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*Money, Government Debt, q, and Investment**

The aim of this study is to analyze empirically the linkages among changes in money and federal debt, Tobin's q variable, and investment expenditures in the United States. The vector autoregressive modeling technique proposed by Hsiao and extended by Caines, Keng, and Sethi is employed. The patterns of Granger-causality from the estimated vector autoregression are consistent with the transmission mechanism outlined by Tobin. Both money and debt Granger-cause q; q in turn causes investment and money and debt's effects upon investment operate primarily through their effects on q. However, neither money nor debt are exogenous.

1. Introduction

The linkages between changes in the quantity of financial assets such as the stock of money and the stock of federal debt and the real sector of the economy have been widely debated in the macroeconomic literature. Yet, B.F. Friedman (1978a) has recently shown that the transmission mechanisms for changes in these financial assets embedded in the general equilibrium models of Tobin (1969) and Brunner and Meltzer (1972) are essentially identical. These models contain at least three assets—money, bonds, and capital; a change in the quantity of money or bonds upsets asset market equilibrium and sets off a chain of portfolio substitutions that ultimately affect the real sector of the economy. In Tobin's model, one of the most important links between the financial and real sectors is the variable that he labels q. This variable represents the ratio of the market value of the economy's capital stock to its replacement cost. Changes in the stock of money or debt alter q and thereby alter private investment expenditures, real output, and prices.[1]

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[1]The effect of an increase (decrease) in the money stock is an unambigious increase (decrease) in q. However, the effect of a change in government debt on q is ambiguous. For a discussion of this ambiguity, see Friedman (1978b).

The empirical relationship between q and investment expenditures has been examined in several recent studies. von Furstenberg (1977), Clark (1979), and Summers (1981) examined the effect of q on aggregate investment expenditures and found a significant, positive relationship. Malkiel, von Furstenberg, and Watson (1979) studied the relationship between industry-level q and investment and also found significant, positive relations between q and investment at the two-digit SIC level. Ciccolo (1978) utilized the causality tests proposed by Granger and Sims and found that the hypothesis of exogeneity of q with respect to investment could not be rejected. However, with the exception of Blanchard (1980), the effect of monetary policy on q has not been studied and there are no empirical estimates of the effect of changes in government debt on q. Blanchard estimated the effects of decreases—both anticipated and unanticipated—in the nominal narrowly defined money supply on q within the context of a small, structural, rational-expectations macro model. He found that both anticipated and unanticipated decreases in nominal money reduce q; these results are in line with the direction of effect predicted by Tobin's model.

The aim of this study is to analyze empirically the linkages among changes in money and federal debt, Tobin's q variable, and investment expenditures in the United States. The effects of changes in both money and government debt on q and investment are estimated. The framework for analysis for this study is based upon the vector autoregressive technique developed by Caines, Keng, and Sethi (1981) and Keng (1982). This technique rather than a structural model is employed since it avoids imposing potentially spurious a priori constraints on the model. Furthermore, unlike the unconstrained vector autoregressions estimated by Sims (1980a, b) and Fischer (1981), this technique allows each variable to depend upon a subset of the variables being considered and allows each variable to enter the equation with a different lag length. The technique is described in more detail in Section 2; the empirical results are presented in Section 3; and, a summary of the principal results is provided in Section 4.

2. Estimation Procedure

The methodology used in this paper to analyze the interrelationships among investment, q, money, and government debt is a variant of the vector autoregressive modeling technique suggested by Sims (1980a, b). Sims proposed fitting an unconstrained vector autoregression (VAR) in which each variable is allowed to influence every other variable with the same lag length. After the VAR is specified, economic hypotheses are formulated and tested at a second stage. The VAR is unconstrained in the sense that all variables are initially treated as endogenous; hence, the VAR can be regarded as an unrestricted reduced form. This procedure stands in contrast to the estimation of a structural model in which a priori constraints are imposed in the specification of the model. Sims' procedure, however, avoids imposing potentially spurious a priori constraints (such as exogeneity of money in the q equation or exogeneity of q in the investment equation) on the model.

The use of the VAR technique is motivated by Fischer's (1981) observation that this technique allows one to capture regularities in the data and to thereby gain insight into the channels through which policy variables operate. As noted by Keng (1982), the procedure does not depend upon the stability of structural parameters that may shift when policy regimes change. The technique does require the consistency of causality relations over time. Thus, as long as a change in policy regimes does not alter the causal relations among the variables considered, the modeling technique is appropriate.[2]

One practical problem that emerges in the estimation of a Sims' type VAR is that the lengthening of the common lag by one increases the number of parameters by the square of the number of variables, and, as Sims points out, increasing the common lag length rapidly depletes the degrees of freedom. This degrees-of-freedom problem becomes significant in estimating Sims' type systems since the lag length must be kept generous in order to avoid underspecifying the lag for one or more variables and thereby avoiding biased coefficient estimates. Furthermore, there is no reason to believe that the same lag length is appropriate for all variables in each equation. As a consequence, the technique used in this study to specify the VAR is based upon the procedure suggested by Caines, Keng, and Sethi (1981) and Keng (1982). The step-wise procedure involves the use of the Granger-causality definition in conjunction with Akiake's final prediction error (FPE) criterion to impose restrictions on the estimation of the VAR. This procedure permits each variable to depend upon a subset of the variables in the sys-

[2]The use of the VAR modeling technique and time series techniques in general has not been uncritically accepted. See, for example, Sims [(1977), pp. 159–213], especially the comments by Zellner, Gordon, and Hendry.

tem and allows different lag lengths for each variable in each equation.

The procedure is illustrated by discussing the specification of the q equation in the model estimated. Since the theory underlying the estimation of the VAR is based upon the use of stationary data [see Hsiao (1981) or Sargent (1979)], the first step is to suitably transform the data to achieve stationarity. The specific transformations employed in this study are discussed in Section 3; at this point it is sufficient to emphasize that stationary data are used.

The next step is the determination of the own lag length for q. This is done by varying the lag in the autoregression $q_t = a_0 + a_{11}(L)q_t + e_t$ from 1 to m where q_t = Tobin's q transformed to be stationary, $a_{11}(L)$ is a distributed lag polynomial such that $a_{11}(L) = \Sigma_{k=1}^{m} a_{11k}L^k$, L is the lag operator so that $L^k q_t = q_{t-k}$, m = highest order lag,[3] and e_t = zero mean white-noise error term. The FPE is calculated for each autoregression and is defined for lag k, $k = 1, \ldots, m$, as

$$\mathrm{FPE}_{(k)} = \frac{T + k + 1}{T - k - 1} \times \frac{\mathrm{SSR}_{(k)}}{T};$$

where T = number of observations used in estimating the autoregression and SSR = sum of squared residuals. The lag length that minimizes the FPE is selected as the order of $a_{11}(L)$.

Hsiao (1981) points out that the FPE criterion is equivalent to using an F-test with a varying significance level. As Judge et al. (1982) note, an intuitive reason for using the FPE is that an increase in the lag length increases the first term but decreases the second term and these opposing forces are balanced when their product reaches a minimum. Thus, according to Hsiao [(1981), p. 88], the FPE criterion is ". . . appealing because it balances the risk due to the bias when a lower order is selected and the risk due to the increase of variance when a higher order is selected."

Once the order of $a_{11}(L)$ is found, a determination of whether the money, government debt, and investment variables enter the q equation is made. The procedure begins with the estimation of the equation $q_t = q_0 + a_{11}(L)q_t + a_{12}(L)X_t + e_t$, where X_t = other variables transformed to be stationary (considered one at a time),

[3]For the purposes of this paper an $m = 15$ is predetermined. The referee pointed out that as a rule of thumb m should not be greater than 25 percent of the sample size. This guide is not violated here.

and $a_{12}(L)$ is a distributed lag polynomial defined in a similar manner to $a_{11}(L)$. $a_{11}(L)$ is fixed at its previously determined order (k) and the lags in $a_{12}(L)$ are varied over ℓ, $\ell = 1, \ldots, m$. The FPEs for the resulting equations are defined for lag ℓ, $\ell = 1, \ldots, m$, as

$$\mathrm{FPE}_{(k,\ell)} = \frac{T + k + \ell + 1}{T - k - \ell - 1} \times \frac{\mathrm{SSR}_{(k,\ell)}}{T}.$$

The lag length for X_t that yields the minimum FPE is selected as the lag order for that variable. This FPE is then compared to the FPE from the previous step. If min $\mathrm{FPE}_{(k,\ell)} <$ min $\mathrm{FPE}_{(k)}$, then the variable X is tentatively said to Granger-cause q and is retained for further consideration in the q equation. If min $\mathrm{FPE}_{(k,\ell)} >$ min $\mathrm{FPE}_{(k)}$, then the variable X is said not to Granger-cause q and is tentatively omitted from the q equation.[4]

Once these equations have been estimated, a determination of the order in which the causal variables are added to the equation must be made. The specific gravity criterion of Caines, Keng, and Sethi (1981) is employed. The specific gravity of q with respect to money is defined as the reciprocal of the FPE in the q-money equation. The specific gravities of q with respect to the other variables are defined analogously. The causal variables are ranked in order of decreasing specific gravity. The variable with the highest specific gravity is added to the q equation with the lag order from the relevant equation. The equation $q_t = a_0 + a_{11}(L)q_t + a_{12}(L)X_{1,t} + a_{13}(L)X_{2,t} + e_t$ is estimated where $X_{1,t}$ is the variable with the highest specific gravity, $X_{2,t}$ is the remaining variable, and $a_{13}(L)$ is defined analogously to $a_{11}(L)$ and $a_{12}(L)$. $a_{11}(L)$ and $a_{12}(L)$ are fixed at their previously determined orders and the lags in $a_{13}(L)$ are varied over $p = 1, \ldots, m$. The FPEs for the resulting regressions are computed and are defined for lag p, $p = 1, \ldots, m$, as

$$\mathrm{FPE}_{(k,\ell,p)} = \frac{T + k + \ell + p + 1}{T - k - \ell - p - 1} \times \frac{\mathrm{SSR}_{(k,\ell,p)}}{T}.$$

As before, the lag length that yields the minimum FPE is selected as the lag order for that variable. The FPE is compared

[4]The Granger-causality statements are tentative at this stage since we are interested in specifying a system and all causality statements must be checked within the context of the system.

to the FPE from the two variable equation containing the variable with the highest specific gravity. If min $\text{FPE}_{(k,\ell,p)} <$ min $\text{FPE}_{(k,\ell)}$, then the variable is tentatively said to Granger-cause q and is retained for further consideration. If, however, min $\text{FPE}_{(k,\ell,p)} >$ min $\text{FPE}_{(k,\ell)}$, then the variable is tentatively omitted from the q equation. The variables found to Granger-cause of are again ranked according to their specific gravity, and the process continues in an analogous fashion until all variables are discarded or added to the q equation.

Similar procedures are used in specifying the other equations in each model. When the four equations for the model are tentatively specified, they are combined to form a system. One potential problem—contemporaneous relationships among the variables of a system—has been ignored to this point. Following Caines, Keng, and Sethi (1981) and Hsiao (1981) it is assumed that any contemporaneous relationships are reflected in the correlation of error terms across the system's equations. Based upon this assumption, full-information maximum likelihood (FIML) is used to estimate this system. The specification of each model is checked by over- and underfitting the system, estimating the modified systems by FIML, and then carrying out likelihood ratio tests of the adequacy of the specified system against each proposed modification. The likelihood ratio statistics are computed as $-2 \log (L^c/L^u)$ where L^c is the maximized likelihood of the constrained system (the modified system for underfits but the specified system for overfits) and L^u is the maximized likelihood of the unconstrained system (the specified system for underfits and the modified system for overfits). This statistic asymptotically follows a chi-square distribution with n-degrees of freedom, where n is the number of imposed constraints.

3. Empirical Results

Specification and Estimation of the Model

The results from the estimation and analysis of a four-variable VAR system for investment, q, money, and government debt are described in this section. The variables employed are: 1) the ratio of real fixed nonresidential investment to the real capital stock (RI/KS), 2) Ciccolo's q variable, 3) the new M1 definition, and 4) interest-bearing public debt held by the public and the Federal Reserve (PD). q is measured as the ratio of the estimated value of nonfinancial corporations by the securities markets to the estimated replacement cost of the physical assets of these corporations. Since q is developed in this fashion, residential construction is omitted from the investment series. A justification for the ratio form of the investment variable based upon the flexible accelerator model is provided in Ciccolo (1978).[5] The debt series that includes both the public's and Federal Reserve holdings is employed in order to test the proposition that the financing of deficits leads to increases in the money supply. This measure, rather than just the public's holdings of debt, is used since, if the Federal Reserve monetizes the debt issued to finance a deficit on a dollar-for-dollar basis, there will be no change in the public's holdings of federal debt but the monetary base and the money supply would rise. It would then appear that there is no relationship between the debt series and the money supply when in fact there was complete monetization of the deficit. The data series and sources are described more fully in the Data Appendix.

Prior to specification of the model, the suggestion of Hsiao (1981) was followed and the data were detrended. For RI/KS and q, a first-difference transformation yielded stationarity while for M1 and PD a second difference of log transformation was required. Following Hsiao (1981), the appropriateness of these transformations was checked by regressing the transformed variables on a constant and time correcting for autocorrelation when necessary. In no case was the coefficient on time significant. However, similar regressions for the levels of RI/KS and q and first differences of logs for M1 and PD yielded significant coefficients on time.

Based upon the procedures described in the previous section, the following model was specified and estimated with FIML using quarterly data over the sample period 1961*i*–1979*iv*:

$$\begin{bmatrix} \mathrm{RI/KS} \\ q \\ \mathrm{PD} \\ \mathrm{M1} \end{bmatrix} = \begin{bmatrix} A_{11}^{8} & A_{12}^{3} & 0 & 0 \\ 0 & A_{22}^{1} & A_{23}^{3} & A_{24}^{8} \\ A_{31}^{12} & A_{32}^{5} & A_{33}^{8} & 0 \\ 0 & A_{42}^{1} & 0 & A_{44}^{8} \end{bmatrix} \begin{bmatrix} \mathrm{RI/KS} \\ q \\ \mathrm{PD} \\ \mathrm{M1} \end{bmatrix} + \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \end{bmatrix}. \tag{1}$$

[5]The results from the preliminary stages of the estimation procedure were not affected when real fixed nonresidential investment was used in place of the ratio of this investment series to the capital stock.

The A_{ij}, $i = 1, \ldots, 4$; $j = 1, \ldots, 4$, are polynomials in the lag operator L; the superscripts represent the maximum power of L and hence the length of the lag. The model estimates are presented in Table 1. However, it should be kept in mind that because of the reduced-form nature of the model it is difficult to interpret the individual autoregressive coefficients.

The adequacy of this specification was checked by over- and underfitting System (1) as indicated in Section 2. The first sequence of tests checks the Granger-causality implications of System (1). As Granger (1969) proved, a zero element in the matrix of lag polynomials for a purely autoregressive system indicates the absence of Granger-causality from one variable to another; that is, since in System (1) $A_{13}(L) = 0$, we tentatively say that PD does not directly Granger-cause RI/KS.[6] The causality implications were checked by sequentially constraining the zero elements in System (1) to be nonzero and the A_{12}, A_{23}, A_{24}, A_{31}, A_{32}, and A_{42} elements to be zero, estimating the resulting models, and computing likelihood ratio statistics. The results from these tests are presented in Table 2. From Table 2 we see that the Granger-causality implications are supported by the likelihood ratio tests. The hypothesis is that $A_{23}(L) = 0$ is rejected at the 10-percent level but not at the 5-percent level; however, an examination of the coefficients and their associated t-statistics reveals that the t-statistic on the third lag in this polynomial is significant at the 5-percent level. Based upon the significance of this coefficient and the rejection of $A_{23}(L) = 0$ at the 10-percent level, it was decided to retain the lag on PD in the q equation.

The second sequence of likelihood ratio tests is designed to check the lag length for the nonzero elements of System (1); the results are also presented in Table 2. None of the overfits is accepted; however, there is some ambiguity on several of the underfits. The original lag length is not rejected at the 10-percent level for $A_{23}(L)$, $A_{31}(L)$, and $A_{33}(L)$. However, in each case there is one coefficient significant at the 5-percent level among those eliminated for the underfit. Because of this and the nonrejection of the

[6] An additional reason for employing the vector autoregressive approach is based upon the results of Nelson and Schwert (1982). Using Monte Carlo simulations they found that the most powerful causality tests are those based on the correct reduced-form model and that parametric tests involving reduced-form models are more powerful than tests employing cross-correlations of univariate ARMA residuals or regressions based on univariate ARMA residuals.

TABLE 1. *Parameter Values for System (1)**

$$\begin{aligned}
RI/KS = {} & \underset{(1.94)}{0.0004} + \underset{(0.39)}{0.038}\, RI/KS_{-1} + \underset{(1.99)}{0.184}\, RI/KS_{-2} + \underset{(2.05)}{0.191}\, RI/KS_{-3} - \underset{(-0.48)}{0.045}\, RI/KS_{-4} + \underset{(0.48)}{0.044}\, RI/KS_{-5} - \underset{(-0.25)}{0.023}\, RI/KS_{-6} \\
& + \underset{(2.37)}{0.223}\, RI/KS_{-7} - \underset{(-3.87)}{0.341}\, RI/KS_{-8} + \underset{(3.33)}{0.012}\, q_{-1} + \underset{(3.57)}{0.014}\, q_{-2} + \underset{(2.56)}{0.001}\, q_{-3}\,; \quad SE = 0.0019\,, \quad DW = 2.16\,.
\end{aligned}$$

$$\begin{aligned}
q = {} & \underset{(-0.09)}{-0.0006} + \underset{(4.34)}{0.474}\, q_{-1} - \underset{(-1.01)}{0.491}\, PD_{-1} + \underset{(0.27)}{0.140}\, PD_{-2} + \underset{(2.35)}{1.111}\, PD_{-3} - \underset{(-0.11)}{0.158}\, M1_{-1} - \underset{(-1.29)}{1.844}\, M1_{-2} - \underset{(-0.28)}{0.408}\, M1_{-3} \\
& - \underset{(-1.81)}{2.710}\, M1_{-4} + \underset{(0.40)}{0.564}\, M1_{-5} - \underset{(-1.85)}{2.617}\, M1_{-6} - \underset{(-2.38)}{3.050}\, M1_{-7} - \underset{(-3.12)}{3.803}\, M1_{-8}\,; \quad SE = 0.0515\,, \quad DW = 1.81\,.
\end{aligned}$$

$$\begin{aligned}
PD = {} & \underset{(1.07)}{0.001} - \underset{(-1.31)}{0.635}\, RI/KS_{-1} - \underset{(-2.43)}{1.147}\, RI/KS_{-2} - \underset{(-0.40)}{0.192}\, RI/KS_{-3} + \underset{(0.59)}{0.262}\, RI/KS_{-4} - \underset{(-2.91)}{1.249}\, RI/KS_{-5} - \underset{(-1.34)}{0.595}\, RI/KS_{-6} \\
& + \underset{(0.84)}{0.371}\, RI/KS_{-7} + \underset{(0.87)}{0.397}\, RI/KS_{-8} - \underset{(-0.67)}{0.330}\, RI/KS_{-9} + \underset{(2.55)}{1.195}\, RI/KS_{-10} + \underset{(0.53)}{0.268}\, RI/KS_{-11} - \underset{(-1.05)}{0.467}\, RI/KS_{-12} - \underset{(-1.24)}{0.020}\, q_{-1} \\
& + \underset{(1.36)}{0.025}\, q_{-2} - \underset{(-2.60)}{0.050}\, q_{-3} + \underset{(3.68)}{0.075}\, q_{-4} - \underset{(-2.20)}{0.046}\, q_{-5} - \underset{(-4.51)}{0.478}\, PD_{-1} - \underset{(-3.93)}{0.458}\, PD_{-2} - \underset{(3.54)}{0.441}\, PD_{-3} - \underset{(-3.58)}{0.475}\, PD_{-4} \\
& - \underset{(-2.23)}{0.291}\, PD_{-5} - \underset{(-1.01)}{0.119}\, PD_{-6} - \underset{(-1.48)}{0.157}\, PD_{-7} - \underset{(-1.94)}{0.176}\, PD_{-8}\,; \quad SE = 0.0073\,, \quad DW = 1.78\,.
\end{aligned}$$

$$\begin{aligned}
M1 = {} & \underset{(2.28)}{0.001} + \underset{(4.14)}{0.034}\, q_{-1} - \underset{(-4.46)}{0.498}\, M1_{-1} - \underset{(-6.12)}{0.647}\, M1_{-2} - \underset{(-3.11)}{0.345}\, M1_{-3} - \underset{(-5.14)}{0.581}\, M1_{-4} - \underset{(-2.83)}{0.297}\, M1_{-5} - \underset{(-1.89)}{0.200}\, M1_{-6} - \underset{(-1.31)}{0.122}\, M1_{-7} \\
& - \underset{(-0.353)}{0.314}\, M1_{-8}\,; \quad SE = 0.0039\,, \quad DW = 2.04\,.
\end{aligned}$$

*SE = standard error of the regression; t-statistics are in parentheses below the coefficients.

TABLE 2. *Specification Tests*

Granger-Causality Tests		*Lag Specification Tests*	
Hypothesis	*Chi-Square Statistic*	*Hypothesis*	*Chi-Square Statistic*
1. $A^{4}_{13}(L) \neq 0$	1.16	Overfits	
2. $A^{4}_{14}(L) \neq 0$	0.60	1. $A^{10}_{11}(L)$	0.52
3. $A^{4}_{21}(L) \neq 0$	3.68	2. $A^{5}_{12}(L)$	0.32
4. $A^{4}_{34}(L) \neq 0$	0.98	3. $A^{3}_{22}(L)$	0.64
5. $A^{4}_{41}(L) \neq 0$	0.30	4. $A^{5}_{23}(L)$	0.52
6. $A^{4}_{43}(L) \neq 0$	2.34	5. $A^{10}_{24}(L)$	0.82
7. $A_{12}(L) = 0$	37.92*	6. $A^{14}_{31}(L)$	0.18
8. $A_{23}(L) = 0$	6.78***	7. $A^{7}_{32}(L)$	0.08
9. $A_{24}(L) = 0$	19.12**	8. $A^{10}_{33}(L)$	4.42
10. $A_{31}(L) = 0$	39.68*	9. $A^{3}_{42}(L)$	1.46
11. $A_{32}(L) = 0$	19.46*	10. $A^{10}_{44}(L)$	3.28
12. $A_{42}(L) = 0$	15.50*		
		Underfits	
		11. $A^{4}_{11}(L)$	14.46*
		12. $A^{1}_{12}(L)$	21.18*
		13. $A^{1}_{23}(L)$	5.50***
		14. $A^{4}_{24}(L)$	14.60*
		15. $A^{8}_{31}(L)$	8.24***
		16. $A^{3}_{32}(L)$	13.90*
		17. $A^{4}_{33}(L)$	6.72***
		18. $A^{4}_{44}(L)$	15.72*

*Significant at .01 level; **significant at .025 level; ***significant at .10 level.

original lag length at the 10-percent level, the original lag length is retained.

The adequacy of the model was further checked by analyzing the cross correlation matrices of residuals from System (1). These matrices were computed using the multiple time series program developed by Tiao et al. (1979), and an examination of the cross-correlation matrices revealed that the residuals are white noise.

Finally, System (1) was compared to a Sims' type VAR where all variables have a common lag length. The lag length was determined in the manner suggested by Tiao and Box (1981). This procedure involves the calculation of partial autoregressive matrices and a likelihood ratio statistic for successive autoregressive models in which the length of the common lag is increased by one. An examination of the partial autoregressive matrices and the likelihood ratio statistic suggests an appropriate model is one with a common lag of four. This model was then estimated using FIML. Within sample and out-of-sample forecasts from the Sims' type model were compared with similar forecasts from System (1). The root-mean-square errors from dynamic out-of-sample simulations over the period 1980*i*–1980*iv* for RI/KS, q, M1, and PD, respectively, are 0.3679×10^{-2}, 0.357×10^{-1}, 0.2503×10^{-1}, and 0.4517×10^{-2} for (1) and 0.3986×10^{-2}, 0.5739×10^{-1}, 0.2421×10^{-1}, and 0.5299×10^{-2} for the Sims' type system. We see that with the exception of M1 the forecasts from System (1) are somewhat better than the forecasts from the Sims' type system. The biggest difference is found for q where the root-mean-square error from the Sims' type system is about 1.6 times the root-mean-square error from System (1). On this basis, all further discussion will focus upon System (1).

Interpretation of the Results

From System (1) we find that the causality implications of Tobin's general equilibrium model are supported. Both money and debt Granger-cause q; q in turn Granger-causes investment. The effect of money and debt on investment appears to be only through their effect on q so that q appears to be a key link between the financial and real sectors of the economy. There is, however, direct feedback from investment and q to government debt and from q to money. The feedback from investment to government debt may reflect the workings of automatic stabilizers on the size of the deficit or it may reflect active attempts by the fiscal authorities to stabilize real output. To the extent that q varies cyclically, the feedback from q to debt may reflect countercyclical policy actions by fiscal authorities. Likewise, the feedback from q to money may reflect countercyclical monetary policy actions or, to the extent that q varies with the level of market interest rates, the feedback may reflect Federal Reserve attempts to stabilize interest rates.[7] In any case, these results suggest that neither money nor government debt is exogenous. Finally, there appears at best to be only indirect feedback from investment to q through the effects of investment on government debt.

[7]For an innovative approach to estimating the response of the Federal Reserve to economic conditions and a review of many previous reaction function studies, see Barth, Sickles, and Wiest (1982).

The dynamic characteristics of the system can be described in several ways. One way is to compute variance decompositions. Variance decompositions (VDCs) show the proportion of forecast error variance for each variable that is attributable to its own innovations and to shocks to the other system variables. The VDCs are generated in the manner described by Sims (1980b). This method recognizes that, in general, the correlation of residuals across equations is not zero. In calculating the VDCs the variables are ordered in a particular fashion. Because of the cross-equation residual correlation, when a variable higher in the order changes, variables lower in the order are assumed to change. The extent of the change depends upon the covariance of the variables higher in the order with those lower in the order. Because of this the VDCs may be sensitive to the ordering of the variables so that it is useful to examine the VDCs based on several orderings.[8]

The orderings reported here reflect the primary focus of the paper on the effects of money and government debt on q and investment. The orderings are: 1) money, q, investment, and government debt; and 2) government debt, q, investment, and money. The VDCs are presented in Table 3 and are computed for horizons of 16 and 20 quarters in order to allow the dynamics of the system to work themselves out. Since the results are not substantially different, the discussion will focus on the 20-quarter horizon results. We see that shocks to money account for a very small amount of the forecast variance for the other system variables. Money innovations account for only 2.1 percent of the variation in q and 3.9 percent of the variation in RI/KS. These results are broadly consistent with those of Sims (1980b) and Fackler (1983). Sims finds that money innovations account for only 4 percent of the variation in industrial production in the postwar period (1948–78) while Fackler finds that money innovations account for only 1.5 percent of the variation in real GNP.

Most of the variance in money is explained by its own innovations; however, shocks to q account for 23 percent of money variance in the first ordering and 41 percent in the second ordering.

[8]In order to calculate the VDCs the variance–covariance matrix was diagonalized. The program to do this was supplied by James Fackler. Furthermore, since much of the macroeconomic literature focuses upon the effects of changes in money growth, System (1) was transformed so that the variables are the level of q and RI/KS and the first differences of logs of money and debt. The results reported in Table 3 do not differ qualitatively from variance decompositions based on the untransformed system.

TABLE 3. *Variance Decompositions*

Ordering 1					Ordering 2				
Relative Variation in	*Explained by* M1	*q*	*RI/KS*	*PD*	*Relative Variation in*	*Explained by* PD	*q*	*RI/KS*	*M1*
16-Quarter Horizon									
M1	76.4	22.6	0.1	0.4	PD	26.6	53.6	16.6	3.2
q	2.4	97.2	0.1	0.2	*q*	0.2	93.5	0.1	6.1
RI/KS	4.2	69.9	25.8	0.1	RI/KS	0.6	71.7	24.3	3.4
PD	4.7	51.1	16.0	28.2	M1	0.9	41.2	0.1	57.8
20-Quarter Horizon									
M1	76.4	23.1	0.2	0.4	PD	25.9	54.1	17.0	3.0
q	2.1	97.6	0.1	0.2	*q*	0.2	93.6	0.1	6.1
RI/KS	3.9	70.2	25.8	0.1	RI/KS	0.6	71.7	24.2	3.5
PD	4.9	50.5	16.0	28.6	M1	0.8	42.9	0.1	56.2

We also note that, with the exception of the percent of money variance explained by q innovations, the results are insensitive to the ordering. This insensitivity is explained by the low cross equation residual correlations.

The contribution of innovations in government debt to the explanations of the variance in investment and q is even less than for money innovations. In fact, the contribution of government debt shocks to the explanation of the variance in any variable but itself is virtually nil, regardless of the ordering. The inconsequential amount of the variance in q explained by debt shocks is broadly consistent with the recent findings of Plosser (1982). Using the methodology developed by Abel and Mishkin (1981), he finds no effect of unanticipated changes in government debt on nominal financial asset values. Although unanticipated movements in government debt appear to have little effect on real variables, shocks to q and investment account for approximately 50 percent and 16 percent, respectively, of the variance in government debt.

A related way of assessing the dynamics is to compute impulse response functions (IRFs) which can be thought of as a type of dynamic multiplier that shows the response of each variable in the system to a shock to one of the system variables. IRFs are presented for one standard deviation shocks to money (based on the first ordering) and government debt (based on the second ordering). As was true for the variance decompositions, variables lower in the order are assumed to change when a variable higher in the order changes and variables higher in the order are given credit for the correlation between those variables and the variables lower in the order. The IRFs are presented in Table 4; in order to facilitate comparisons across variables, the elements of the table are in elasticity form. The response of a particular variable to, say, a money shock is multiplied by the ratio of the sample period means of money to the other variable.[9]

We see that a shock to money initially raises q and investment. The effect on q declines over time, with the peak effect occuring in period 1; in fact, the twentieth period effect is slightly negative, although it is very small. The pattern of movement in investment displays some oscillation with the effect gradually damp-

[9]IRFs for shocks to money when the ordering is debt, q, investment, and money and for shocks for debt when the ordering is money, q, investment, and debt are not presented since the ordering made little difference in the computation of the variance decompositions.

TABLE 4. *Impulse Response Functions*

Variable Shocked	Period	M1	q	RI/KS	PD
M1 (Ordering 1)					
	1	0.6413	0.0643	0.0158	−0.2092
	4	0.0619	0.0311	0.0385	−0.1746
	16	0.3398	0.0249	0.0141	0.0026
	20	0.1821	−0.0006	0.0208	−0.2239
PD (Ordering 2)					
	1	−0.0326	−0.0131	0.0044	0.5128
	4	0.0353	0.0031	0.0036	0.0625
	16	−0.0009	−0.0021	0.0051	0.2932
	20	0.0019	−0.0014	0.0047	0.2594

ing out. The peak effect occurs in period 4. The positive effect on q and investment is not unexpected in light of the transmission mechanism outlined by Tobin (1969) and is consistent with Blanchard's (1980) results.

Debt shocks lower q (the exception is the effect in period 4) but are associated with increases in investment. This result can be explained by the fact that there is a positive covariance between debt and q and debt and investment so that when debt is shocked there are also positive shocks to q and investment. The negative effect of debt on q as embedded in the coefficients on debt in the q equation outweights the positive shock to q but is not strong enough to offset the positive shock to investment.

4. Conclusion

The purpose of this paper has been to investigate empirically the interrelationships among investment, Tobin's q, money, and government debt over the period from 1961 to 1979. The framework for analysis is based upon the vector autoregressive modeling technique developed by Caines, Keng, and Sethi (1981) and Keng (1982).

The patterns of Granger-causality are consistent with the transmission mechanism outlined by Tobin (1969). Both money and government debt Granger-cause q, although the evidence for this in the case of debt is weaker than for money. q in turn causes investment; money and debt's effects upon investment operate primarily through their effects on q since no direct causality from these variables to investment is discovered. However, neither money nor debt is exogenous; there is feedback from q to money and from q and investment to debt.

The dynamics of the system are investigated by computation of variance decompositions and impulse response functions. The variance decompositions suggest that shocks to money explain little of the variance in q and investment. Furthermore, government debt shocks have virtually no effect on the variance of either q or investment. The impulse response functions reveal that innovations in money raise q while innovations in debt lower q.

Finally, an interesting extension of the current study would be the more complete multiple causality analysis suggested in Caines, Keng, and Sethi (1981) and Keng (1982). This analysis begins with the estimation of bivariate autoregressive *models* for the variables under consideration. Restricted bivariate models are constructed next and a stage-wise hypothesis testing procedure is used to determine the Granger-causality relations among the variables. For each variable, the causal variables are ranked by their specific gravities. The FPE criterion is then employed to specify each equation of the VAR. These authors note that the bivariate models and their stage-wise causality testing provide a complete analysis of the interrelations among the variables of interest and thus helps in the specification of the VAR.

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Data Appendix

The data used in this study are from the following sources:

1. money—M1B series, Federal Reserve Bank of New York;
2. interest-bearing public debt held by public and Federal Reserve—Treasury Bulletin, Table OFS-1, seasonally adjusted by the author using the X-11 program;

3. real gross private domestic nonresidential fixed investment, Citibank Data Tape;
4. real capital stock (total nonresidential fixed investment), Citibank Data Tape;
5. q—provided by J.H. Ciccolo. The q series as constructed by Ciccolo is an estimate of the ratio of the market value of nonfinancial corporations to the replacement cost of the physical assets of these corporations. The numerator is the sum of the equity value of these firms (computed by capitalizing dividends paid by these corporations by Standard and Poor's dividend/price ratio) plus the value of the debt of these firms (computed by capitalizing interest payments by these corporations by Moody's BAA bond rate). The denominator is an estimate of the replacement value of nonfinancial corporation's plant and equipment plus inventories.