series in the sense that some were computed from the contemporaneous values of others. Later it was

¹The growth rate of $x(t) = g_x$:

$$g_x = \frac{dx(t)}{dt} \cdot \frac{1}{x(t)} = \frac{d \ln[x(t)]}{dt},$$

$$g_x \approx \log_e x(t) - \ln x(t-1).$$

discovered that this problem had arisen due to the fact that the magnitude of the data after taking logarithm and first differences were in the order of .001 and the computer program was treating them as almost zeros. But exact linear dependency really was not present and the computation problem was solved by multiplying the growth rates of real GNP (RGNP), the price deflator (PD), the M1 money stock (M1), and total nonfinancial debt (C) by 100.

The sample cross correlation matrices (CCM) of the transformed data for 112 observations (1952:II to 1980:I) over 18 lags indicates that a low order vector moving average (MA) model is not appropriate since sample CCMs are all significant up to 18 lags and no cutting off behavior at low lags is observed (see Table 4.1).

We next examined the sample partial autoregression matrices to see if a vector autoregressive (AR) model was appropriate and, if it was, what was the right order for that vector AR model. Therefore, autoregressive models of successively higher order were fitted to the data and the sample CCMs of the residual series after each fitted autoregressive model were obtained and examined. Table 4.2 displays the summary statistics of the stepwise autoregressions of up to six lags. (Actually, stepwise autoregressions of up to 12 lags were fitted but since partial autoregression matrices were insignificant after lag four, for the sake of brevity, Table 4.2 displays summary statistics for models only up to six lags.) In Table 4.2., the χ^2 statistic is significant in the first four lags, indicating the possibility of a vector AR model of

Table 4.1. Cross correlation matrices in terms of +, -, and •^a

Lags 1 through 6:

+	-	+	•	-	+	-	+	•	-	•	-	•	•	-	•	-	•	•	•	-	-	•	•	•	•	-	•	•	•					
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+
+	+	+	+	+	+	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+

Lags 7 through 12:

•	•	•	•	•	•	•	-	-	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•					
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+

Lags 13 through 18:

•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•					
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+
•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+	•	+	+	+	+

^a+ denotes a value greater than $2/\text{SQRT}$ (no. of observations),
 - denotes a value less than $-2/\text{SQRT}$ (no. of observations), and
 • denotes a nonsignificant value based on the above criterion.

Table 4.2. Stepwise autoregression summary

Lag	Significance of partial AR coefficients	Chi-SQ test M(l) statistic	Residual variances (diagonal elements of Σ)
1	• • + • - • + • • + • • + • • • • + + • + • + • +	403.84	.643E+00 .115E+00 .256E+00 .104E+00 .120E-01
2	• • + • • - • • + - • • • • + • • • + • • • • • -	77.13	.577E+00 .911E-01 .223E+00 .898E-01 .900E-02
3	• • • • • - • • • - • • • + • • + • • • • • • • +	40.47	.550E+00 .813E-01 .207E+00 .789E-01 .807E-02
4	- • - + -	44.77	.487E+00 .790E-01 .198E+00 .717E-01 .594E-02
5	• • • • • • • • • • • • + • • • • • + + • • • • -	28.63	.470E+00 .745E-01 .177E+00 .605E-01 .541E-02
6	• • • • • • • • • - • - + • • • • • • + • • • • •	25.92	.463E+00 .697E-01 .159E+00 .544E-01 .501E-02

^aChi-squared critical values with 25 degrees of freedom are: five percent, 37.7, one percent, 44.3.

order four. The residual variances strongly decrease as the lags increase through the fourth lag, and the decrease in variances is less as the lags increase from lag four and this supports the vector AR(4) model.

In addition, if one examines the cross correlation matrices of residual after AR(1), AR(2), AR(3), and AR(4), one observes that even after the AR(3) model there are some significant residual cross correlations at lag 4 and also at lag 6. Table 4.3 displays the cross correlations of residuals after AR(4) fit. There are no significant values up to lag 6. The significant values occur after lag 6 and have no pattern. They can be safely ignored.

Therefore, at the identification stage it was decided that the vector AR(4) was an appropriate model. At the estimation stage, the vector autoregressive model of order four with a constant term and with conditional likelihood method was estimated. At this stage, 120 parameters were estimated, 105 of which were coefficients of the vector AR(4) model (the full model) and 15 were the error covariance matrix elements.

The objective is to find a parsimonious model that has residuals which appear to be generated by a white noise process. After estimation of the model, the autoregressive parameter estimates along with their corresponding standard errors were examined and those estimated coefficients that were not significantly different from zero were set equal to zero. (It should be noted here that the coefficients which were

Table 4.3. Residual cross correlation matrices in terms of +, -, and • after an AR(4) fit^a

Lags 1 through 6:

• • • • •	• • • • •	• • • • •	• • • • •	• • • • •	• • • • •
• • • • •	• • • • •	• • • • •	• • • • •	• • • • •	• • • • •
• • • • •	• • • • •	• • • • •	• • • • •	• • • • •	• • • • •
• • • • •	• • • • •	• • • • •	• • • • •	• • • • •	• • • • •
• • • • •	• • • • •	• • • • •	• • • • •	• • • • •	• • • • •

Lags 7 through 12:

• • • • •	• • • - •	• • • • •	• • • • +	• • • • •	• • • • •
• • • • -	• • • • •	• • • • •	• • • • -	• - • • •	• • • • •
+ • • • •	• • - - •	• • • • •	• • • • •	• • • • •	• • • • •
• • • • •	• • - - •	• • • • -	• • • • •	• • • • •	• • • • •
• • • • •	• • • • •	• • • • •	• • • • •	• • • • •	+ • • • •

Lags 13 through 18:

• • • • •	• • • • •	• • • • •	• • • • •	• • • • •	• • • • •
• • • • •	• • • • •	• • • • •	• • • • •	• • • • +	• • • • •
• • • • •	• • • • •	• • • • •	• • + + •	• • • • •	• • • • •
• • • • •	• • • • •	• • • • •	• • + • •	• • • • •	• • • • •
• • • • •	• • • • •	• • • • •	• • • • •	• • • • •	• • • • •

^a+ denotes a value greater than $2/\sqrt{\text{no. of observations}}$,
 - denotes a value less than $-2/\sqrt{\text{no. of observations}}$, and
 • denotes a nonsignificant value based on the above criterion.

insignificant but were large in absolute value were not set to zero. This practice is in accordance with Sims' (1972, p. 545) argument, "... that coefficients which are 'large' from the economic point of view should not be causally set to zero no matter how statistically insignificant they are." Also, SCA, the computer program used in this study, did not allow imposition of any restriction on the values of the constant vector. So, even if some of the elements in the constant vector were insignificant, they were not set to zero.)

The restricted model was estimated and the residual cross correlation matrices of that model were carefully checked. The restricted models were reexamined and new restricted models were estimated. In short, the above steps were repeated several times until the "appropriate" model was found. This model, model 1, has 42 parameters and is reported in Table 4.4 (standard errors appear in parentheses).

Table 4.5 displays the cross correlation matrices of residuals of model 1. One can observe that there are no significant values up to lag 6. The significant values occur after lag 6 and have no pattern to them. Therefore, they can be safely ignored.

The forecasts of model 1 for four quarters ahead, the period 1980:II to 1981:I, for growth rate of real GNP (YH), inflation rate (PH), growth rate of M1 money supply (MH), growth rate of total nonfinancial debt (CH), and the log level of interest rate (LGR) are reported in Table 4.6.

Table 4.4. Main model or model 1

	ϕ_1									
Constant vector	1.147 (.343)	0	-.551 (.2)	.461 (.156)	0	-1.155 (.654)				
	-0.141 (0.153)	0	.3 (.081)	.255 (.063)	-.197 (.098)	.992 (.19)				
	-0.196 (0.191)	0	-.198 (.112)	.626 (.074)	0	-.791 (.318)				
	0.447 (0.103)	.094 (.028)	0	.270 (.05)	0	0				
	0.006 (0.040)	.032 (.012)	0	.066 (.019)	0	1.257 (.083)				
	ϕ_2					ϕ_3				
	0	0	.411 (.17)	0	.452 (.617)	0	0	0	.284 (.219)	0
	-.154 (.039)	0	0	.39 (.087)	0	-.092 (.036)	.173 (.076)	0	0	-.843 (.188)
	0	.159 (.101)	0	0	.994 (.305)	0	0	0	.183 (.110)	0
	0	0	0	.314 (.073)	0	0	.133 (.056)	0	.232 (.081)	0
	0	0	0	0	-.579 (.126)	0	0	.043 (.022)	0	.460 (.132)
	ϕ_4									
	-.201 (.084)	0	0	0	0					
	0	0	0	0	0					
	0	0	0	0	0					
	-.067 (.028)	0	0	0	0					
	.012 (.012)	0	-.039 (.023)	0	-.211 (.090)					

^aFigures in parentheses are standard errors.

Table 4.4. continued

Another representation of the full model estimated for the period (1952:II-1980:I) is as follows:

$$\begin{aligned} \dot{R}GNP_t = & 1.147 - .551\dot{P}_{t-1} + .461\dot{M}_{t-1} - 1.55R_{t-1} + .411\dot{M}_{t-2} + .452R_{t-2} \\ & (.343) (.2) \quad (.156) \quad (.654) \quad (.17) \quad (.617) \\ & + .284\dot{C}_{t-3} - .201RGNP_{t-4} \\ & (.219) \quad (.084) \end{aligned}$$

$$\begin{aligned} \dot{P}_t = & -.141 + .3\dot{P}_{t-1} + .255\dot{M}_{t-1} - .197\dot{C}_{t-1} + .992R_{t-1} - .154RGNP_{t-2} \\ & (.153) (.081) \quad (.063) \quad (.098) \quad (.19) \quad (.039) \\ & + .39M_{t-2} - .092RGNP_{t-3} + .173\dot{P}_{t-3} - .843R_{t-3} \\ & (.087) \quad (.036) \quad (.076) \quad (.188) \end{aligned}$$

$$\begin{aligned} \dot{M}_t = & -.196 - .198\dot{P}_{t-1} + .626\dot{M}_{t-1} - .791R_{t-1} + .159\dot{P}_{t-2} + .994R_{t-2} \\ & (.191) (.112) \quad (.074) \quad (.318) \quad (.101) \quad (.305) \\ & + .183\dot{C}_{t-3} \\ & (.11) \end{aligned}$$

$$\begin{aligned} \dot{C}_t = & .447 + .094RGNP_{t-1} + .27\dot{M}_{t-1} + .314\dot{C}_{t-2} + .133\dot{P}_{t-3} + .232\dot{C}_{t-3} \\ & (.103) (.028) \quad (.05) \quad (.073) \quad (.056) \quad (.081) \\ & - .067\dot{C}_{t-4} \\ & (.028) \end{aligned}$$

$$\begin{aligned} R_t = & .006 + .032RGNP_t + .066\dot{M}_{t-1} + 1.257R_{t-1} - .579R_{t-2} + .043\dot{M}_{t-3} \\ & (.04) (.012) \quad (.019) \quad (.083) \quad (.126) \quad (.022) \\ & + .46R_{t-3} + .012RGNP_{t-4} - .039\dot{M}_{t-4} - .211R_{t-4} \\ & (.132) \quad (.012) \quad (.023) \quad (.09) \end{aligned}$$

Error covariance matrix: Σ

	1	2	3	4	5
1	.655556				
2	-.017497	.093566			
3	.118275	.026445	.221929		
4	.043494	.012190	.060283	.080953	
5	.013469	.004052	-.010250	-.002252	.010080

Table 4.5. Cross correlation matrices of residuals in terms of +, -, and •^a

Lags 1 through 6:

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• • • • • • • • • • • • • • • •
• • • • • • • • • • • • • • • •
• • • • • • • • • • • • • • • •
• • • • • • • • • • • • • • • •
• • • • • • • • • • • • • • • •

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Lags 7 through 12:

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• • • • • • • - • • • • • • • • • •
• • • • - • • • • • • • • • • • • • •
+ • • • • • • • - - • • • • • • • • • •
• • • • • • • - - • • • • • • • • • • +
• • • • • • • • • • • • • • • - • • • • •

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^a+ denotes a value greater than $2/\text{SQRT}$ (no. of observations),
 - denotes a value less than $-2/\text{SQRT}$ (no. of observations), and
 • denotes a nonsignificant value based on the above criterion.

To get the forecasts for the next four quarters, the data were updated by four observations (1980:II to 1981:I), and the model was reestimated over the period 1952:II to 1981:I. Forecasts for the next four quarters (1981:II to 1982:I) for the same variables are reported in Table 4.7.

For the next sets of forecasts, repeatedly the data were updated by four observations, a new adequate model was estimated, and forecasts were obtained. The forecasts for the period 1982:II to 1985:I are presented in Table 4.8.

To test whether the growth rate of M1 money supply is Granger causally prior to the growth rate of real GNP, nominal interest rate, inflation rate, and growth rate of credit, the forecasts of all these variables based on the full information set, i.e., from the full model or model 1, need to be compared to the corresponding forecasts based on the full information set excluding the growth rate of M1 money supply. Therefore, multivariate models with four variables -- growth rate of real GNP, growth rate of prices, growth rate of total nonfinancial debt, and log levels of interest rate -- in the same manner that was carried out for model 1, were estimated and forecasts were obtained. We call the vector ARIMA model for the vector $[YH \ PH \ CH \ LGR]_t'$ model 2; the dynamic forecasts of this model are presented in Table 4.9.

To test the hypotheses of whether the growth rate of real GNP is Granger causally prior to the inflation rate, growth rate of M1 money stock, growth rate of credit, and the level of nominal interest rate, the forecasts of these variables from model 1 should be compared to their

Table 4.6. Forecasts of model 1 for 1980:II through 1981:I

Time period	Observation no.	YH		PH		MH		CH		LGR	
		Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error
1980:II	113	-0.045	0.810	2.279	0.306	1.533	0.471	2.658	0.285	2.597	0.100
1980:III	114	-0.084	0.864	2.061	0.352	1.742	0.569	2.450	0.330	2.480	0.166
1980:IV	115	0.468	0.929	2.055	0.404	1.950	0.593	2.651	0.371	2.442	0.201
1981:I	116	0.591	0.955	2.050	0.437	1.965	0.599	2.677	0.407	2.437	0.236

Table 4.7 Forecasts of model 1 for the period 1981:II through 1982:I

Time period	Observation no.	YH		PH		MH		CH		LGR	
		Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error
1981:II	117	0.474	0.845	2.337	0.309	1.324	0.601	2.584	0.303	2.642	0.106
1981:III	118	-0.306	0.901	1.747	0.369	1.738	0.665	2.512	0.356	2.630	0.181
1981:IV	119	0.239	0.961	1.905	0.429	1.897	0.671	2.512	0.391	2.513	0.222
1982:I	120	0.298	0.980	2.116	0.459	2.016	0.677	2.492	0.419	2.505	0.263

Table 4.8. Forecasts of model 1 for the period 1982:II through 1985:I

Time period	Observation no.	YH		PH		MH		CH		LGR	
		Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error
1982:II	121	0.800	0.841	2.015	0.317	1.546	0.563	2.342	0.289	2.567	0.103
1982:III	122	0.332	0.897	2.160	0.369	1.823	0.606	2.092	0.334	2.453	0.174
1982:IV	123	0.678	0.945	1.848	0.411	1.716	0.612	2.289	0.361	2.488	0.212
1983:I	124	0.840	0.961	1.747	0.442	1.924	0.615	2.511	0.391	2.456	0.253
1983:II	125	2.257	0.839	1.418	0.329	2.521	0.598	2.636	0.292	2.199	0.104
1983:III	126	1.554	0.887	1.485	0.394	1.790	0.659	2.634	0.339	2.362	0.175
1983:IV	127	0.908	0.944	1.496	0.434	1.389	0.665	2.386	0.370	2.328	0.214
1984:I	128	0.413	0.963	1.378	0.469	2.015	0.669	2.177	0.403	2.257	0.258
1984:II	129	0.386	0.836	0.982	0.333	1.290	0.594	2.367	0.295	2.223	0.102
1984:III	130	0.490	0.883	1.078	0.396	1.629	0.659	2.519	0.344	2.103	0.173
1984:IV	131	0.693	0.941	1.043	0.434	2.066	0.664	2.436	0.374	2.018	0.211
1985:I	132	0.780	0.961	1.161	0.472	2.046	0.671	2.409	0.410	2.005	0.254

Table 4.9. Forecasts of model 2 for the period 1980:II through 1985:I

Time period	Observation no.	YH		PH		CH		LGR	
		Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error
1980:II	113	0.037	0.850	2.383	0.326	2.511	0.284	2.615	0.104
1980:III	114	0.051	0.898	2.121	0.363	2.444	0.316	2.587	0.173
1980:IV	115	0.264	0.942	2.054	0.405	2.616	0.340	2.558	0.210
1981:I	116	0.434	0.976	2.085	0.417	2.651	0.364	2.510	0.236
1981:II	117	0.679	0.890	2.690	0.330	2.922	0.291	2.597	0.112
1981:III	118	0.108	0.939	1.811	0.374	2.357	0.322	2.668	0.185
1981:IV	119	0.500	0.983	1.916	0.421	2.313	0.345	2.682	0.219
1982:I	120	0.373	1.017	2.265	0.433	2.568	0.366	2.603	0.244
1982:II	121	-0.181	0.900	1.825	0.360	2.370	0.289	2.581	0.114
1982:III	122	0.199	0.946	2.092	0.395	2.260	0.321	2.396	0.181
1982:IV	123	0.512	0.988	2.112	0.429	2.420	0.344	2.355	0.215
1983:I	124	0.691	1.020	1.819	0.444	2.434	0.365	2.390	0.243
1983:II	125	1.165	0.885	1.401	0.369	2.708	0.287	2.124	0.113
1983:III	126	1.148	0.931	1.494	0.413	2.622	0.319	2.102	0.180
1983:IV	127	1.005	0.974	1.647	0.445	2.694	0.342	2.124	0.214
1984:I	128	0.830	1.006	1.645	0.461	2.617	0.365	2.165	0.240
1984:II	129	1.333	0.888	1.340	0.362	2.991	0.285	2.340	0.111
1984:III	130	1.012	0.939	1.408	0.396	3.003	0.318	2.386	0.178
1984:IV	131	0.777	0.984	1.617	0.440	2.875	0.342	2.382	0.211
1985:I	132	0.707	1.019	1.720	0.459	2.741	0.366	2.392	0.237

corresponding values predicted by model 3. Model 3 is the vector ARIMA model for the full information set excluding real GNP, i.e., including only inflation rate, M1 growth rate, growth rate of credit, and log levels of nominal interest rate or the vector $[PH \ MH \ CH \ LGR]_t'$.

Model 3 was identified, estimated, and diagnostically checked the same way as was explained for the full model. Forecasts were obtained in the same manner as the full model as well. The resulting forecasts of this model for the period 1980:II to 1985:I are presented in Table 4.10.

The family of model 4 are the vector ARIMA models for the vector $[YH \ PH \ MH \ LGR]_t'$. Forecasts of these models are compared to the corresponding forecasts of the main model in order to test hypotheses of whether growth rate of total nonfinancial debt is Granger causal prior to the growth rates of real GNP, prices, M1 money stock, and the log level of nominal interest rate. Table 4.11 displays the forecasts of these models for the period 1980:II through 1985:I.

To test the hypotheses of whether the nominal interest rate is Granger causally prior to the growth rate of output, M1 money stock growth rate, growth rate of credit, and inflation rate, the family of model 5 was identified, estimated, and diagnostically checked by the same method explained for the main model. The family of model 5 provides the forecasts of each variable based on the information set that does not include the nominal interest rate. Therefore, to test the above causal hypotheses these forecasts will be compared to the forecasts based on the same information set plus the interest rate time series data.

Table 4.10. Forecasts of model 3 for the period 1980:II through 1985:I

Time period	Observation no.	PH		MH		CH		LGR	
		Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error
1980:II	113	2.190	0.323	1.358	0.450	2.661	0.295	2.602	0.093
1980:III	114	1.953	0.370	1.642	0.504	2.360	0.360	2.480	0.155
1980:IV	115	2.058	0.389	1.957	0.522	2.431	0.340	2.423	0.191
1981:I	116	1.996	0.420	1.882	0.534	2.681	0.377	2.383	0.220
1981:II	117	2.289	0.322	1.383	0.561	2.565	0.305	2.449	0.099
1981:III	118	1.905	0.375	0.491	0.583	1.921	0.335	2.399	0.173
1981:IV	119	1.859	0.395	2.308	0.600	1.703	0.348	2.342	0.211
1982:I	120	2.205	0.417	2.760	0.616	2.647	0.380	2.282	0.240
1982:II	121	1.862	0.329	1.608	0.560	2.296	0.301	2.636	0.099
1982:III	122	1.843	0.382	2.024	0.581	2.436	0.333	2.505	0.170
1982:IV	123	1.564	0.400	1.750	0.597	2.378	0.348	2.453	0.206
1983:I	124	1.653	0.423	1.745	0.611	2.320	0.380	2.442	0.239
1983:II	125	1.240	0.333	2.904	0.595	2.966	0.298	2.233	0.099
1983:III	126	1.286	0.393	2.264	0.617	2.997	0.328	2.473	0.166
1983:IV	127	1.579	0.412	2.074	0.631	2.908	0.348	2.575	0.202
1984:I	128	1.697	0.437	2.609	0.644	2.754	0.381	2.634	0.237
1984:II	129	0.954	0.333	2.155	0.595	2.397	0.298	2.251	0.096
1984:III	130	1.497	0.392	2.429	0.613	2.759	0.326	2.245	0.168
1984:IV	131	1.443	0.412	2.489	0.624	2.984	0.344	2.256	0.210
1985:I	132	1.467	0.439	2.009	0.636	2.797	0.376	2.366	0.252

Table 4.11. Forecasts of model 4 for the period 1980:II through 1985:I

Time period	Observation no.	YH		PH		MH		LGR	
		Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error
1980:II	113	-0.152	0.817	2.301	0.337	1.630	0.470	2.574	0.101
1980:III	114	-0.095	0.858	2.021	0.390	1.626	0.553	2.499	0.168
1980:IV	115	0.339	0.928	2.014	0.424	1.784	0.576	2.469	0.212
1981:I	116	0.376	0.958	2.078	0.458	1.905	0.588	2.425	0.253
1981:II	117	0.631	0.846	2.316	0.339	1.775	0.602	2.558	0.106
1981:III	118	-0.107	0.896	1.988	0.404	2.035	0.659	2.654	0.180
1981:IV	119	0.360	0.963	2.225	0.441	1.674	0.668	2.665	0.220
1982:I	120	-0.066	0.987	2.354	0.471	1.823	0.673	2.557	0.255
1982:II	121	0.813	0.842	2.070	0.347	1.678	0.577	2.591	0.104
1982:III	122	0.396	0.896	2.242	0.406	1.961	0.624	2.482	0.176
1982:IV	123	0.737	0.947	1.731	0.437	2.019	0.635	2.517	0.219
1983:I	124	1.041	0.971	1.944	0.467	1.737	0.645	2.540	0.266
1983:II	125	2.325	0.838	1.338	0.354	2.637	0.596	2.202	0.105
1983:III	126	1.646	0.885	1.467	0.419	2.707	0.650	2.345	0.176
1983:IV	127	1.380	0.948	1.650	0.450	1.976	0.662	2.349	0.218
1984:I	128	0.935	0.973	1.555	0.483	2.508	0.682	2.337	0.264
1984:II	129	0.320	0.836	0.982	0.355	1.721	0.596	2.243	0.103
1984:III	130	0.506	0.881	0.960	0.415	1.662	0.654	2.160	0.173
1984:IV	131	0.672	0.947	1.094	0.446	1.711	0.666	2.097	0.215
1985:I	132	0.541	0.972	1.080	0.484	1.793	0.681	2.077	0.260

The predicted values of growth rate of real GNP, the inflation rate, growth rate of M1 money stock, and the growth rate of total nonfinancial debt, our credit variable, due to model 5 appear in Table 4.12.

Forecasts are for the period 1980:II through 1985:I.

Finally, to test the hypotheses whether the inflation rate is Granger causally prior to the growth rate of output, growth rate of M1 money supply, growth rate of credit, and the nominal interest rate, we need to estimate the vector ARIMA models for the information set excluding the inflation rate. Forecasts of these models then need to be compared to the corresponding forecasts based on the full information set or forecasts of model 1.

If the forecasts of a given variable from the main model were superior to the forecasts of that variable from the ARIMA models that exclude the inflation rate from their variable set, then the inflation rate is said to Granger cause that variable. The family of models that exclude the inflation rate from their variable set, in this study, is called model 6. The forecasts of these models for the period 1980:II to 1985:I are listed in Table 4.13.

After obtaining all the necessary sets of forecasts, to make causal inferences different sets of forecasts are formally compared to one another by calculating the forecast errors defined as the true value minus the predicted value and then forming the γ and Σ variables. γ is the difference of forecast errors and Σ is the sum of them. Then, the following regression model is estimated and its coefficients will be tested as to whether they are positive or not.

Table 4.12. Forecasts of model 5 for the period 1980:II through 1985:I

Time period	Observation no.	YH		PH		MH		CH	
		Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error
1980:II	113	0.006	0.841	2.039	0.343	1.442	0.492	2.548	0.294
1980:III	114	0.318	0.905	1.886	0.385	1.517	0.584	2.410	0.351
1980:IV	115	0.318	0.964	1.984	0.407	1.549	0.616	2.530	0.393
1981:I	116	0.413	0.989	1.872	0.442	1.505	0.635	2.440	0.435
1981:II	117	0.598	0.870	2.160	0.343	1.204	0.639	2.463	0.310
1981:III	118	-0.179	0.951	2.157	0.394	1.537	0.692	2.475	0.375
1981:IV	119	-0.235	1.013	2.209	0.417	1.543	0.701	2.440	0.414
1982:I	120	0.166	1.027	2.110	0.455	1.552	0.712	2.371	0.449
1982:II	121	0.714	0.870	1.820	0.347	1.931	0.626	2.289	0.299
1982:III	122	1.212	0.969	1.823	0.394	1.601	0.681	2.416	0.369
1982:IV	123	1.146	1.026	1.522	0.415	1.569	0.692	2.276	0.409
1983:I	124	0.730	1.039	1.703	0.454	1.522	0.706	2.399	0.446
1983:II	125	2.351	0.875	1.433	0.350	2.686	0.622	2.767	0.299
1983:III	126	2.142	0.953	1.449	0.402	2.066	0.672	2.719	0.366
1983:IV	127	1.575	1.000	1.578	0.424	1.881	0.680	2.587	0.399
1984:I	128	0.923	1.020	1.674	0.455	2.400	0.700	2.687	0.423
1984:II	129	1.342	0.871	1.088	0.352	1.830	0.628	2.647	0.300
1984:III	130	1.158	0.944	1.437	0.404	1.863	0.686	2.763	0.366
1984:IV	131	0.987	0.989	1.392	0.425	1.866	0.696	2.557	0.403
1985:I	132	1.077	1.011	1.482	0.456	2.234	0.715	2.587	0.431

Table 4.13. Forecasts of model 6 for the period 1980:II through 1985:I

Time period	Observation no.	YH		MH		CH		LGR	
		Forecast	Std. error	Forecast	Std. error	Forecast	Std. error	Forecast	Std. error
1980:II	113	-0.221	0.826	1.553	0.472	2.679	0.287	2.609	0.098
1980:III	114	-0.157	0.853	1.598	0.538	2.421	0.331	2.554	0.153
1980:IV	115	0.058	0.911	1.767	0.556	2.562	0.359	2.518	0.186
1981:I	116	0.359	0.941	1.926	0.569	2.528	0.399	2.478	0.220
1981:II	117	0.993	0.852	1.194	0.567	2.545	0.305	2.567	0.104
1981:III	118	-0.157	0.882	1.614	0.606	2.388	0.351	2.665	0.169
1981:IV	119	-0.031	0.929	2.083	0.612	2.344	0.379	2.676	0.204
1982:I	120	0.176	0.961	1.785	0.617	2.315	0.406	2.578	0.236
1982:II	121	0.128	0.848	1.841	0.557	2.331	0.295	2.604	0.106
1982:III	122	0.482	0.898	1.866	0.603	2.277	0.345	2.481	0.167
1982:IV	123	0.496	0.951	2.097	0.605	2.450	0.376	2.450	0.201
1983:I	124	0.666	0.971	2.103	0.608	2.478	0.404	2.530	0.237
1983:II	125	2.057	0.837	2.542	0.586	2.678	0.295	2.251	0.104
1983:III	126	1.488	0.889	1.952	0.629	2.661	0.343	2.458	0.170
1983:IV	127	0.729	0.949	1.584	0.632	2.657	0.371	2.409	0.207
1984:I	128	0.345	0.972	2.357	0.635	2.643	0.395	2.396	0.247
1984:II	129	0.688	0.835	1.919	0.585	2.794	0.292	2.288	0.103
1984:III	130	0.565	0.883	2.020	0.628	2.852	0.339	2.257	0.168
1984:IV	131	0.759	0.944	2.084	0.630	2.779	0.367	2.260	0.207
1985:I	132	0.836	0.968	2.231	0.633	2.645	0.392	2.320	0.246

$$\gamma_t = \alpha + \beta(\Sigma_t - \bar{\Sigma}) + \epsilon_t; \bar{\Sigma} \text{ is the sample mean of } \Sigma.$$

ϵ_t is an error term with mean zero and variance $\sigma^2 \epsilon_t$ and can be treated as independent of Σ_t (see Ashley et al., 1980, p. 1154).

In the above regression model, to test whether the intercept α is positive is actually the test of whether one set of forecast errors has larger mean than the other set. And, the test of positiveness of β is basically testing to see if one set of forecast errors has larger variability than the other or is the comparison of mean squares of the two sets of forecast errors (see Appendix B).

Let

$e_{inY} \equiv$ nth forecast error of growth rate of real GNP by model i ,

$e_{inP} \equiv$ nth forecast error of growth rate of prices by model i ,

$e_{inM} \equiv$ nth forecast error of growth rate of M1 money stock by model i ,

$e_{inC} \equiv$ nth forecast error of growth rate total nonfinancial debt by model i , and

$e_{inR} \equiv$ nth forecast error of nominal interest rate by model i

where $n = 1, 2, \dots, 20$,

$i = 1, 2, \dots, 6$,

and let

$$\gamma_{jnY} = e_{jnY} - e_{inY}$$

$$\gamma_{jnP} = e_{jnP} - e_{inP}$$

$$\gamma_{jnC} = e_{jnC} - e_{inC}$$

$$\gamma_{jnM} = e_{jnM} - e_{inM}$$

$$\gamma_{jnR} = e_{jnR} - e_{inR}$$

where $n = 1, 2, \dots, 20,$

$j = 2, 3, \dots, 6.$

And, finally, let

$$\Sigma'_{jnY} = e_{jnY} + e_{inY}$$

$$\Sigma_{jnY} = \Sigma'_{jnY} - \bar{\Sigma}_{jY}$$

$$\Sigma'_{jnP} = e_{jnP} + e_{inP}$$

$$\Sigma_{jnP} = \Sigma'_{jnP} - \bar{\Sigma}_{jP}$$

$$\Sigma'_{jnC} = e_{jnC} + e_{inC}$$

$$\Sigma_{jnC} = \Sigma'_{jnC} - \bar{\Sigma}_{jC}$$

$$\Sigma'_{jnM} = e_{jnM} + e_{inM}$$

$$\Sigma_{jnM} = \Sigma'_{jnM} - \bar{\Sigma}_{jM}$$

$$\Sigma'_{jnR} = e_{jnR} + e_{inR}$$

$$\Sigma_{jnR} = \Sigma'_{jnR} - \bar{\Sigma}_{jR}$$

for $j = 2, 3, \dots, 6,$

$n = 1, 2, \dots, 20.$

The following four regression models were estimated in order to test whether the growth rate of M1 money supply, growth rate of total nonfinancial debt (credit), nominal interest rate, and the inflation rate Granger cause the growth rate of real GNP. In estimation of these forecast errors of model 1 and models 2, 4, 5, and 6, respectively, were used.

The estimation results appear in Table 4.14. In these regression models, dependent variables are γ_{jY} for $j = 2, 4, 5,$ and 6 and independent variables are Σ_{jY} for $j = 2, 4, 5,$ and 6 .

Table 4.14. Regression results of tests 1-4 (do \dot{M} , \dot{C} , R , and \dot{P} cause \dot{RGNP} ?)

Test #	j = model #	Intercept	β coefficient	Durbin-Watson statistic
1	2	-0.00785 (0.05)	0.012051 (0.26)	1.78 ^a
2	4	-0.0416 (-0.88)	-0.0263 (-1.16)	1.53
3	5	0.24755 (1.91)	-0.0139995 (-0.36)	1.83*
4	6	-0.04265 (-0.7266)	-0.008131 (-0.29)	1.96*

^a* indicates cases for which the first order serial correlation was a problem in Tables 4.14-4.18. For these cases, ρ , the first order correlation coefficient, was estimated and then the data were transformed to remove the serial correlation and then the regression models were reestimated.

^bThe values in parentheses are t-ratios in Tables 4.14-4.18.

Next, to test the hypotheses whether the growth rate of income, M1 money stock, credit, and nominal interest rate Granger cause growth rate of prices or the inflation rate, forecast errors of models 1, 3, 2, 4, and 5 were used. The estimation results are presented in Table 4.15. In the following regression models, γ_{jP} were the dependent variables with $j = 3, 2, 4,$ and $5,$ respectively. The independent variables were Σ_{jP} with $j = 3, 2, 4,$ and $5,$ respectively.

The regression models presented in Table 4.16 were estimated using forecast errors of models 1, 3, 4, 5, and 6, respectively. The coefficients of these models were tested to see if the growth rate of real GNP, inflation rate, growth rate of total nonfinancial debt, and the nominal interest rate are Granger causally prior to the growth rate of M1 money supply. In these regression models, the dependent variables are γ_{jM} with $j = 3, 4, 5,$ and 6 and the independent variables are Σ_{jM} with $j = 3, 4, 5,$ and $6,$ respectively.

Table 4.17 displays the regression models that were estimated in order to test whether the growth rate of income, prices, money, and the interest rate Granger cause growth rate of total nonfinancial debt. The forecast errors of models 1, 3, 6, 2, and 5 were used, respectively. In these regression models, the dependent variables are γ_{jC} with $j = 3, 6, 2,$ and 5 and the independent variables are Σ_{jC} with $j = 3, 6, 2,$ and $5.$

Finally, Table 4.18 presents the regression models estimated by using forecast errors of models 1, 3, 6, 2, and 4. The coefficients of these models are tested to see whether the growth rate of income, prices,

Table 4.15. Regression results of tests 5-8 (do $\dot{R}G\dot{N}P$, \dot{M} , \dot{C} , and R cause \dot{P} ?)

Test #	j = model #	Intercept	β coefficient	Durbin-Watson statistic
5	3	-0.01652 (-0.21)	-0.020306 (-0.49)	1.983
6	2	0.19634 (1.96)	0.088459 (3.81)	1.68*
7	4	0.0525 (1.78)	0.007022 (0.27)	1.52*
8	5	-0.01404 (-0.14)	-0.07923 (-1.87)	1.43*

Table 4.16. Regression results of tests 9-12 (do $\dot{R}G\dot{N}P$, \dot{P} , \dot{C} , and R cause \dot{M} ?)

Test #	j = model #	Intercept	β coefficient	Durbin-Watson statistic
9	3	-0.1961 (-1.79)	0.028124 (0.57)	1.44*
10	4	-0.109595 (-2.12)	0.00626 (0.269)	1.24*
11	5	-0.107385 (-0.90)	-0.0048 (-0.18)	1.56*
12	6	0.02669 (.24)	0.0063 (0.23)	2.00*

Table 4.17. Regression results of tests 13-16 (do $\dot{R}GNP$, \dot{P} , \dot{M} , and R cause \dot{C} ?)

Test #	j = model #	Intercept	β coefficient	Durbin-Watson statistic
13	3	-0.08135 (-1.06)	-0.13196 (-1.76)	1.42
14	6	-0.0988 (-1.97)	-0.08234 (-2.90)	1.38*
15	2	-0.13915 (-3.936)	-0.17747 (-5.070)	1.93
16	5	-0.05185 (-1.59)	-0.11725 (-3.82)	1.70

Table 4.18. Regression results of tests 17-20 (do $\dot{R}GNP$, \dot{P} , \dot{M} , and \dot{C} cause R ?)

Test #	j = model #	Intercept	β coefficient	Durbin-Watson statistic
17	3	-0.050797 (-0.79)	0.15626 (1.85)	1.54*
18	6	0.0422 (1.46)	-0.000366 (-0.01)	1.25*
19	2	-0.06849 (-0.68)	-0.017923 (-0.26)	1.67*
20	4	-0.0318 (-2.80)	0.00832 (0.27)	1.43

money, and credit Granger cause the nominal interest rate. The dependent variables for these models are γ_{jR} with $j = 3, 6, 2,$ and 4 and the independent variables are Σ_{jR} with $j = 3, 6, 2,$ and $4,$ respectively.

The economic interpretations of the results are discussed in the following chapter.

CHAPTER V. ECONOMIC IMPLICATIONS OF THE ANALYSIS

The economic implications of the analysis are based on the causal relationships derived. Therefore, in this chapter we review the causal relationships that emerge from tests #1 through #20, and then discuss the macroeconomic implications of those relationships.

Inspection of estimated regression coefficients presented in Table 4.14 suggests that relative to the information set real GNP growth rate ($\dot{R}GNP$), the inflation rate (\dot{P}), the growth rate of money (\dot{M}), the growth rate of credit (\dot{C}), and the nominal interest rate (R), the only variable that Granger causes real income or output is the nominal interest rate. (In test #3, the intercept is positive and significant at the five percent significance level.)

In test #1, the intercept is negative but not significant. The slope coefficient, which tests whether the mean squares of the forecast errors (MSE) of model #2 exceeds the MSE of model #1, is positive but not significant. This implies that the causal relationship from the growth rate of money to the growth rate of real income is not statistically significant enough to enable us to conclude that \dot{M} causes $\dot{R}GNP$ in Granger sense. In other words, tests #1 through #4 imply that growth in real GNP is not directly influenced by the growth rates of M1 money supply, credit, or the inflation rate but it is directly influenced by the level of nominal interest rates.

This result is in accordance with J. Fackler's (1985) conclusions but conflicts with B. Friedman's (1981b) conclusion that "although

neither money nor credit incrementally explains real income in the absence of the other, both do so in the presence of one another."

Table 4.15 reveals that relative to the information set $\dot{R}GNP$, \dot{P} , \dot{M} , \dot{C} , and R , the growth rates of money and credit are both Granger causally prior to the growth rate of prices. It can be observed that in tests #6 and #7 both of the estimated coefficients are positive and in test #6 they are both highly significant. In tests #5 and #8, both coefficients are negative and therefore it cannot be concluded that the direction of causation is from the growth rate of income or the nominal interest rate to the inflation rate.

Tests #9 through #12 suggest that the growth rate of money is not caused by any of the variables in the information set. In tests #9 and #10, β coefficients are positive but not significantly different from zero, where the intercept terms are both negative and significant. In test #11, both coefficients are negative. In test #12, both coefficients are positive but not significantly different from zero.

Tests #13 through #16, presented in Table 4.17, suggest that the growth rate of total nonfinancial debt is not caused by any of the variables considered in this study.

In Table 4.18, results of tests #17 through #20 reveal that only the inflation rate Granger causes the nominal interest rate. In test #18, the intercept of the regression equation is positive and significant at the 0.10 significance level. Therefore, it is concluded that the information in the past values of inflation rate help reduce the forecast

errors of the nominal interest rate, i.e., the inflation rate Granger causes the nominal interest rate.

Now, test #1 and test #6 state that the growth rate of money does not cause the growth rate of real GNP but causes inflation or that increases in the growth rate of money causes nominal income to rise.

Tests #6 and #10 imply that there exists a unidirectional causal relationship from money to the inflation rate. Also, tests #7 and #11 indicate that the causal relationship between the growth rate of credit (\dot{C}) and the inflation rate (\dot{P}) is unidirectional and is from \dot{C} to \dot{P} .

Tests #8 and #18 show that the causal relationship between the inflation rate and the nominal rate of interest is unidirectional and is from the inflation rate to the nominal interest rates.

Tests #3 and #17 imply that there is a feedback relationship between the growth rates of output and the short-term nominal interest rates.

All of these results suggest that growth rates of money and credit both indirectly influence the economic growth through their influence on the inflation rate which in turn influences the interest rates and then income. And, this is the route through which the monetary policy influences the real variables in the economy. Moreover, although the channels through which growth rates of money and credit influence economic activity as discovered by this study are different from the channels of influence described by other studies which employ a different framework (VAR methodology) to investigate similar causal relationships, some important macroeconomic implications are the same in the sense that as far as the determination of the inflation rate, nominal interest

rates, and output are concerned, both the growth rate of money and the growth rate of credit "matter." And although this result leaves a channel for the monetary policy to affect the economy, it is not in total accordance with the neo-monetarist position that monetary policy shocks could explain nearly all cyclical variations in real variables in the economy or the proposition that changes in the growth rate of money supply are responsible for the post-war U.S. business cycles. This is because, as was found in this study, money does not directly cause real income. Also, money does not directly Granger cause the nominal rate of interest. And, it is only the nominal interest rate that is in direct causal relationship with income and in fact there exists a feedback relationship between the nominal interest rates and income or that these two variables are jointly determined.

This is also consistent with Sims' (1980) finding that the interest rate innovations are not simply anticipated money stock innovations and that an upward unit surprise (innovation) in nominal interest rates results in a decline in both money and output and so he concluded that "... in both periods (prewar and post-war) some of the observed comovements of industrial production and money stock are attributed to common responses to surprise changes in the interest rate" (p. 253).

Therefore, it is plausible for money to have some influence on the economy but for monetary policy not to be responsible for creating business cycles. Again, variations in output are primarily explained or jointly determined by variations in nominal interest rates. Nominal interest rates are influenced by the behavior of the economic decision

makers who make decisions using all the information available to them, including the economic and political changes outside the domestic economy.

In fact, Fama (1982) suggests the insight that "the incremental predictive content of nominal variables for future real variables arises solely because economic agents have some information about the future real activity -- beyond that contained in current and lagged real variables -- which shows up first in the equilibrium price of financial assets, particularly nominal interest rates" (p. 202).

The growth rate of money is independent of the growth rate of credit, since the growth rate of credit does not cause growth rate of money and is not caused by it either (tests #11 and #15). Therefore, the information contained in the growth rate of total nonfinancial debt about future inflation rate and output is over and above the information contained in the lagged values of money. The monetary policy implication of this finding is that in order to achieve the desirable paths for the movements of the goal variables -- the inflation rate, output growth, and the unemployment rate -- the monetary authority is better off to target and watch the growth rates of both money and credit.

The nominal interest rate, which provides the primary link between the financial and the real sectors of the economy, is determined by the interaction of the credit and the money markets. The implication of this for the macroeconomic modeling strategy would be that it makes sense to have exclusive representation of credit market as well as the money market. This proposition is in line with J. Fackler's (1985) argument

that in highly aggregated macroeconomic models of the economy, there exists four markets: money, goods, bonds, and labor markets. "By Walras's law, any one market may safely be dropped and by now it is almost traditional, in this particular aggregation, that the bond market, or the market for credit is ignored" (p. 28). Later he concludes that "existing evidence suggests that important information may be lost by suppressing the credit market, ... ignoring credit may provide biased estimates of the linkages between the financial and real sectors" (p. 37).

Also, B. Friedman (1981b) concluded that "... neither money nor credit is sufficient to account fully for the effect of financial markets in determining real economic activity. Instead, what appears to matter is an interaction between money and credit. This result is consistent with a macroeconomic modeling strategy that deals explicitly with both the money market and the credit market"

Another issue to be addressed by this study was the question of the breakdown of the past close relationship between the growth rate of M1 money supply and the output growth rate due to the deregulation of financial industry.

Given that the causal relationships derived in this study are primarily based on the out-of-sample forecasting performance of the multivariate time series models over the 1980-1985 period, the period after the introduction of the Monetary Control Act of 1980, the causal relationship between money and income can shed some light on the above question. However, although the conclusion that M1 money growth rate and

output growth are independent is hardly rejecting the hypothesis of breakdown of that relationship. Nevertheless, the finding that growth rate of M1 money has a direct causal effect on the inflation rate and then on the real variables of the economy, it can be asserted that M1 money supply can still serve as a useful short-run policy guide and that the monetary authority can still take advantage of the influence of changes in the M1 money supply growth rate on the economy.

The growth rate of output and the inflation rate are found to be independent. The inflation rate does not cause the output growth and is not caused by it either (tests #4 and #5). This finding implies that over a one-year period, the Philips curve is vertical or that there is no tradeoff between the inflation rate and the unemployment rate.

CHAPTER VI. SUMMARY AND CONCLUSIONS

This dissertation centered around an empirical specification of relationships among five macroeconomic variables -- three quantities and two relative prices representing commodity, money, and credit markets.

Granger's definition of temporal causation was the framework for investigating the interrelations of the economic time series of interest, i.e., real GNP, the GNP price deflator, the M1 money stock, total nonfinancial debt, and the 4-6 month commercial paper rate.

The methodology utilized was the multivariate autoregressive moving average (ARMA) approach for building multivariate time series models. This methodology is proposed by Tiao and Box (1981) and is an extension of Box and Jenkins (1970) methodology for constructing univariate time series models.

Although the concept of causality has been the topic of empirical and theoretical investigation by many economists such as Sims (1972, 1980), B. Friedman (1981a, 1981b), J. Fackler (1985), and Litterman and Weiss (1985) to name a few, it should be emphasized that the current study is distinct from the former empirical studies in two respects. The first distinction is that, in relating different economic time series together, all of the named authors have either used regression analysis or VAR methodology. This study has employed the multivariate ARMA approach which has not been much used in the literature and is closely connected with the concept of temporal causation defined by Granger (1969).

Secondly, to make inferences about causal relationships, a statistical procedure proposed by Ashley et al. (1980) was employed. This approach, which is explicitly designed to test causal hypotheses in a time series context, is more faithful to the definition of Granger causality since it is based on the out-of-sample forecasting performance of the models. Other studies drew their causal conclusions on the basis of parameters of the estimated models, i.e., they based their conclusions on the in-sample data.

The causal relationships discovered in this study are as follows: The growth rate of money and total nonfinancial debt are Granger causally prior to the growth rate of prices or the inflation rate. The inflation rate Granger causes the nominal interest rates. And, there is a feedback relationship between the nominal interest rates and the growth rate of real income.

A few caveats have to be mentioned: (1) Granger causality is a statistical concept and conclusions are relative to the given information set used in a study. (2) The test proposed by Ashley et al. (1980) for comparison of forecast errors was based on the usage of one-step-ahead forecast errors whereas in this study, to economize on the computation costs of estimation of multivariate models, one-, two-, three-, and four-step-ahead forecasts were used. Forecasts farther into the future have larger standard errors and therefore are less accurate. (3) This study did not deal with the problem of expectations and, for example, was not concerned with decomposition of the growth rate of money into anticipated and unanticipated money, and no efforts were made to

decompose the nominal interest rates into its components, real interest rate and expected inflation rate.

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APPENDIX A

Granger's causality definition utilizes time-series relationships. Variable x is said to "Granger cause" variable y , given an information set that includes at least x and y , if the present value of y , y_t , can be predicted more accurately using past values of x than by not doing so. The accuracy of prediction is measured by variance of prediction error.

Let \bar{A}_t be the information set which includes all the information on x and y up to and including $(t-1)$. Three definitions are introduced.

1. x causes y if $\sigma^2(y_t/\bar{A}_t) < \sigma^2(y_t/\bar{A}_t - \bar{x}_t)$, where $\sigma^2(y_t/(\cdot))$ is variance of prediction error given set (\cdot) , and \bar{x}_t is the set of past values of x .

2. x causes y instantaneously if $\sigma^2(y_t/\bar{A}_t, x_t) < \sigma^2(y_t/\bar{A}_t)$.

3. Feedback exists between x and y if x causes y and y causes x .

There are three ways that one can empirically test the causality between two variables in Granger's sense.

1. Use an autoregressive model. If one wants to know whether y causes x or not, one regresses x on its own past and past values of y . Then one tests the null hypothesis that y does not cause x , i.e., tests whether coefficients of the lagged y 's are zero, against the alternative hypothesis. This test is based on Granger (1969).

2. Using univariate Box-Jenkins techniques, build the forecasting model for each series and find the residual series for each variable. For example, suppose u_t and v_t are the residual series of the univariate model of x_t and y_t , respectively. By definition of residuals u_t and v_t

are reflecting the part of variations of x_t and y_t , respectively, that could not be explained by their own past. To test whether y causes x , one can regress u_t on past values of v_t and test the null hypothesis that coefficients of v_t 's are all zero against the alternative hypothesis. This test was used by Granger (1973).

3. The third way to find out whether y causes x is to regress y_t on past current and future values of x . If the coefficients of future values of x were not significant then y does not cause x .

APPENDIX B

In order to see why the test of positiveness of coefficients of the following regression model suggested by Ashley et al. (1980) is a test of comparison of the forecast errors of two different models -- one with n variables and the other with $n-1$ variables -- consider the following.

Assume:

$$\gamma_t = a + b(\Sigma_t - \bar{\Sigma}) + \epsilon_t$$

where ϵ_t is a white noise process.

We know that the least squares estimators of b and a are as follows:

$$b = \frac{\text{cov}(\gamma, \Sigma)}{\text{var}(\Sigma)}$$

and

$$a = \bar{\gamma} - b(\bar{\Sigma} - \bar{\Sigma}) \text{ or } a = \bar{\gamma} = \mu(\gamma)$$

where cov , var , and μ denote the sample covariance, variance, and mean over the out-of-sample period. Let

$$\gamma_t = e_{n-1,t} - e_{n,t} \text{ and } \Sigma_t = e_{n-1,t} + e_{n,t}$$

where e_n and e_{n-1} are forecast errors of models with n and $n-1$ variables, respectively.

We can write

$$\begin{aligned}
 \text{cov}(\gamma, \Sigma) &= \text{cov}[(e_{n-1} - e_n), (e_{n-1} + e_n)] \\
 &= E[(e_{n-1} - e_n) - (\mu_{n-1} - \mu_n)][(e_{n-1} + e_n) - (\mu_{n-1} + \mu_n)] \\
 &= E[(e_{n-1} - \mu_{n-1}) - (e_n - \mu_n)][(e_{n-1} - \mu_{n-1}) + (e_n - \mu_n)] \\
 &= E[(e_{n-1} - \mu_{n-1})^2 - (e_n - \mu_n)^2] \\
 \text{cov}(\gamma, \Sigma) &= E(e_{n-1} - \mu_{n-1})^2 - E(e_n - \mu_n)^2
 \end{aligned}$$

or

$$\text{cov}(\gamma, \Sigma) = \text{MSE}(e_{n-1}) - \text{MSE}(e_n)$$

and again since $\gamma = e_{n-1,t} - e_{n,t}$,

$$\mu(\gamma) = \mu_{n-1} - \mu_n.$$

According to Ashley et al. (1980), we can conclude that the n variable model out performs the model with $n-1$ variables (same n variables minus one of them), if we can reject the joint null hypothesis $\text{cov}(\gamma, \Sigma) = \phi$ and $\mu(\gamma) = 0$ in favor of the alternative hypothesis that both quantities are nonnegative and at least one is positive. This test is equivalent to the following test:

$$H_0: a = b = 0,$$

$$H_a: a \geq 0 \text{ or } b \geq 0 \text{ and at least one is positive.}$$

Given the above equalities, the test of $a = 0$ is really the test of $\mu(\gamma) = \mu_{n-1} - \mu_n = 0$ against $\mu_{n-1} - \mu_n > 0$ and $b = 0$ is the test of $\text{MSE}(e_{n-1}) - \text{MSE}(e_n) = 0$ against $\text{MSE}(e_{n-1}) > \text{MSE}(e_n)$.

The criteria for judgment are: If either of the two least square estimates of a and b is significantly negative, the n -variable model clearly cannot be judged a significant improvement. If one estimate is negative but not significant, we can use a one-tailed t -test on the other estimated coefficient. If both estimates are positive, we can perform an F -test of the null hypothesis that both population values are zero and report a significance level equal to half that obtained from the tables.