EMPIRICAL COMPARISONS OF CREDIT AND MONETARY AGGREGATES USING VECTOR AUTOREGRESSIVE METHODS

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I. INTRODUCTION

Attention has been given recently to the issue of targeting a credit aggregate or to using information on a credit aggregate in addition to information on monetary aggregates in the implementation of monetary policy. In February 1983, the FOMC adopted an "associated range" of growth for total domestic nonfinancial debt (DNF) and decided "to evaluate debt expansion in judging responses to monetary aggregates." Much of the renewed interest in credit aggregates has been stimulated by Professor Benjamin Friedman.[1]

Unquestionably one of the attributes of credit that has attracted Friedman and others is its velocity behavior. Chart 1 displays on a ratio scale the quarterly level of velocity (GNP/financial aggregate) from 1960 to 1982, for four aggregates: M1, M2, and two credit aggregates. The credit aggregates are debt owed by domestic nonfinancial sectors (DNF), and the private domestic nonfinancial sector's holding of currency, deposits and credit market instruments. The latter *asset* measure is the so-called "debt proxy" (DP) as coined by Henry Kaufman. Of the four aggregates, only the velocity for Ml has a decidedly upward trend over this period. Friedman has stressed that his preferred credit measure, DNF, as a percent of GNP has been about level, remaining within a few percentage points of its 1960 value of 144 percent. Chart 1, however, indicates that this ratio has moved up recently; in fact, it reached a level of 153 percent at the end of June 1983.[2]

It appears from Chart 1 that M1 velocity may be more variable than DNF, but the variability of velocity is not necessarily indicative of its predictability. Chart 2 presents errors in forecasting year over year growth rates in velocity, where the forecasts equal the average of all previous four quarter changes.[3] On the basis of this simple prediction scheme, it is not apparent that the velocity of M1 is more unpredict-

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[1] See Friedman [1981], [1982], [1983A], [1983B].

[2] Note that Friedman uses the reciprocal of velocity in his work. Thus, the recent decline in velocity represents an increase in the debt to income ratio.

[3] If V_{tq} is the level of velocity in year t and quarter q, the forecast of $100(V_{tq}/V_{t-1,q} - 1)$ is made by averaging all past growth rates for the q^{th} quarter.

Chart 1

COMPARISON OF CREDIT AND MONETARY AGGREGATES VELOCITIES

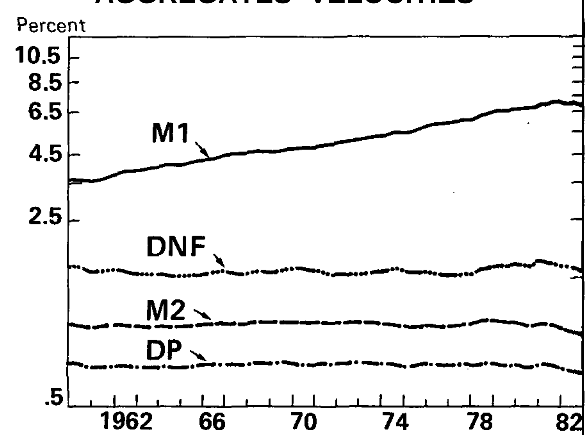
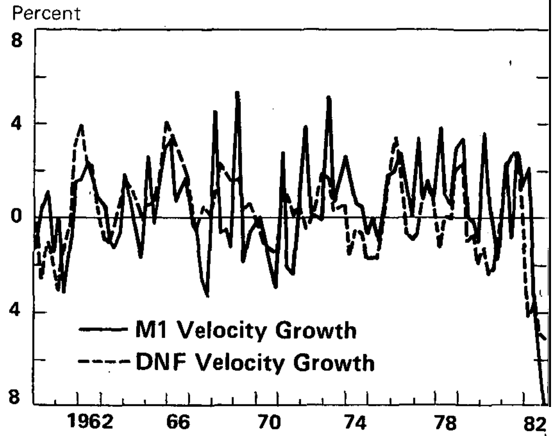


Chart 2

COMPARISON OF AGGREGATES
4 QTR. VELOCITY CHANGES
DEVIATION OF EACH
FROM ITS AVERAGE GROWTH



able than the velocity of DNF. In 1982, the history of neither aggregate predicted the sharp decline in velocity.

For monetary aggregates it is customary to make more detailed comparisons of velocity and its predictability from the vantage point of a theory of demand for the aggregate. For M1 or M2 there is a voluminous body of theory and empirical work to draw on. For credit aggregates, however, there is no established theory of aggregate debt holdings.[4] In the absence of such an analytical framework, Friedman bases much of his empirical work on a form of statistical time series analysis, vector autoregression (VAR), which does not require a theoretical economic model.[5] One conclusion that can be reasonably inferred from Friedman's work is that the DNF credit aggregate performs at least as well as any of the monetary aggregates in the VAR exercises.

This paper reports on some further work using the same VAR methodology. Our results do not tend to support Friedman's policy recommendation that the FOMC establish a two target policy for monetary control consisting of M1 and DNF. Specifically, we show that Friedman's empirical results are quite sensitive to slight changes in either arbitrary or seemingly innocuous assumptions concerning data construction and the form of the VAR. Our results provide additional support to earlier warnings by others that policy implications drawn on the basis of VAR results should be scrutinized with great care.[6]

The remainder of this paper is organized as follows: Section II provides a critical review of the VAR methodology and Section III presents the empirical work. All of Section II need not be read in order to understand Section III. A concluding section provides an overall evaluation of this approach.

II. EXPLANATION OF METHODOLOGY

1. Basic Regressions

In its present form, vector autoregression is a tool for summarizing the relationships among a group of variables, e.g., economic time series; at various lags. A vector autoregression is not a single regression equation but a *system* of regressions with one equation for each variable in the system. Generally, the list of variables in the system is not based on prior' statistical testing. Given the variables selected, estimation of the autoregressive system consists of nothing more than a set of ordinary least squares regressions with the current value of each of the included variables being regressed on the lagged values of all the variables in the system. For example, if the vector autoregression includes only two variables, say M1 and GNP, and say, eight lags on each variable, then the vector autoregression consists of two regressions. In the "M1 equation," M1 would be regressed on eight lagged values of itself and eight lagged values of GNP ; in the "GNP regression" GNP would be regressed on the same set of sixteen explanatory variables. Note that in VAR models, current values of variables never appear, on the right-hand side of any equation in the system. Thus, in a vector autoregression all current variables are treated as endogenous; all lagged variables are, of course, predetermined variables. The number of lagged values of each variable to he included on the right-hand side of each regression must also be determined.

[4] Recent papers by Papademos and Modigliani [1983] and Gordon [1982] have made important contributions to the development of general equilibrium theory in which aggregate credit holdings can be analyzed.

[5] Within the economics profession the VAR model has been popularized in recent years by researchers at the University of Minnesota and the Federal Reserve Bank of Minneapolis, notably Robert Litterman [1982] and Professor Christopher Sims [1980A], [1980B]. While the primary uses of VAR have been in forecasting and data description, more recent applications, such as Sims [1982], have attempted to use this tool for policy analysis.

[6] See Zellner [1979], Gordon and King [1982], and Cooley and LeRoy [1982].

While there exist statistical criteria to determine the maximal lag length, usually an arbitrary lag length is chosen for all variables in all equations.

These simple regressions constitute the only statistical estimation involved in vector autoregression. In fact, the simplicity of the estimation procedure and the ready availability of user-oriented computer programs that carry out such estimation are significant "advantages" of this approach. At the same time, however, one practical problem is the large number of parameters in the vector autoregression specification. When a constant is included in each equation, the number of parameters in each equation equals the number of variables in the system times the number of lags plus one. In the example cited above there are thus seventeen parameters to be estimated in each of the two equations. Accordingly, one must either limit the number of variables and/or lags in the system or else very long data series must be available.[7] Even if long series are available, the use of data from the remote past may be of dubious value when there is a strong suspicion of significant qualitative change in the economic environment, such as technological innovation or major changes in regulation or other policies.

2. The Moving Average Representation and Impulse Response Function

The regressions described in Part I are known as the *autoregressive representation* of the vector autoregression; the reason for this terminology being that the current values of all the variables in the system are regressed on their own lagged values (taken as a system). Another, perhaps more informative way of presenting the information contained in the vector autoregression, is the *moving average representation (MAR).* This representation can be obtained directly from the autoregressive version as follows: The right-hand side of any regression equation contains a statistical disturbance term in addition to the explanatory variables. This disturbance reflects the fact that the sum of terms involving the explanatory variables (here only lagged values of all variables in the system) does not explain the dependent variable exactly at each observation. There will always be some discrepancy or disturbance. Since the explanatory variables in a vector autoregression include observations only prior to the current period, the disturbance is the only contributing factor to a given dependent variable's value that is new to the current period. Accordingly, the current disturbance in the equation for a given variable is known as the *innovation* for that variable in the current period. A time series of such innovations exists for each variable in the vector autoregression. The moving average representation expresses current values of the dependent variables in terms of current and lagged values of the innovations in all variables of the system. In principle, an infinite number of lags is needed to obtain the entire moving average representation.

By a process of successive substitution we can derive the moving average representation from the autoregressive representation. An autoregressive system of order n and dimension m is a system of m variables containing lags from 1 to n. For example, for a second order system of dimension three, the autoregressive representation relates the current values of the dependent variables at time t, say x_t, y_t, z_t, as functions of a fixed number of their own lags, x_{t-1}, x_{t-2}, y_{t-1}, y_{t-2}, z_{t-1}, z_{t-2}. Each lagged value of each variable can be expressed as functions of still prior lagged values of all variables and the innovation that occurred at the given lag, e.g., x_{t-1} depends on x_{t-2}, x_{t-3}, y_{t-2}, y_{t-3}, z_{t-2}, z_{t-3} *and* the disturbance for x_{t-1}, call it ϵ^x_{t-1}. The magnitudes y_{t-1} and z_{t-1} similarly depend on the same set of lagged variables and on ϵ^y_{t-1} and ϵ^z_{t-1}, respectively. If we then repeat this calculation for the variables dated t—2, t—3, t—4, and so forth, we find that the innovations at these prior dates also enter the expression for x_t, y_t, and z_t. Such substitutions, when repeated into the infinite past, yield the moving average representation in which x_t, y_t, and z_t depend on the current innovations, ϵ^x_t, ϵ^y_t, ϵ^z_t, the lagged one period innovations, ϵ^x_{t-1}, ϵ^y_{t-1}, ϵ^z_{t-1}, the lagged two period innovations, ϵ^x_{t-2}, ϵ^y_{t-2}, ϵ^z_{t-2}, and so forth. In practice, of course, it is impossible to calculate exactly all of the coefficients in the infinite moving average representation; in most problems, however, coefficients for the recent past suffice. The moving average representation is used mainly to analyze the short- to medium-run effects on each variable of given innovations to each of the variables. For example, in a system with real GNP, the price level, a monetary aggregate and, possibly, other policy and nonpolicy variables one can estimate the effects of a shock (innovation) to money on real GNP and prices after, say, one quarter, two quarters, one year, two years, and so forth. Similarly, it is possible to calculate the effects of a shock to any given variable on the variable itself or on any other variable in the system. In

[7] See Litterman [1982] and Doan, Litterman, and Sims [1983] for an approach which restricts the number of freely estimated parameters.

other words, the moving average representation traces out over time the effect of any given innovation on any given variable. The entire time path of effects of one innovation on one variable is called an *impulse response function*. For example, one can talk of the responses of real GNP to a monetary shock as the impulse response function of real GNP with respect to money. The impulse response functions are, in principle, of interest to policymakers because they describe the effects and timing of policy variables on the variables of ultimate concern.

As a practical matter, however, there is one aspect of the determination of the impulse responses that may undermine their usefulness. While by construction the innovations in any series are serially uncorrelated, the innovations may be correlated contemporaneously. Therefore, it is not correct to interpret the effects of an innovation in a given variable, say, x, as deriving solely from ϵ^x. Part of an innovation in x may be due to the contemporaneous influence of other innovations on the x innovation. Thus, for example, if the innovations in money and GNP are contemporaneously correlated, it is not correct to interpret the effect of an innovation in money on GNP as due solely to "exogenous" influences on the money supply, such as policy. Such contemporaneous correlation causes difficulty in interpreting a coefficient in the moving average representation as the effect of a given innovation on a given variable at a given lag. For example, recall that the coefficient in the moving average representation of the GNP on the first lagged innovation to money may be interpreted as the effect on GNP of last period's shock to money. However, if last period's shock to money is highly correlated with last period's GNP shock (contemporaneous "as of last period"), then it is not correct to attribute all of the money innovation to the independent effect of money. The contemporaneous correlation links the money and GNP innovations in a way that may prohibit further meaningful decomposition.

There is a way around this problem but it is quite possible that the problems involved in implementing the solution are as serious as the original problem. Briefly, it is possible to apply certain mathematical transformations to the correlation matrix of the innovations to generate a new set of innovations that are not contemporaneously correlated. However, this transformation is not unique, i.e., it can be implemented in several ways depending on how the variables in the system are ordered.[8] Thus, the transformation may generate qualitatively different impulse response patterns depending on the ordering of the variables. This problem would not he serious if the untransformed innovations did not happen to be highly correlated in the first place or if the answers to questions of major concern were not sensitive to the ordering of variables in the transformation. Unfortunately the reported results show that for some systems estimated by Friedman neither condition holds. In particular, in the systems that include nominal GNP and either a monetary or a credit aggregate the innovations are sufficiently correlated that the ordering of variables in the transformation substantially affects the results of the transformation. Such systems do not yield unequivocal conclusions.

3. Variance Decompositions

The most important question in comparing money and credit aggregates is to determine whether movement in the financial aggregate exerts an independent influence on the broader policy objectives. The strength of this influence is also critical.

An impulse response function describes the effect of an innovation in a given variable on the movement of the level of the same or another variable in the system. For example, the impulse response function of GNP with respect to money describes how the level of GNP changes over time in response to a shock to money. The set of impulse response functions for an entire system can be viewed as a decomposition of the levels of the variables in the system

[8] The terms "ordered" and "ordering" refer to the order of the variables in setting up the transformation. The only aspect of the transformation that is truly germane to this exposition is the fact that the ordering is arbitrary but conclusions may sometimes differ depending on the ordering of variables that is chosen. The intuition behind the transformation can be explained quite easily. Recall that the purpose of the transformation is to allocate contemporaneous correlation of the innovations. The variables are ordered in some fashion, say, first variable, second variable, and so forth. The first variable's innovations are assumed to be independent, i.e., all correlation between this innovation series and other innovation series affects only the other innovations. The second variable's innovations are assumed to be independent except for the part correlated with the first variable's innovations. The transformation subtracts from the second variable's innovations the part attributable to the first variable and only that part. The third variable's innovations are assumed to be independent except for the parts due to the first and second variable's innovations which are subtracted out. In general, the transformation eliminates the correlation from any given innovation series and those series that appear prior to it in the particular ordering. This sequential process of eliminating correlated parts of the innovation series results in a set of transformed innovations that are not contemporaneously correlated.

Table I

BIVARIATE VAR ESTIMATES

Dependent Variable	Coefficients on Lagged NGNP 1	2	3	4	5	6	7	8	Coefficients on Lagged Financial Aggregate 1	2	3	4	5	6	7	8
M1	−.07	.02	−.15	.16	−.02	−.22	.45	−.19	1.21	−.21	.15	−.26	.49	−.17	−.41	.21
	(−1.1)	(.3)	(−1.7)	(1.7)	(−.2)	(−2.3)	(4.7)	(−2.8)	(10.9)	(−1.2)	(.9)	(−1.7)	(3.2)	(−1.0)	(−2.2)	(1.7)
NGNP	.99	−.12	.77	−.08	−.04	.03	.21	−.19	.58	.01	−.61	.15	−.10	−.02	−.17	.19
	(8.9)	(−.7)	(.5)	(−.5)	(−.2)	(.2)	(1.3)	(−1.7)	(3.1)	(.02)	(−2.3)	(.6)	(−.03)	(−.06)	(−.6)	(.9)
DNF EOQ	.04	−.05	−.04	−.00	−.01	−.01	−.06	−.03	1.3	.3	−.2	−.09	.3	−.3	−.1	.1
	(1.3)	(−1.1)	(−.8)	(.04)	(−.3)	(−.1)	(1.3)	(.8)	(11.8)	(.02)	(−1.3)	(−.6)	(2.1)	(−1.9)	(−.9)	(1.3)
NGNP	1.07	−.29	.34	−.11	.04	.14	.22	.35	.37	.65	−1.0	.36	−.30	.20	−.12	−.10
	(9.7)	(−1.8)	(.2)	(−.7)	(.3)	(.9)	(.1)	(.3)	(1.0)	(1.1)	(−1.9)	(.7)	(−.6)	(.4)	(−.2)	(−.3)
DNF QA	.04	−.06	.00	−.02	.01	−.02	.03	.02	2.02	−1.52	.95	−.76	.79	−.67	.09	.09
	(2.2)	(−2.3)	(.01)	(−1.0)	(.6)	(−.6)	(1.4)	(1.1)	(19.1)	(−6.5)	(3.4)	(−2.7)	(2.9)	(−2.5)	(.4)	(1.0)
NGNP	1.09	−.28	−.01	−.09	.01	.18	−.02	.08	.52	.81	−2.34	2.56	−2.87	3.39	−3.31	1.27
	(10.2)	(−1.9)	(−.08)	(−.6)	(.04)	(1.2)	(−.1)	(.7)	(.8)	(.6)	(−1.4)	(1.5)	(−1.7)	(2.0)	(−2.4)	(2.2)

into components due to the various shocks to these variables. It is also possible to decompose variation in the system into components due to variation in the shocks. This decomposition is generally done in terms of the forecast error variance. The value of a given variable k periods into the future will be based on all current and past innovations and on innovations that are yet to be realized in the k periods yet to occur. The information available today (time t) includes the actual values of current and past innovations while the future innovations are random variables whose expected values are zero.[9] Consider now a k period ahead forecast of the variable y_{t+k}. In order to obtain the forecast of y_{T+K} write the moving average representation of y_{t+k} including all innovations up to t+k, substitute in the values for innovations known at time t, and set to zero values of the innovations which may occur between t+1 and t+k.

Now consider the variance of the forecast error. Since at time t all innovations dated t and earlier are known by assumption, these innovations contribute nothing to the forecast error. Instead, the forecast error will be due to the existence of nonzero innovations to y_{t+k} which may occur between t+1 and t+k. If we use the variation of innovations in the past as the estimate for the variation of future innovations, it is possible to get an estimate of the forecast error variance. The word “variation” in this context refers not only to the variance of each innovation series but to the contemporaneous covariances among all pairs of innovations. As with the impulse response function, it is precisely this covariation that generates problems for interpreting the decomposition of the forecast error variance.

We have seen that the forecast error variance for a given variable is equal to a sum of terms in the variances and covariances of all the innovation series. The variance decomposition (VARD) presents a summary of this information by listing the fraction of the overall forecast error variance accounted for by each of the types of innovations. This variance allocation, or variance accounting, can be done for the forecast error of each variable for any forecast horizon. In this way, one can analyze the way in which the variances of each variable’s innovations influences the movements (i.e., the variation) in each of the variables in the system. In principle, the variance decomposition contains very important information because it shows which variables have relatively sizable independent influence on other variables in the system.

The fly in the ointment is the same problem as the one mentioned in the previous discussion, of the impulse response function: alternative orderings of the variables may imply substantially different allocations of explanatory power. Thus, the importance of a given variable in terms of the extent to which its innovations influence other variables may depend critically on the (arbitrary) ordering that is chosen.

III. EMPIRICAL RESULTS

1. Selected VAR Estimates

We follow Friedman’s specification in assuming that the endogenous variables in the VAR specification enter as natural logarithms and that the equation contains a constant, a linear time trend, and

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[9] Deterministic time trends may also be incorporated into the analysis.

Constant	Trend	$F_{financial}$	F_{GNP}	$\bar{R}^2$	Q(30)	Residual Standard Deviation
.06	.00035	180.7	5.2	.9997	14.29	.0052
(1.2)	(1.2)					
.17	.0010	3.44	47.5	.9998	17.97	.0088
(2.1)	(2.1)					
.05	.00019	357.9	2.86	.9999	31.73	.0030
(1.8)	(2.3)					
.15	.00050	2.31	38.6	.9998	23.25	.0091
(1.7)	(1.8)					
.02	.00010	1243.7	3.91	.9999	27.61	.0014
(1.6)	(2.2)					
.13	.00048	2.88	40.8	.9998	20.70	.0089
(1.5)	(1.7)					

eight lags on each (endogenous) variable in the system.[10] In this paper, we also used the longest sample period available from 1954:Q2 until 1982:Q4.[11] Four different VAR systems were estimated: a two-variable system consisting of a financial aggregate and nominal GNP, (Table I); a three-variable system consisting of a financial aggregate, real GNP and the GNP deflator and two systems containing a short-term interest rate in addition to financial and real sector variables. In the latter category are the estimates from a trivariate model (Table II) for a financial aggregate, nominal GNP and the commercial paper rate and a four-variable system consisting of a financial aggregate, real GNP, the GNP deflator and the commercial paper rate.[12] (Appendix A lists the definitions for the abbreviations used throughout this section.) The following notation is used in the tables : estimated t-ratios are listed in parentheses beneath the regression coefficients; Q(30) is the Box-Pierce Chi-square statistic with 30 degrees of freedom to test the hypothesis that the residuals from each equation are serially uncorrelated; the symbol F_x (for x = financial, NGNP, RCP), represents the F-statistic which tests the hypothesis that the coefficients on all lagged x's are simultaneously equal to zero; it is distributed with 8 and 97 degrees of freedom in the bivariate models and with 8 and 89 degrees of freedom in the trivariate model.

In the bivariate system (Table II) all variables are significant at the five percent level. In the trivariate system containing an interest rate (Table III, M1 is significant at the ten percent level in the interest rate and nominal GNP equations; DNF, on the other hand, is insignificant at this level in both of these equations.

2. Impulse Response Functions

Recall that the impulse response function for GNP with respect to a money shock describes the response over time of GNP to an innovation or a shock to money in a given period. Charts 3 and 4 depict the impulse responses of the natural logarithms of the inverse of velocity, ln(F/NGNP), to a one percent shock in the financial aggregate, F. For systems that include real GNP and the GNP deflator instead of nominal GNP, the response of nominal GNP to a given shock is obtained by summing the responses of real GNP and the GNP deflator. In general, one would expect an initial fall in velocity in response to a positive shock to the aggregate because nominal GNP responds to the financial stimulus with a lag. As income begins to respond to the stimulus and the effect of the shock on financial assets dissipates, velocity will gradually rise. The impulse response function that emerges typically has a damped, sinusoidal shape.

According to Friedman, the purpose of looking at these impulse response functions is to assess the stability of the relationship between nominal GNP and each financial aggregate. If, as expected, the response pattern damps out and is smooth, then the relationship is considered to be stable. Presumably a relatively stable relationship is conducive to more effective monetary policy.[13,14]

[10] See Friedman [1981] and [1983B]. We also examined specifications which only contained four lags, see footnote 17.

[11] The results do not appear to be sensitive to the sample period chosen. See Offenbacher, McKelvey, and Porter [1982] for results from a shorter sample period from 1959 to 1980.

[12] In order to conserve space, VAR estimates for the four-variable model and the three-variable model without interest rates are not shown. The results for M2 were also eliminated from Tables I and II to trim their size. The inferences drawn for the debt proxy are similar in spirit to the ones drawn for DNF, so for the sake of brevity we only report those for DNF in this paper. The interested reader may consult Offenbacher and Porter [1983] for a discussion of the empirical results for the debt proxy, as well as the M2 results that were not shown in the two tables.

[13] Analytically, one can assess the stability by looking at the eigenvalues of the first-order "stacked" representation of the system. An inspection of these eigenvalues reveals that all of the estimated systems are stable. It follows from this result that the associated impulse response functions are stable and will eventually converge to zero.

[14] Stability is not used here in the statistical sense to denote stability of the coefficients over different time periods. Friedman does not discuss the implications of relevant economic theory for the expected pattern of the impulse response function of ln(F/NGNP). For credit

(footnote continued on page 22)

Table II

TRIVARIATE VAR ESTIMATES FOR FINANCIAL AGGREGATE, NOMINAL GNP, AND COMMERCIAL PAPER

Dependent Variable	Coefficients on Lagged NGNP 1	2	3	4	5	6	7	8
M1	−.02	.02	−.18	.13	−.01	−.19	.39	−.10
	(−.2)	(.2)	(−2.1)	(1.6)	(−.1)	(−2.2)	(4.7)	(−1.5)
NGNP	.91	−.11	.06	−.07	−.09	.09	.17	−.04
	(7.7)	(−.7)	(.4)	(−.4)	(−.6)	(.6)	(1.1)	(−.3)
RCP	3.3	−.92	−1.29	−.12	−.50	−1.08	1.10	.27
	(2.5)	(−.5)	(−.7)	(−.1)	(−.3)	(−.6)	(.6)	(.2)
DNF EOQ	−.00	−.02	.02	.01	−.03	−.04	.08	.04
	(−.1)	(−.5)	(.5)	(.2)	(−.6)	(−.9)	(1.8)	(1.1)
NGNP	1.00	−.16	.09	−.14	−.15	.11	.07	.06
	(8.6)	(−1.0)	(.6)	(−.9)	(−.9)	(.7)	(.5)	(.4)
RCP	5.56	−3.84	0.0	−1.83	1.16	−1.89	.37	.21
	(4.3)	(−2.1)	(0.0)	(−1.0)	(.7)	(−1.1)	(.2)	(.1)
DNF QA	.10	−.03	.03	−.01	.06	−.03	.04	.03
	(.5)	(−1.5)	(1.3)	(−.6)	(.3)	(−1.5)	(1.8)	(1.5)
NGNP	1.00	−.15	.03	−.10	−.06	.16	.03	.11
	(8.8)	(−1.0)	(.2)	(−.2)	(−.4)	(1.0)	(.2)	(.8)
RCP	5.29	−3.11	−.78	−1.16	.41	−1.30	.07	.25
	(4.0)	(−1.8)	(−.4)	(−.7)	(.2)	(−.7)	(0.0)	(.2)

Dependent Variable	Coefficients on Lagged Financial Aggregate 1	2	3	4	5	6	7	8
M1	1.05	−.01	.03	−.18	.45	−.21	−.15	−.03
	(9.2)	(−0.0)	(.2)	(−1.2)	(2.8)	(−1.2)	(−.8)	(−.2)
NGNP	.35	.15	−.59	.20	.16	−.39	.20	−.02
	(1.7)	(.5)	(−2.1)	(.7)	(.5)	(−1.1)	(.6)	(−.1)
RCP	3.55	−1.33	2.08	−10.1	7.8	1.1	−3.9	.20
	(1.5)	(−.4)	(.7)	(−3.3)	(2.4)	(.3)	(−1.0)	(.1)
DNF EOQ	1.03	.42	−.09	−.08	.34	−.28	−.19	.16
	(9.7)	(.3)	(−.6)	(−.6)	(2.5)	(−.20)	(−1.3)	(1.8)
NGNP	−.09	.67	−.85	.45	−.46	.34	.01	−.01
	(−.2)	(1.2)	(−1.6)	(.9)	(−.9)	(.6)	(0.0)	(−.4)
RCP	−1.14	7.15	−10.1	−.91	1.16	13.59	−10.8	1.3
	(−.3)	(1.1)	(−1.7)	(−.2)	(.2)	(2.2)	(−1.7)	(.3)
DNF QA	1.80	−1.32	.92	−.75	.83	−.74	.18	.05
	(17.1)	(−6.1)	(3.7)	(−3.0)	(3.4)	(−3.0)	(.9)	(.7)
NGNP	−.17	1.27	−2.29	2.51	−2.99	3.48	−2.89	1.03
	(−.2)	(.8)	(−1.3)	(1.4)	(−1.7)	(2.0)	(−2.0)	(1.8)
RCP	3.36	−.83	−7.68	−3.88	14.6	2.65	−11.8	4.07
	(.4)	(−0.0)	(−.4)	(−.2)	(.7)	(.1)	(−.7)	(.6)

Impulse responses, shown in the upper left panels of Charts 3 and 4 for the bivariate systems provide the first important result regarding the effects of minor changes in the specification. The ordering of variables follows Friedman's work with NGNP preceding the financial aggregate in constructing the impulse response function. That is; the innovation in GNP is assumed to be independent of all the other innovations. The responses to M1 shocks (upper left panel of Chart 3) appear fairly stable by Friedman's criteria; although the response function oscillates with a short period, it damps out rather quickly. We examine the debt series, DNF, as end-of-quarter series (as in Friedman's work) and as a "quarterly average" series to maintain comparability with the way the monetary aggregates are targeted.[15] The responses reported in the upper left-hand panel of Chart 3 for DNF using both measurement schemes seem considerably less stable than the M1 responses. The picture of DNF's impulse response function that emerges is somewhat different from that obtained by Friedman partly because he displayed the response function for only 20 quarters; the difference between

aggregates, the implications of economic theory are not readily apparent. This question deserves further detailed attention. For monetary aggregates, the relevant theory exists and the impulse responses can be assessed on the basis of their correspondence with this theory. Since Friedman did not use this criterion and, in the interest of brevity, this issue is not pursued here. It is worth noting, however, that this issue has been examined in the context of St. Louis reduced form equations by Charles Freedman of the Bank of Canada and Tom Gittings of the Federal Reserve Bank of Chicago.

Table III

BIVARIATE IMPULSE RESPONSE FUNCTIONS UNDER ALTERNATIVE ORDERINGS

	Domestic Nonfinancial Debt (DNF)				M1		M2	
	Quarterly Average		End-of-Quarter		Quarterly Average		Quarterly Average	
Quarter	(NGNP, F)	(F, NGNP)	(NGNP, F)	(F, NGNP)	(NGNP, F)	(F, NGNP)	(NGNP, F)	(F, NGNP)
1	1	−.95	1	−.29	1	.46	1	.74
2	1.5	−.55	.9	−.42	.63	.05	1.35	1.06
3	.15	−1.52	.12	−.94	−.06	−.58	.92	.65
4	−.004	−1.37	.003	−.9	−.04	−.56	.84	.61
5	−.73	−1.61	−.38	−.99	−.27	−.71	.85	.71
6	−.3	−.76	−.11	−.5	−.07	−.36	.89	.83
7	−.49	−.89	−.6	−.44	.31	−.06	.89	.85
8	−.88	−1.35	−.29	−.67	−.03	−.28	.45	.46
9	−.15	−.77	−.25	−.65	−.12	−.28	−.01	.04
10	.25	−.47	−.23	−.68	.11	−.12	−.28	−.24
11	.59	−.17	−.11	−.58	.02	−.13	−.49	−.46
12	1.02	.28	.19	−.44	.17	.01	−.67	−.64
13	.88	.18	−.02	−.44	.15	−.02	−.8	−.77
14	.85	.17	.02	−.36	−.11	−.18	−.86	−.82
15	1.08	.35	.08	−.27	−.03	−.04	−.79	−.74
16	1.12	.34	.17	−.19	.11	.03	−.63	−.59
17	1.16	.36	.27	−.12	.06	.03	−.49	−.46
18	1.1	.31	.29	−.11	.14	.1	−.39	−.38
19	.91	.18	.31	−.09	.05	.02	−.3	−.3
20	.88	.21	.34	−.06	−.01	−.04	−.22	−.23
21	.85	.24	.36	−.03	.12	.1	−.14	−.16
22	.78	.23	.39	.01	.1	.09	−.09	−.12
23	.76	.25	.39	.04	.07	.07	−.07	−.1
24	.73	.25	.39	.05	.1	.08	.07	−.09

[15] The not seasonally adjusted series on an end-of-quarter basis were taken from the Federal Reserve Board's flow-of-funds databank in February 1983. They were seasonally adjusted using Statistics Canada's multiplicative, quarterly version of X-11 ARIMA. At the time this work was completed there was a discontinuity in the data when the International Banking Act facility was phased in at the end of 1981. To limit the effect of this "outlier" on the estimates of the seasonal factors, the seasonal adjustment estimation period stopped in 1981:Q4. The forecasted adjustments for 1982 were then used to adjust the 1982 data. The quarterly average debt series were constructed as the average of the adjacent end-of-quarter figures. The revised series for M1 and M2 do not cover the period before 1959:Q1. To construct data for this period we took the unrevised growth rates of the aggregates and extrapolated backwards from the revised 1959:Q1 levels. Since no end-of-quarter series exists for the monetary aggregates, we could not examine M1 and M2 on this basis.

1	2	3	4	5	6	7	8	Constant	Trend	$F_{financial}$	F_{GNP}	F_{RCP}	$\bar{R}^2$	Q(30)	Residual Standard Deviation
Coefficients on Lagged RCP															
−.019	.009	.014	−.022	.017	−.011	−.002	.001	.019	.00013	193.2	5.00	5.30	.9998	11.17	.0043
(−3.5)	(1.0)	(1.4)	(−2.0)	(1.5)	(−1.0)	(−.3)	(.3)	(.4)	(.4)						
.000	−.025	.036	−.044	.034	−.018	−.008	−.002	.19	.0013	1.97	35.0	2.74	.9998	18.41	.0078
(0.0)	(−1.5)	(2.0)	(−2.1)	(1.7)	(−1.0)	(−.5)	(−.2)	(2.2)	(2.4)						
1.25	−.87	.88	−.39	.15	−.24	.19	−.11	−1.22	−.0076	2.95	1.42	52.8	.9667	12.65	.0873
(11.1)	(−4.8)	(4.4)	(−1.7)	(.6)	(−1.2)	(1.0)	(−1.0)	(−1.2)	(−1.2)						
.004	−.013	.004	−.009	.009	−.007	.006	−.006	.081	.0050	307.8	2.30	6.0	.9999	27.15	.0022
(1.5)	(−3.1)	(.9)	(−1.9)	(1.7)	(−1.4)	(1.3)	(−2.1)	(3.2)	(4.4)						
.002	−.03	.020	−.015	.009	−.002	−.014	−.001	.220	.0012	.65	42.0	2.33	.9998	16.60	.0083
(.2)	(−1.8)	(1.2)	(−.8)	(.5)	(−.1)	(−.9)	(−0.0)	(2.30)	(2.8)						
1.20	−.79	.83	−.42	.36	−.44	.12	0.0	−.629	−.0015	1.23	2.83	40.5	.9621	12.66	.0931
(10.6)	(−4.5)	(4.4)	(−2.0)	(1.6)	(−2.1)	(.6)	(0.0)	(−.6)	(−.3)						
.002	−.006	.001	−.004	.004	−.003	.002	−.003	.04	.0003	1133.9	2.95	5.61	.9999	25.87	.0012
(1.7)	(−2.8)	(.5)	(−1.6)	(1.3)	(−1.0)	(.9)	(−1.9)	(3.2)	(4.4)						
.001	−.023	.016	−.013	.009	−.002	−.012	−.002	.209	.0012	.88	43.0	2.06	.9998	13.93	.0082
(0.0)	(−1.5)	(.9)	(−.7)	(.4)	(−0.0)	(−.9)	(−.2)	(2.2)	(2.8)						
1.19	−.77	.83	−.42	.38	−.46	.14	−.009	−.73	−.0019	.91	2.54	39.4	.9611	10.95	.09439
(10.4)	(−4.3)	(4.2)	(−1.9)	(1.6)	(−2.10)	(.7)	(−0.0)	(−.7)	(−.4)						

Chart 3

IMPULSE RESPONSE FUNCTIONS FOR M1 AND DNF

RESPONSE OF F/NGNP TO A 1% SHOCK IN F

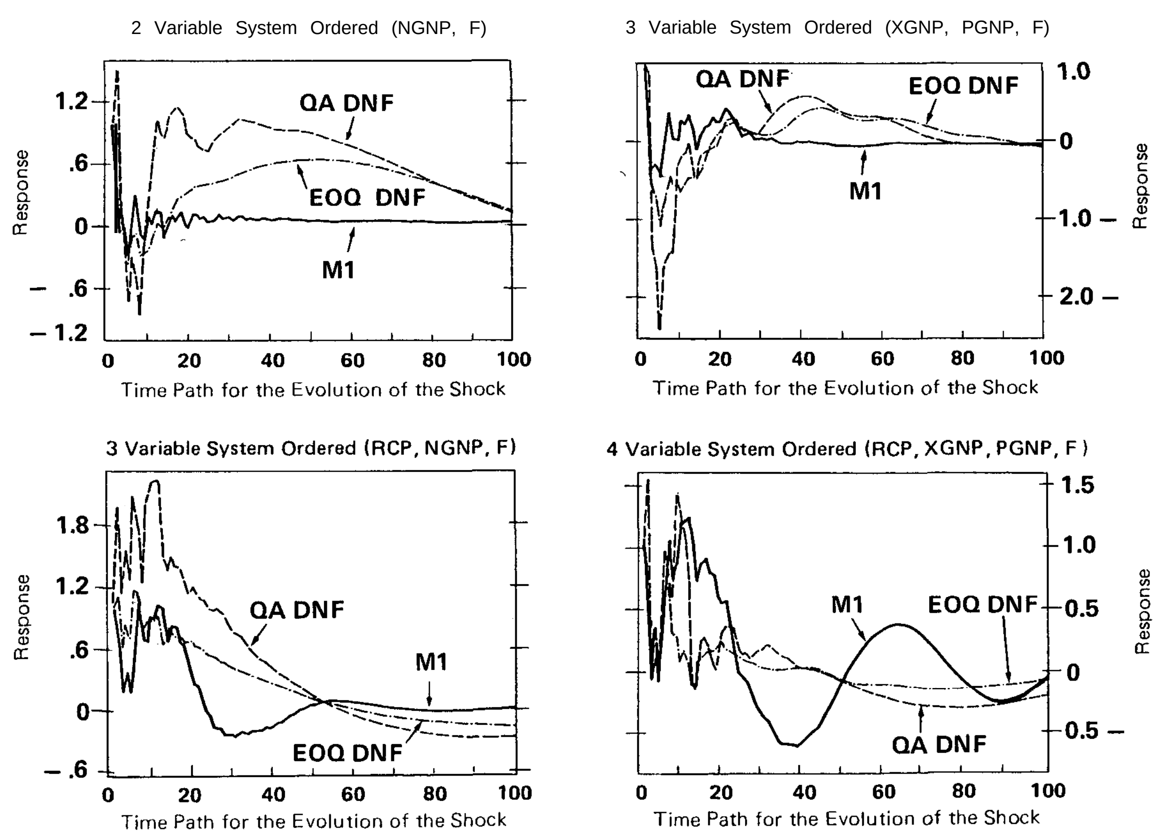
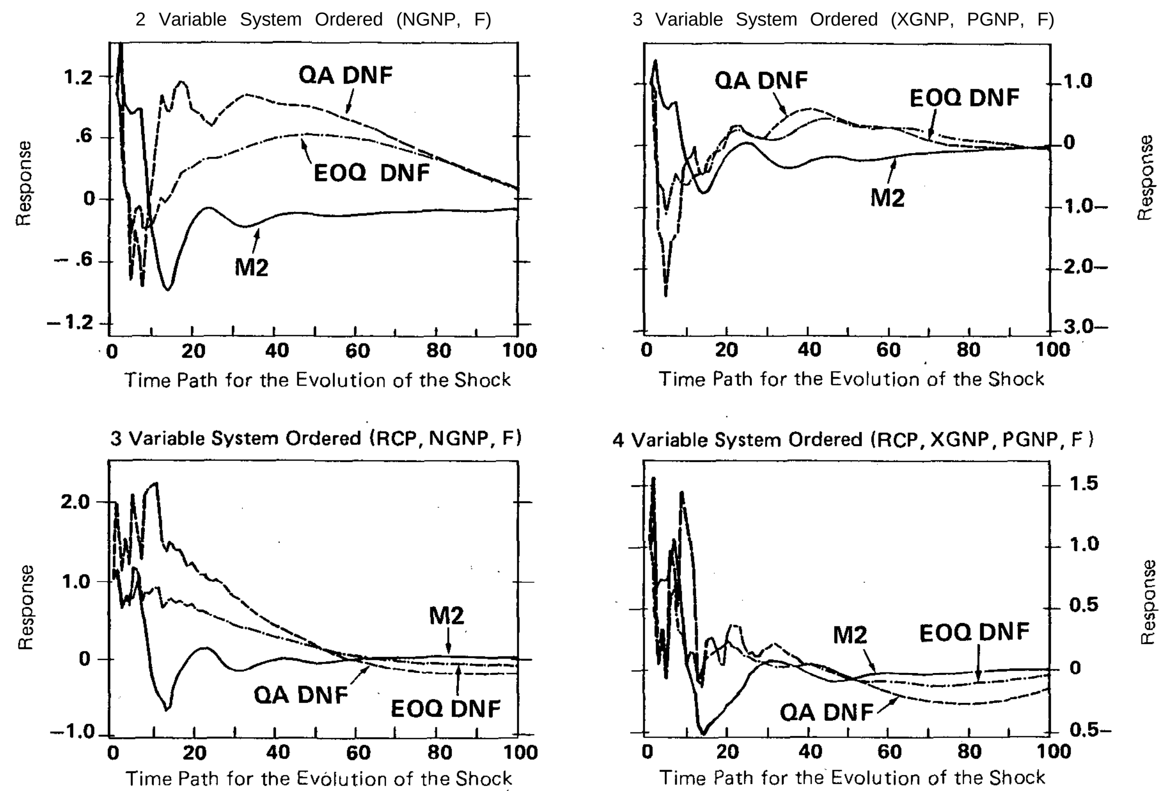


Chart 4

IMPULSE RESPONSE FUNCTIONS FOR M2 AND DNF

RESPONSE OF F/NGNP TO A 1% SHOCK IN F



M1 and end-of-quarter DNF is more evident beyond the 20th lag. The impulse response for M2 in the bivariate model (upper left panel of Chart 4) also seems fairly stable. The responses of quarterly average data are considerably less stable than those of the end-of-quarter data. These results do not support the notion that the credit aggregate is as stable as the monetary aggregates in impulse response functions derived from the bivariate system.

Table III displays the impulse response function from period 1 to 24 for DNF and the two monetary aggregates using both orderings-(F, NGNP) and (NGNP, F)-and both measures of DNF. (Recall that Charts 3 and 4 used the (NGNP, F) ordering.) As noted above, one of the drawbacks of the impulse response functions is their sensitivity to the ordering of variables when the innovations are correlated. The correlation of the innovations is .31 in the system with quarterly average DNF, .38 in the system with end-of-quarter DNF, .32 in the system with M1, and only .16 with M2. Though the M1 and DNF correlations are similar, the DNF impulse response functions differ much more on average in the alternative orderings than the M1 response (lower panel of Table IV). With the smallest correlation in the innovations, M2 exhibits the smallest difference in the impulse response function in the alternative orderings.

Trivariate systems with a financial aggregate, real GNP (XGNP) and the implicit GNP deflator (PGNP) (upper right-hand panels of Charts 3 and 4 or with nominal GNP, the commercial paper rate and a financial aggregate (lower left-hand panels) also favor the monetary aggregates over the credit aggregates. In the systems with XGNP, PGNP and F, the M1 impulse responses are noticeably smoother than the DNF responses (quarterly average and end-of-quarter). Impulse responses for end-of-quarter DNF are once again also smoother than for their quarterly average counterparts. Furthermore, while the M1 responses in the bivariate system are similar to the M1 responses in the trivariate XGNP, PGNP, F system, DNF's velocity responses in the analogous trivariate system have greater amplitude than in the bivariate system with DNF. Fairly similar results are also obtained for the M2-DNF comparison in this system.

Three variable systems (NGNP, F and the commercial paper rate (RCP)) provide the most striking example of the difference between quarterly average and end-of-quarter data construction (lower left panels). For the M1-DNF comparison, the end-of-quarter DNF responses are considerably smooth& than M1 responses and are somewhat more damped. On the other hand, the quarterly average DNF impulse responses are much more variable than their M1 counterparts. In addition, the estimated lag coefficients on credit in the VAR NGNP equation that lies behind this impulse response function are not significant at the 50 percent significance level while corresponding M1 parameters are significant just above the five percent significance level.[16] Similar results also hold for a comparison of M2 and DNF.

Four-variable systems (real GNP, the price deflator, the commercial paper rate and a financial aggregate) lend some support to Friedman's notions that DNF has about as stable relationship to GNP as the monetary aggregates. In these systems M1 and M2 variability is greater over some range (from 20 to 80 quarters) than is the associated variability of DNF. However, the credit aggregates damp more slowly than M1 or M2 and, as with the three variable systems containing interest rates, the influence of credit on GNP is much weaker than the influence of M1 (or M2) on GNP.[17]

3. Variance Decompositions

As noted in Section II, the variance decomposition (VARD) results may be useful in judging whether the direction of influence in the relationship between a given financial aggregate and a policy objective (such as nominal GNP) runs from the aggregate to the objective or vice-versa. Entries in Charts 5-8 report the share of the total forecast error variance of a given variable that can be attributed to independent movements in the innovations of the same or another variable. For example, the left panel of Chart 5 displays the variance decomposition of NGNP in a bivariate model containing NGNP and M1 with M1 taken first in the ordering and NGNP second, (M1, NGNP). This chart shows that, at a lag of 10 quarters, about one-third of the variance of NGNP can be attributed to current and lagged shocks in NGNP with the remainder attributable to current and lagged shocks in M1.

Charts 5-7 display the VARDs of NGNP and F for bivariate models. For M1 and M2 in both orderings the contribution of the monetary aggregate in explaining NGNP tends to increase or stay the same over the entire range of lags shown. The credit aggregate DNF, on the other hand, explains an increasing share of NGNP until a lag of about 10

Table IV

SUMMARY STATISTICS FOR IMPULSE RESPONSE FUNCTIONS

Aggregate	Method of Measurement[1]	Ordering	Average[2]	Average Sum of Squares[3]
DNF	QA	(NGNP, F)	.54	.70
	EOQ	(NGNP, F)	.13	.15
DNF	QA	(F, NGNP)	−.29	.54
	EOQ	(F, NGNP)	−.38	.24
M1	QA	(NGNP, F)	.10	.07
	QA	(F, NGNP)	−.10	.07
M2	QA	(NGNP, F)	.04	.44
	QA	(F, NGNP)	−.01	.33

ABSOLUTE DIFFERENCES BETWEEN ALTERNATIVE ORDERINGS

Aggregate	Method of Measurement[1]	Mean	Average Sum of Squares
DNF	QA	.84	.90
DNF	EOQ	.53	.36
M1	QA	.20	.08
M2	QA	.07	.01

[1] QA denotes quarter average and EOQ denotes end-of-quarter.

[2] The mean of the 24 values in Table III.

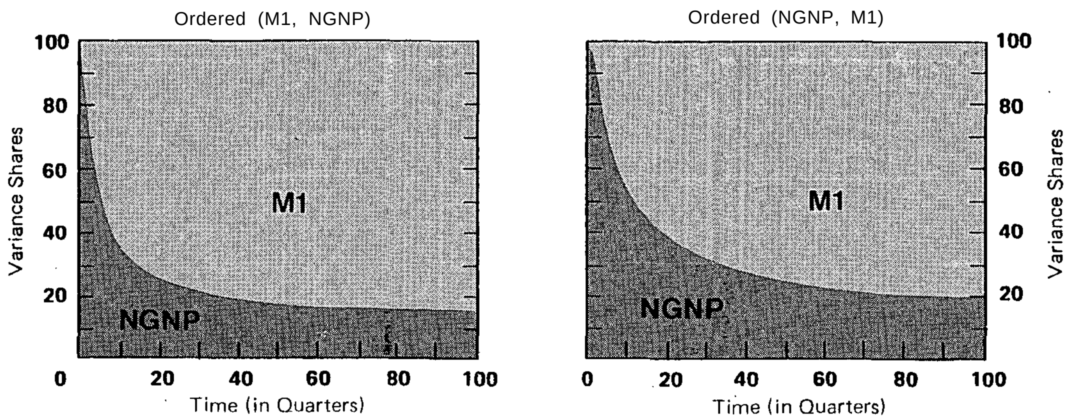
[3] The mean of the sum of squares of the 24 values in Table III.

[16] The joint significance of the F-test for DNF and M1 have significance levels of .539 and .059, respectively (Table II).

[17] The discussion in the text refers only to systems estimated with eight lags on all the variables. This lag length was chosen for comparability with Friedman's work but various F-tests for the significance of coefficients on lags 5-8 suggest that only the first four lags are significant. For all the nominal GNP equations in systems mentioned above we tested whether the coefficients of variables lagged 5 to 8 periods were significantly different from zero. For systems involving DNF and M1 we were never able to reject this hypothesis at the 5 percent level of significance. In the systems with real GNP and prices we tested the significance of the lag 5 to lag 8 coefficients in both the real GNP equations and the price equations. Again for the equations we checked we could not reject the hypothesis that these coefficients were zero at the 5 percent level of significance for systems with M1 and DNF. In general, the overall patterns of responses for four-lag systems, Offenbacher and Porter [1983, Charts 8 and 9], confirm the comparisons made above between money and credit aggregates. The main difference between the four- and eight-lag systems is that the latter have more cyclical impulse response patterns-a result that is not surprising.

Chart 5

VARIANCE DECOMPOSITIONS OF NGNP FOR BOTH ORDERINGS OF A BIVARIATE SYSTEM WITH NGNP AND M1



quarters, and thereafter its contribution decreases in both orderings. In the VARDs for financial aggregates, M1 and M2 explain a greater proportion of their own variance when they are ordered second in the system, while the reverse is true for DNF. On balance, the monetary aggregates in these bivariate specifications respond much less to movements in NGNP over time than does the credit aggregate.[18]

The most interesting results are those associated with the inclusion of interest rates (Chart 8). The contrast between the results for the two-variable and three-variable systems containing NGNP, RCP, and F is most striking for DNF. In the three-variable system DNF's role shrinks drastically. This debt measure explains a very small percentage of NGNP in both orderings examined, (DNF, RCP, NGNP) and (RCP, NGNP, DNF)-under 8 percent at all lags-whereas in the two-variable system it accounted for about 40 to 70 percent of the variance of NGNP after 10 quarters, depending on the ordering.[19] On the other hand, the M1 contribution levels off to around.20 percent. Thus, while none of the financial aggregates' innovations has a large role in explaining NGNP, the two monetary aggregates have a stronger influence than the credit aggregate.[20]

Another interesting feature of the trivariate systems with interest rates is the reciprocal influence of RCP and the financial aggregates, i.e., the influence of innovations in each of these variables on movement in the other. On the basis of this comparison, DNF clearly appears as an endogenous variable since its innovations account for at most two percent of RCP's forecast error variance while RCP's innovations account for over 80 percent of DNF's forecast error

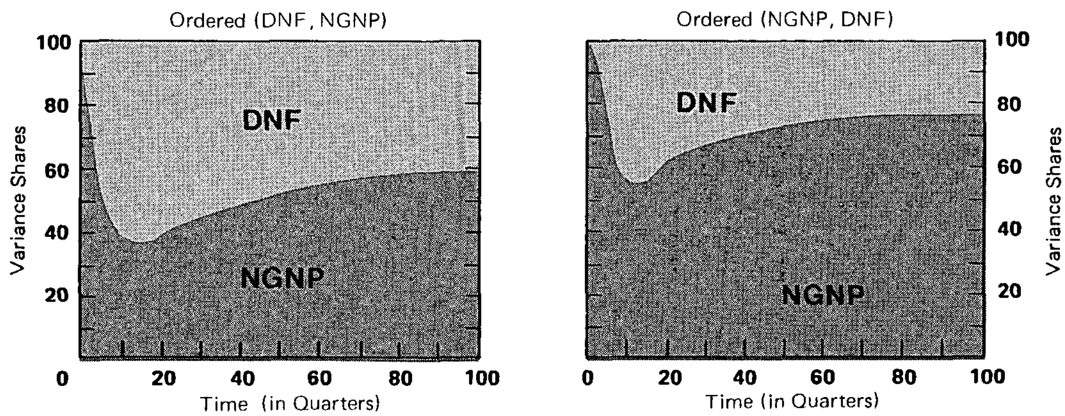
[18] In the trivariate system (XGNP, PGNP and F) the monetary aggregate M2 appears to do the best job of explaining movements 'in each component of 'the three-variable system at least after 10 quarters or so. For example, in the VARDs for the deflator, M2 eventually explains between 70 and 85 percent of the variance of the price deflator, depending on the ordering; M1 and DNF, on the other hand, each explain considerably less of the variation, in prices. See Offenbacher and Porter [1983, Charts 14 to 17).

[19] See Offenbacher and Porter [1983] for a more complete description of the results including those for the ordering (RCP, NGNP, F).

[20] The effects of including an interest rate that are reported here are qualitatively similar to the effects of including an interest rate in another vector autoregression that started out with M1, industrial production and the CPI. Those results were reported by Sims [1980A]. Friedman also did some work with interest rates but the results he reports are not as extensive as the ones reported here. Friedman reports a strong influence of interest rates. He interprets this result as being consistent with his policy proposal to add a credit aggregate target on the grounds that both interest rates and the volume of credit convey similar information since they are determined in the same market, the credit market. There are at least two important difficulties with this conclusion. First, Friedman's interpretation of the role of interest rates is only one of a number of plausible explanations; some of the others would not support Friedman's policy proposal. Second, and more importantly, the magnitude of the interest rate's influence in the two systems is so much greater than the influence of the volume of credit that it seems hard to justify-a volume of credit target rather than an interest rate target. Of course, interest rate targeting has its own problems that need not be discussed here. The upshot is that a credit target does not seem justified on the grounds that Friedman proposes.

Chart 6

VARIANCE DECOMPOSITIONS OF NGNP FOR BOTH ORDERINGS OF A BIVARIATE SYSTEM WITH NGNP AND DNF



variance after 12 quarters. A similar comparison for M1 shows that RCP is about twice as important in explaining M1 than is M1 in explaining RCP regardless of the ordering. Furthermore, DNF innovations explain a considerably smaller share of both NGNP movements and movements in DNF itself as compared with the share of M1 innovations in explaining NGNP and M1 itself.[21]

[21] See Offenbacher and Porter [1983] for the detailed charts describing these results.

IV. CONCLUSIONS

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 decompositions, and the inclusion of variables in the model. Thus, no reliable inferences may be drawn. When our results are considered along with Friedman's, it seems the most that

Chart 7

VARIANCE DECOMPOSITIONS OF NGNP FOR BOTH ORDERINGS OF A BIVARIATE SYSTEM WITH NGNP AND M2

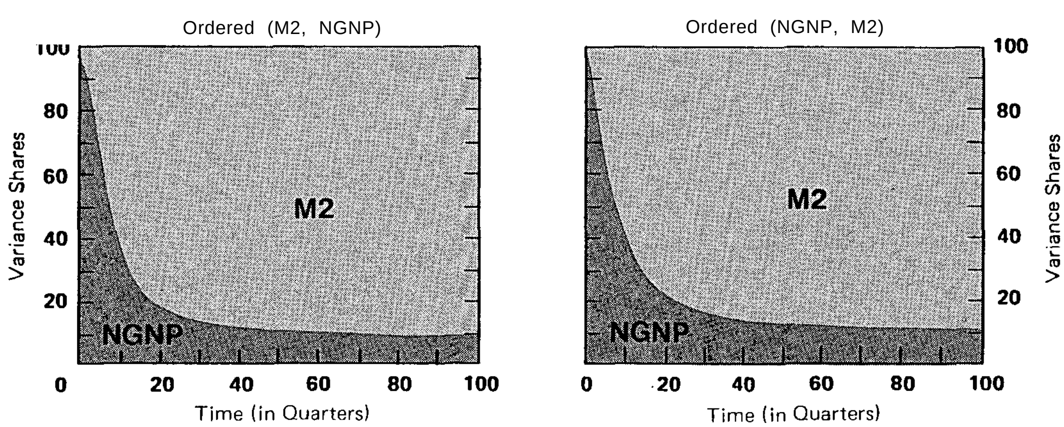
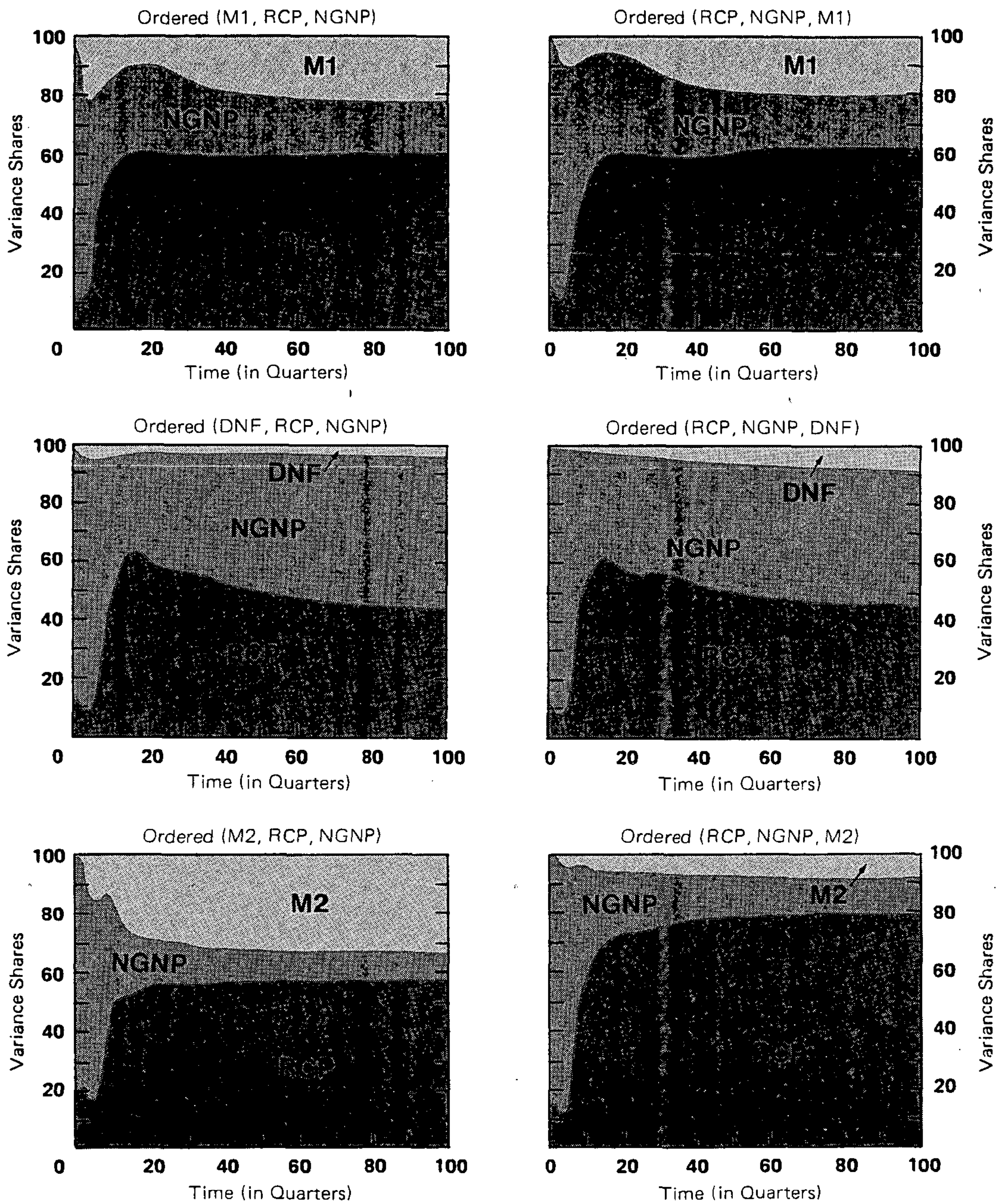


Chart 8

VARIANCE DECOMPOSITIONS OF NGNP FOR TWO ORDERINGS OF TRIVARIATE SYSTEMS



can be said in Friedman's favor is that VAR methods are not capable of distinguishing the proper monetary policy target.

Finally, a more fundamental characteristic of the VAR methodology must be recognized. Suppose, for the sake of argument, that the empirical analysis were to indicate that DNF had more desirable properties than the monetary aggregates in the impulse response functions and variance decompositions. Would this justify targeting DNF (or M1 in the opposite case)?

Since the VAR model is not a structural model, it cannot predict the effects on the economy of a structural change such as the adoption of a specific monetary policy for debt expansion. Because the VAR model is a reduced-form model, changes in the structure, including policy regime changes, will tend to alter the VAR coefficients. Rather, the VAR model functions as a data reduction device. Because structural economic theories of debt have not reached the empirical stage, such "black box" devices may be helpful only in pinpointing empirical regularities, in forecasting (without policy implications), and in providing theorists with useful insights in the sense that empirically valid structural models can be expected to generate reduced forms with properties similar to the properties of the black box reduced forms. However, VAR models should not be used to make structural policy inferences.[22]

[22] See Cooley and LeRoy [1982] for a forceful discussion of the issues raised in this paragraph.

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APPENDIX A

Abbreviations Used in Text

DNF - total credit market debt owed by domestic nonfinancial sectors

DP - the so-called "debt proxy" consisting of currency, deposits and credit market instruments held by private domestic nonfinancial sectors

EOQ - indicates that series measured on an end-of-quarter basis

F - a financial aggregate

M1 - quarterly average money supply measure

M2 - quarterly average money supply measure

MAR - moving average representation

NGNP -nominal GNP

PGNP - implicit GNP deflator (1972=100)

QA - indicates that series measured on a quarterly average basis

RCP - commercial paper rate (4-6 month)

VAR - vector autoregression

VARD - variance decomposition

XGNP - real GNP (1972 dollars)