Causality Between the Money Supply and Share Prices: A VAR Investigation

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This paper reexamines the interaction between the money supply and share prices in the wake of recent volatility of share prices in the United States. The objective is to explore the validity of theoretical links underlying this interaction in order to draw some implications concerning policies designed to curb share market volatility. The results over the sample period 1973 to 1991 indicate that changes in the money supply have direct and indirect significant impacts on changes in share prices. Further, there is evidence of a causal impact of volatility in share prices on fluctuations in real output. Yet evidence suggests that the design of monetary policy has not considered all possible ways of exploiting these relationships.

INTRODUCTION

For many years the economic impact of the money supply on share prices has been debated in the economics literature. This topic has regained popularity in the wake of recent share market volatility in the United States. This volatility has drawn the attention of many economists and policy officials since the 1987 share market crash. The crash sent shock waves through the world's financial markets. Credit markets and commodity markets registered sharp swings in response (Federal Reserve Bank of Kansas City Symposium Series, 1988). The crash and its accompanying swings have raised the question of what, if anything, can be done to moderate volatility in share prices. A debate has emerged concerning the design of monetary policy and possible intervening actions by the Fed in order to prevent a share market crisis similar to that of 1987.

The quantity theory of money (Brunner, 1961; Friedman, 1961; and Friedman and Schwartz, 1963) states that an increase in the money supply results in a change in the equilibrium position of money with respect to other assets, including equity shares, in the portfolio balance of asset holders. As a result, asset holders adjust the proportion of their portfolios represented by money balances. This adjustment alters the demand for other assets that compete with money balances, including equity shares. An increase in the money supply is expected to create excess supply of money balances and, in turn, excess demand for shares. Share prices are expected to rise as a result. This channel of interaction

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between changes in the money supply and share prices has been described by advocates of the quantity theory of money as the *direct channel*.

There are indirect channels of interaction between the money supply and share prices. These indirect channels focus on the impact of changes in the money supply on variables that guide investors' decisions concerning the allocation of their portfolios between money balances and alternative assets. A rise in the money supply creates excess supply of money chasing a limited amount of goods and services in the economy. In the context of mainstream rational expectations natural rate macromodels, the resulting excess demand will affect real output and the price level in the short run, with magnitudes that are dependent on factors determining the slope of the short-run supply curve. In the long run, however, the full impact of the increase in the money supply will be absorbed in the price level. The resulting increase in the price level may stimulate inflationary expectations in the economy, which has a positive impact on the nominal interest rate. Higher nominal interest rates will affect investors' choices regarding the proportion of their portfolios to be held in terms of money balances because the nominal interest rate measures the opportunity cost of holding money balances. A rise in this opportunity cost will motivate asset holders to substitute other financial assets, including equity shares, for money in their portfolios.

Even though the direct and indirect impacts of the money supply on share prices have been recognized, this relationship has stirred another debate in efficient market models (Fama, 1970; Cagan, 1972; and Pearce, 1987). The debate has focused on the definition of efficiency and its implication concerning the time of the adjustment of share prices to changes in the money supply. Share prices in an efficient market reflect all publicly available information about the future profitability of firms. That is, historical data are useless in developing trading rules because such information already is incorporated in share prices. This implies that past changes in the money supply should not be able to predict share prices. These changes are caused by observed economic disturbances that had been reflected previously in share prices.

Changes in the money supply are hypothesized to lead changes in share prices. Whether the share market is efficient determines the lag length of the response of share prices to changes in the money supply. One can speculate, however, on the possibility of a causal relationship between share prices and the money supply. If the Fed counters shocks in the economic system with monetary policy, then a change in share prices may motivate Fed officials to vary the rate of growth of the money supply. A decrease in share prices caused by traders' increased pessimism may be interpreted as a signal of a possible recession. In an effort to counteract this possibility, Fed officials may expand monetary growth in order to boost share prices and reverse any contractionary signs. Changes in share prices may have a causal impact on the money supply according to this channel.

The above discussion suggests the possibility of a bidirectional causality between share prices and money supply. Several investigations have examined the existence of this bidirectional causality. The econometric methodology and the findings of the various studies have varied. Sprinkel (1964) used a graphical approach to illustrate the relationship between changes in share prices and monetary growth. In contrast, Regalski and Vinso (1977) used cross correlation analysis to detect the bidirectional relationship between money supply and share returns. Other studies have utilized bivariate regressions for the empirical investigation of the relationship between money supply and share prices (Kraft and Kraft, 1977a; Sorenson, 1982; Pearce and Roley, 1985; and Mookerjee, 1987).

Other investigations have been concerned about various determinants of share prices including real output, the interest rate, and expected inflation (Kraft and Kraft, 1977b; Schwert, 1981; Pearce and Roley, 1985; James, Koreisha, and Partch, 1985; and Hashemzadah and Taylor, 1988). All these studies, except the latter study, have used bivariate regressions to analyze the relationship between share prices and their major determinants. But share prices involve a set of relationships that jointly explain the behavior of these prices because of the likely problem of simultaneity bias. A single estimation procedure may be inappropriate for what is essentially a system of equations.

James, Koreisha, and Partch (1985) used a vector autoregressive moving average (VARMA) model to examine simultaneously the links between share prices and their major determinants. Their empirical model comprises share prices, real output, the money supply, and the nominal interest rate as a proxy for expected inflation. While changes in the nominal interest rate reflect changes in inflationary expectations, the nominal interest rate may vary in response to changes in the real interest rate independently from expected inflation. Thus, it is preferable to account for expected inflation and the nominal interest rate independently as two measures of the opportunity cost agents consider as they compare shares to other assets in their portfolio balance. In addition, the current analysis departs from that of James, Koreisha, and Partch (1985) by employing new techniques that avoid the ad hoc assumptions used in earlier investigations for the determination of the lag structure and the direction of causality among the variables. Finally, James, Koreisha, and Partch (1985) end the sample period for their investigation in 1981. The excessive volatility that the share market has exhibited lately suggests the need for a fresher look. This investigation provides this fresher look at causes underlying the recent volatility of share prices from 1973:1 to 1991:1.

THEORETICAL BACKGROUND

A brief theoretical background that explains the interaction between the money supply and share prices is provided. The starting point for this interaction is the equilibrium condition in the money market in standard macromodels:

$$(1)\ \left(\frac{M}{P}\right)^{s} \left(\frac{M}{P}\right)^{D}$$

where:

$\left(\frac{M}{P}\right)^{s}$ = Supply of real money balances; and

$\left(\frac{M}{P}\right)^{D}$ = Demand for these balances.

It is assumed that the log of the money supply is determined by the central bank and denoted by m. Accordingly, the rate of growth of the money supply can be expressed as follows:

$$(2)\ D_m = D_p + D\log\left(\frac{M}{P}\right)^D,$$

where:

D(.) = First difference operator; and

p = Log of the price level.

The equilibrium condition in the money market is dependent on factors that influence the public's willingness to hold money, $D\log(M/P)^D$.

These determinants can be expressed as follows:

$$(3)\ D_m = D_p + f(D_y, D_p{}^e, D_r),$$

where:

f(.) = Functional form; and

D_y = Change in real income;

$D_p{}^e$ = Public's expectation of the inflation rate; and

D_r = Change in the nominal interest rate.

A rise in real income is expected to increase the demand for money for transactions. In addition, the speculative demand for money depends negatively on rates of return for all assets viewed by economic agents as substitutes for money in their portfolios, including physical and financial assets. It is expected, therefore, that the demand for money varies negatively in response to an increase in expected inflation and the nominal interest rate. Expected inflation measures the yield foregone on physical assets. These assets appreciate in value with inflation, which compensates holders for the rise in the price level that has a negative impact on their holdings of real money balances. Similarly, the nominal interest rate measures the rate foregone on financial assets that real money balances do not offer. Consequently, both p^e and r represent the opportunity costs of holding money balances. A rise in the opportunity cost stemming from these sources has a negative impact on the public's preference to hold money balances.[1]

[1]This specification for money demand is consistent with the view of the monetarists, who envision money as a substitute for a wide range of assets in the portfolio. See Friedman (1956).

Equilibrium in the money market implies that all portfolios are in balance. A change in the money supply creates excess supply of money which necessitates portfolio adjustment. Share prices will be affected in this process as agents increase their demand for equities following an increase in the money supply. Changes in the money supply also can affect portfolio adjustment and, in turn, share prices indirectly by affecting the variables that determine agents' decisions on money demand. Mainstream rational expectations natural rate macromodels of the variety of Lucas (1972) and Fischer (1977) produce the possibility of the short-run nonneutrality of changes in the money supply. Changes in the money supply are likely to affect real output and the price level in the short run. In the long run, however, money is predicted to be neutral. Changes in the money supply are expected to be absorbed fully in the price level, and output remains at its full equilibrium value.

These implications suggest that the change in the money supply may determine the rate of growth of real income, D_y, in the short run. The change in the price level following the increase in the money supply also will affect agents' expectations of inflation, $D_p{}^e$. In addition, changes in the money supply will affect the nominal interest rate through their impact on inflationary expectations and the change in the real interest rate necessary to equilibrate the money market following an increase in the money supply. These effects induce changes in the public's preference to hold money balances. The resulting portfolio balance adjustment necessitates a change in share prices.[2]

Changes in the money supply are expected to lead inflation, real output, the nominal interest rate, and share prices. Nonetheless, a theoretical possibility exists for a reverse causation from each of these variables to the money supply. If Fed officials are following an endogenous money supply rule, changes in the money supply may be induced by disturbances in real output growth, the inflation rate, the interest rate, or share prices.[3] Under this theoretical possibility, a reverse causation may exist from these variables to the money supply.

THE MODEL AND ESTIMATION PROCEDURE

To provide some evidence on the channels underlying the relationships between the money supply and share prices, a vector autoregressive model comprising share prices,

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[2]While these theoretical implications are based on portfolio balance theory in a closed economy, it is likely that these implications are reinforced in an open economy. Changes in the domestic interest rate may have further impact on share prices through the international capital flow induced by these changes. Yet other variables that do not determine portfolio balance in a closed economy are likely to have a unique impact in an open economy. The most significant among these variables is the exchange rate. In an experiment in which the exchange rate of the dollar per SDRs (special drawing rights issued by the IMF) was added to the current empirical model, there was no evidence of a significant causal relationship between share prices and this exchange rate. The results of this experiment are available upon request.

[3]The relevance of these variables to the monetary policy rule is a pure theoretical possibility. The list of variables is neither inclusive, nor is the endogenous money rule, if it exists, expected to be stable over time. Part of the difficulty is that the decision on the optimal monetary rule has been subject to a continuous debate. One aspect of this debate has centered on the issue of rules versus discretion. While some advocate the use of discretionary monetary policy to stabilize the economy (Fischer, 1977), others (Friedman, 1961; Lucas, 1972) have argued that the Fed should inject money at a steady rate over time.

Another debate has emerged among those who advocate discretionary monetary policy rules on what the optimal target to be established by Fed officials should be. A classic example of this literature is Poole (1970).

money supply, real output, the inflation rate, and the nominal interest rate is estimated. The estimation of this model will reveal information about the channels of interaction between these variables. The VAR technique was selected for the empirical investigation for a number of reasons. A single estimation procedure is inappropriate for what is essentially a system of equations that, therefore, suffers from simultaneity bias. Further, the theoretical relationship between share prices and their major underlying determinants is complicated by a number of direct and indirect channels. The complexity of this relationship makes it difficult to approximate these channels using structural theoretical representation without running the risk of misspecification bias. In the absence of this structural representation, it is not possible to estimate a system of simultaneous equations for the empirical investigation of the theoretical relationship under consideration.

The model is estimated using seasonally adjusted monthly data for share prices (SP), the narrowly defined money stock (M1), real output as measured by industrial production (IP), the short-term interest rate as measured by the three month treasury bill rate (SR), and the aggregate price level as measured by the consumer price index (CPI).[4] The model is estimated from 1973.1 to 1991.1.[5]

Let W_t denote a five component vector, i.e., $W_t = (SP_t, M1_t, IP_t, SR_t, CPI_t)$. Then a five variable VAR model can be written as:

$$(4)\quad \begin{bmatrix} SP_t \\ M1_t \\ IP_t \\ SR_t \\ CPI_t \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \\ \phi_{30} \\ \phi_{40} \\ \phi_{50} \end{bmatrix} + \begin{bmatrix} \phi_{11}(L)\phi_{12}(L)\phi_{13}(L)\phi_{14}(L)\phi_{15}(L) \\ \phi_{21}(L)\phi_{22}(L)\phi_{23}(L)\phi_{24}(L)\phi_{25}(L) \\ \phi_{31}(L)\phi_{32}(L)\phi_{33}(L)\phi_{34}(L)\phi_{35}(L) \\ \phi_{41}(L)\phi_{42}(L)\phi_{43}(L)\phi_{44}(L)\phi_{45}(L) \\ \phi_{51}(L)\phi_{52}(L)\phi_{53}(L)\phi_{54}(L)\phi_{55}(L) \end{bmatrix} \begin{bmatrix} SP_t \\ M1_t \\ IP_t \\ SR_t \\ CPI_t \end{bmatrix} + \begin{bmatrix} e_{t1} \\ e_{t2} \\ e_{t3} \\ e_{t4} \\ e_{t5} \end{bmatrix}$$

where:

[4]An empirical proxy for D_p^e is necessary before estimation. There are two competing hypotheses to be considered in this regard. The adaptive expectation hypothesis posits that agents' forecast of the inflation rate can be approximated best using the past inflation rate. The rational expectation hypothesis, in contrast, requires that the forecast for inflation should account for the lags of variables in addition to lagged inflation that are relevant to the change in the price level. These variables include all variables in the VAR system: money supply, real output, interest rate, and share prices. The first difference of the log of the current price level is used to approximate the expected inflation at time t in the empirical model which is consistent with both the rational and adaptive expectation hypotheses. Whether the inflation process is forecast best using the adaptive or the rational expectation approach is determined by the significance of the lags of the remaining variables of the VAR system to the forecast of inflation.

[5]Because the focus of the investigation is on the change in share prices that fluctuate daily, it is necessary to maximize the frequency of observations in the sample in order to capture many of these fluctuations. Only monthly data were available, however; data for GNP and the GNP deflator are not even available on a monthly basis. Therefore, real output is measured using the index of industrial production and the aggregate price level using the Consumer Price Index. The description and sources of data are provided in the appendix. The starting point for the sample is determined by the availability of monthly data from the IFS data tapes.

Subscripts = Matrix ordering;

$\phi_{ij}(L) = \sum_{k=1}^{m_{ij}} \phi_{ijk}L^k$;

m_{ij} = Degree of the polynomial $\phi_{ij}(L)$;

L = Lag operator such that $L^k x_t = x_{t-k}$;

ϕ_{i0} *(i=1 to 5)* = *Intercepts in each equation;* and

$e_t' = (e_{t1}, e_{t2}, e_{t3}, e_{t4}, e_{t5})$ = White noise vector satisfying $E(e_t) = 0$, $E(e_t, e_s) = \Sigma$ for $t = s$, $E(e_t, e_s) = 0$ *for* $t \neq s$.

Granger (1980, p. 347) states that W_j is a prima facie cause of W_i in mean if ϕ_{ij} is *significantly different from zero and* W_i *causes* W_j *in mean if* ϕ_{ij} *is significantly different* from zero. W_i causes W_j in mean indicates that the past of W_i is relevant to the realized present and future mean values of W_j. That is, one is better able to forecast future values of W_j by projecting W_j on its past values and the past values of W_i. If the least squares criterion is used, W_i causes W_j in mean is consistent with a smaller forecast error in predicting W_j when one accounts for W_i in the information set used for the forecast (Granger, 1969). If W_i causes W_j and W_j causes W_i, then there is a feedback relationship between W_i and W_j. Further, W_j does not cause W_j if and only if $\phi_{ij}(L) = 0$. Hsiao (1982) defines *indirect causality* as the case where W_j does not cause W_i, but W_j causes a third variable W_s that causes W_i. Thus, W_j causes W_i indirectly via W_s. Note that the conclusion that W_j indirectly causes W_i requires that $\phi_{ij}(L) = 0$ and that ϕ_{sj} and ϕ_{is} are significantly different from zero.

Estimation of the VAR model requires determination of the appropriate lag length of each $\phi_{ij}(L)$ polynomial in the model. This study uses Hsiao's (1979, 1980) sequential procedure, which is based on Granger's definition of causality and Akaike's (1969, 1970) criterion for the minimum final prediction error (FPE). A lower order of $\phi_{ij}(L)$ than necessary may not account for lags in the model and, in turn, creates the risk of biased estimates. On the other hand, a higher order of $\phi_{ij}(L)$ than necessary may account for irrelevant lags in the model and thereby creates the risk of inefficient estimates. As Hsiao (1981) suggests, the FPE criterion is intended to provide a formal way of balancing this risk. This is accomplished by choosing the order of the lags using an approximate F test with varying significance levels.

Without loss of generality, the specification details of the first equation of the VAR model are discussed. W_1 is regressed on its own lags as follows:

(5) $W_{1t} = \phi_{10} + \phi_{11}(L)W_{1t} + e_{1t}$,

where:

$$\phi_{11}(L) = \sum_{k=1}^{M} \phi_{11k} L^k; \text{ and}$$

M = Arbitrarily chosen maximum lag of the $\phi_{11}(L)$ polynomial.

In this study, M equals 12 for all variables.[6] Let SSE(k) define the sum of squares due to the residuals in equation (4). The optimal lag length, k, of the polynomial ϕ_{11} is the one that minimizes the FPE which is defined as follows:

$$(6)\ FPE(k) = \left(\frac{n+k+1}{n-k-1}\right)\left(\frac{SSE(k)}{n}\right),$$

where:

n = Number of observations.

Let m_{11} denote the value of k that minimizes the FPE in equation (6). Next, the optimal lag lengths in bivariate models are determined for the remaining variables:

$$(7)\ W_{1t} = \phi_{10} + \phi_{11}(L)W_{1t} + \phi_{1j}(L)\ W_{jt} + e_{1t}.$$

For a given W_j, (j=2 to 5), the optimal lag length is k which minimizes the following FPE:

$$(8)\ FPE(m_{11},k) = \left(\frac{n+m_{11}+k+1}{n-m_{11}-k-1}\right)\left(\frac{SSE(m_{11},k)}{n}\right)$$

To determine the order of the variables added in each stage, the specific gravity criterion of Caines, Keng, and Sethi (1981) is employed. The specific gravity of W_j with respect to W_1 in equation (7) is defined as the reciprocal of the FPE(m_{11},k). The variable that gives the highest specific gravity (i.e., the smallest FPE(m_{11},k)) of the four variables considered in the bivariate regressions is considered to be the most important to the explanation of W_1 and, accordingly, is added to the W_1 equation. Let this variable be W_2 with an optimal lag length m_{12}. The FPE corresponding to W_2 given W_1 is denoted by FPE(m_{11},m_{12}). Hsiao (1979, 1981) recommends comparison of FPE(m_{11}) with FPE(m_{11}, m_{12}); if FPE(m_{11},m_{12}) > FPE(m_{11}), W_2 is not a prima facie cause of W_1 and, in turn, is not added to the W_1 equation. Moreover, none of the remaining four variables is a prima facie cause of W_1 and, in turn, the specification of the W_1 equation is

[6]The common practice in investigations using monthly data was used to determine the maximum lag length. Such investigations typically show that twelve lags are sufficient to capture the serial correlation pattern. Experiments with longer lags provided evidence supporting this notion; none of the additional lags were significant for any of the variables in the VAR system.

complete. If $FPE(m_{11},m_{12}) < FPE(m_{11})$, W_2 is added to the W_1 equation producing the following bivariate model:

$$(9)\ W_{1t} = \phi_{10} + \phi_{11}(L)W_{1t} + \phi_{12}(L)\ W_{2t} + e_{1t}.$$

To specify the trivariate regression equation, the above procedure is repeated, i.e., consider:

$$(10)\ W_{1t} = \phi_{10} + \phi_{11}(L)W_{1t} + \phi_{12}(L)W_{12} + \phi_{13}(L)w_{jt} + e_{1t},$$

where:

W_j = One of the remaining three variables.

Again, for each W_j the FPE is given by:

$$(11)\ FPE(m_{11},m_{12},k) = \left(\frac{n+m_{11}+m_{12}+k+1}{n-m_{11}-m_{12}-k-1}\right)\left(\frac{(SSE,m_{11},m_{12},k)}{n}\right)$$

The value of k that minimizes equation (11) is the optimum lag length for that W_j variable. Let W_3 with lag length m_{13}, for example, minimize equation (11). This minimum is denoted by $FPE(m_{11},m_{12},m_{13})$. If $FPE(m_{11},m_{12},m_{13}) > FPE(m_{11},m_{12},m_{13})$, then none of the remaining three variables are added to the bivariate equation and the specification is complete. If $FPE(m_{11},m_{12},m_{13}) < FPE(m_{11},m_{12})$, however, then W_3 is added as a third variable. The relevance of the fourth and fifth variables are analyzed by repeating the above procedure.

Having determined the lag lengths of the variables in the VAR model, the model is estimated using the iterative seemingly unrelated regression procedure of Zellner (1962). This procedure is a joint estimation procedure that takes into account the covariance among the residuals of the estimated variables of the VAR model. Kmenta and Gilbert (1968) and Dhrymes (1971) have shown that the estimates obtained by iterating Zellner's procedure to convergence are equivalent to the maximum likelihood estimates. Thus, the current estimates are equivalent to the maximum likelihood estimates.[7] A likelihood ratio (LR) test is used to test the prima facie cause from the jth to the ith variable. Because the LR test is based on the assumption that the errors are multivariate normal, the residuals are tested for multivariate normality using the Bera and John (1983) multivariate normality tests. Let $\hat{e}_i$ be the estimated residual vector from the ith equation; the steps to compute the Bera and John test are as follows. First, compute:

$$(12)\ T_i = \Sigma_t \hat{e}_{it}^3/n,\ T_{ii} = \Sigma_t \hat{e}_{it}^4/n,\ T_{ij} = \Sigma_t \hat{e}_{it}^2 \hat{e}_{jt}^2/n,\ i \neq j.\ k = 1, 2, \ldots, n,$$

[7]Convergence is established given a specified objective criterion that is based on minimizing the sum of the squared residuals of the empirical model. This paper's estimation is based on the convergence criterion built into the seemingly unrelated regression procedure on the RATS software.

where:

v = Number of variates in the multivariate normal distribution. Then compute

(13) $C_1 = n\Sigma_i T_i^2/6$,

which in large numbers follows a χ^2 distribution under the null hypothesis that the residuals follow a normal distribution with v variates. If C_1 is significant, the null hypothesis of normal residuals is rejected. If C_1 is not significant, Bera and John recommend computing:

(14) $C_2 = n\{\Sigma_i(T_{ii} - 3)^2/24 + \Sigma_{i<j}(T_{ij} - 1)^2/4\}$

$C_3 = n\{\Sigma_i T_i^2/6 + \Sigma_i(T_{ii} - 3)^2/24\}$.

Under the null hypothesis, C_2 and C_3 are asymptotically distributed as χ^2 with $v(v+1)/2$ and $2v$ degrees of freedom, respectively.

Let $\hat{\Sigma}$ and $\hat{\Sigma}'$ be the estimated variance-covariance matrices from the unrestricted and the restricted models, respectively. The likelihood ratio test statistic is given by:

(15) $-2\ln\lambda = n\{\ln|\hat{\Sigma}| - \ln|\hat{\Sigma}'|\}$

Asymptotically this statistic follows a χ^2 distribution with degrees of freedom equal to the number of restrictions.

Sims (1980, 1982) has shown that the strength of the Granger causal relations can be measured from the variance decomposition of the VAR model. The variance decomposition reveals the relative contributions of the system's innovations to the variance of the forecast error for all variables in the VAR model. Hence, this decomposition quantifies the magnitudes of the causal relationships among variables in the VAR model. The VAR model can be written as a vector moving average model of infinite order, i.e.,

(16) $W_t = \Gamma(L)e_t = \sum_{i=0}^{\infty} \Gamma_i e_{t-i}$

where:

$\Gamma(L)$ = (5x5) matrix in the lag operator L.

Because the covariance matrix Σ is positive definite, a nonsingular matrix P can be found such that $P\Sigma P' = I$. Thus, equation (16) can be written as:

$$(17)\ W_t = \sum_{i=0}^{\infty} \Gamma_i P^{-1} P e_{t-i}$$

$$= \sum_{i=0}^{\infty} \psi_i \varepsilon_{t-i},$$

where:

$\psi_i \quad = \quad \Gamma_i P^{-1};$

$\psi_0 \quad = \quad I$; and

$\varepsilon_{t-i} \quad = \quad Pe_{t-i}.$

Note that $E(\varepsilon_t \varepsilon_t') = I$; i.e., ε_t is a vector of uncorrelated random shocks each with unit variance. The matrices ψ_i represent the reactions of the system W_t to unit innovations in $\varepsilon_{jt}(j = 1, 2, 3, 4, 5)$. The forecast error covariance matrix, Ω, of an h-step-ahead forecast is given by:

$$(18)\ \Omega(h) = \psi_0 \psi_0' + \psi_1 \psi_1' + \ldots + \psi_{h-1}\, \psi_{h-1}'.$$

The sum of the jth diagonal elements of $\psi_0 \psi_0', \ldots, \psi_{h-1}\, \psi_{h-1}'$ is the forecast error variance of the h-step forecast of variable W_j. The contribution of innovations in the sth variable to this forecast error variance is given by:

$$(19)\ \psi_{js,0}^2 + \psi_{js,1}^2 + \ldots + \psi_{js,h-1}^2$$

where:

$\psi_{js,k}$ = jsth element of ψ_k.

The variance decomposition shows how the forecast error variance of a particular variable can be decomposed into the components accounted for by current and lagged innovations of different variables in the system. As Sims notes, "a variable that is optimally forecasted from its own lagged values will have all its forecast error variance accounted for by its own innovations" (Sims 1982, p. 131). Thus, if a small portion of the forecast error variance in SP_t is explained by other variables in the system, it can be interpreted as evidence of a weak prima facie causal relation from the system's variables to share prices.

EMPIRICAL RESULTS

It is important that the series be stationary for the validity of the conclusion on causality using the procedure described above. The first difference after the log transformation yielded stationary series for all variables.[8] The estimated final model is:

$$
(20)\quad \begin{bmatrix} \dot{SP}_t \\ \dot{M1}_t \\ \dot{IP}_t \\ \dot{SR}_t \\ \dot{CPI}_t \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \\ \phi_{30} \\ \phi_{40} \\ \phi_{50} \end{bmatrix} + \begin{bmatrix} \overset{2}{\phi}_{11}(L) & \overset{11}{\phi}_{12}(L) & 0 & \overset{3}{\phi}_{14}(L) & \overset{7}{\phi}_{15}(L) \\ 0 & \overset{5}{\phi}_{22}(L) & \overset{1}{\phi}_{23}(L) & \overset{6}{\phi}_{24}(L) & 0 \\ \overset{6}{\phi}_{31}(L) & 0 & \overset{2}{\phi}_{33}(L) & 0 & 0 \\ \overset{3}{\phi}_{41}(L) & \overset{4}{\phi}_{42}(L) & \overset{3}{\phi}_{43}(L) & \overset{6}{\phi}_{44}(L) & \overset{7}{\phi}_{45}(L) \\ \overset{2}{\phi}_{51}(L) & \overset{8}{\phi}_{52}(L) & 0 & \overset{2}{\phi}_{54}(L) & \overset{9}{\phi}_{55} \end{bmatrix} \begin{bmatrix} \dot{SP}_t \\ \dot{M1}_t \\ \dot{IP}_t \\ \dot{SR}_t \\ \dot{CPI}_t \end{bmatrix} + \begin{bmatrix} e_{t1} \\ e_{t2} \\ e_{t3} \\ e_{t4} \\ e_{t5} \end{bmatrix}
$$

Note that all variables of the vector autoregressive model in equation (20) are measured in first difference of the logs where the dots above the variables denote this transformation. First, the residual vector $\hat{e}_t = (\hat{e}_{1t}, \hat{e}_{2t}, \hat{e}_{3t}, \hat{e}_{4t}, \hat{e}_{5t})$ is tested for multivariate normality using the test suggested by Bera and John (1983). The test statistics C_1, C_2, and C_3 given in Bera and John (1983, pp. 108-109) were computed and yielded the following values: $C_1 = 7.0E\text{-}9$, $C_2 = 717.50$, and $C_3 = 307.50$. C_1 is not significant, and C_2 and C_3 are significant at the 5 percent significance level. Thus, the residuals are not exactly multivariate normal, so the LR tests should be viewed with caution.[9]

The likelihood ratio tests are performed to test the adequacy of the model specification. The likelihood ratio statistics testing the specification of the zero and nonzero polynomials are reported in Table 1. To test the lack of relationship among some variables in the model, the lag lengths of all zero polynomials uniformly are set equal to 4.[10] The likelihood ratio statistics for the null hypotheses of zero coefficients on these lags are reported for tests 1 through 7 of Table 1. None of these statistics is statistically significant. The results support the zero polynomials appearing in the final specification of equation (20).

Next, the accuracy of the lag length of the nonzero polynomials appearing in equation (20) is tested. This is accomplished by increasing or decreasing the lag length and testing for the significance of the change in the lag length. First, all nonzero polynomials

[8]The decision on stationarity is based on the results of the Dickey-Fuller (1981) unit root tests.

[9]The density function for the estimated residuals is consistent with the normality hypothesis in some aspects; C_1 is not significant. The distribution of the estimated residuals is not consistent, however, with the remaining more stringent restrictions that are unique to the normality distribution; C_2 and C_3 are significant. While the distribution of the residuals is close to multivariate normal, it is not exactly multivariate normal. This leads to doubts about the validity of conclusions based on marginally significant likelihood ratio statistics, where these conclusions may be sensitive to any variation in the distribution of the residuals from the multivariate normal. None of the statistically significant results reported in Table 1 is subject to this criticism, which lends more confidence to conclusions based on these results.

[10]Experiments with longer lags of the zero polynomials are also consistent with this conclusion.

Table 1—Likelihood Ratio Tests

Hypothesis	Degrees of Freedom	χ^2 Statistic
Panel A Model Specification		
1. $\phi_{13}=\phi_{13}^{4}$	4	1.57537
2. $\phi_{21}=\phi_{21}^{4}$	4	8.339830
3. $\phi_{25}=\phi_{25}^{4}$	4	4.126852
4. $\phi_{32}=\phi_{32}^{4}$	4	7.191289
5. $\phi_{34}=\phi_{34}^{4}$	4	3.043128
6. $\phi_{35}=\phi_{35}^{4}$	4	3.043128
7. $\phi_{53}=\phi_{53}^{4}$	4	1.640260
Tests 1 through 7 test the statistical significance of the zero polynomials in equation (20)		
8. $\phi_{11}^{2}=\phi_{11}^{4}$, $\phi_{12}^{11}=\phi_{12}^{12}$, $\phi_{14}^{3}=\phi_{14}^{5}$, $\phi_{15}^{7}=\phi_{15}^{9}$	7	6.780995
9. $\phi_{22}^{5}=\phi_{22}^{7}$, $\phi_{23}^{1}=\phi_{23}^{3}$, $\phi_{24}^{6}=\phi_{24}^{8}$	6	4.168454
10. $\phi_{31}^{6}=\phi_{31}^{8}$, $\phi_{33}^{2}=\phi_{33}^{4}$	4	1.507586
11. $\phi_{41}^{3}=\phi_{41}^{5}$, $\phi_{42}^{4}=\phi_{42}^{6}$, $\phi_{43}^{3}=\phi_{43}^{5}$, $\phi_{44}^{6}=\phi_{44}^{8}$, $\phi_{45}^{7}=\phi_{45}^{9}$	10	11.01502
12. $\phi_{51}^{2}=\phi_{51}^{4}$, $\phi_{52}^{8}=\phi_{52}^{10}$, $\phi_{54}^{2}=\phi_{54}^{4}$, $\phi_{55}^{9}=\phi_{55}^{11}$	8	7.093019
Tests 8 through 12 test the statistical significance of additional lags of the nonzero polynomials in equation (20)		
13. $\phi_{12}^{11}=\phi_{12}^{9}$, $\phi_{14}^{3}=\phi_{14}^{1}$, $\phi_{15}^{7}=\phi_{15}^{5}$	6	25.31880*
14. $\phi_{22}=\phi_{22}$, $\phi_{24}=\phi_{24}$	4	11.53202**
15. $\phi_{31}=\phi_{31}$	2	9.88371**
16. $\phi_{41}=\phi_{41}$, $\phi_{42}^{4}=\phi_{42}^{2}$, $\phi_{44}^{6}=\phi_{44}^{4}$, $\phi_{45}^{7}=\phi_{45}^{5}$	8	32.46096*
17. $\phi_{51}=\phi_{51}$, $\phi_{52}=\phi_{52}$, $\phi_{54}=\phi_{54}$, $\phi_{55}=\phi_{55}$	6	40.14613*
Tests 13 through 17 test the statistical significance of reducing the lag length of the nonzero polynomials in equation (20)		
Panel B Causality Directions		
18. $\phi_{12}^{11}=0$	11	30.35094*
19. $\phi_{14}^{3}=0$	3	35.6910*
20. $\phi_{15}^{7}=0$	7	17.64061**
21. $\phi_{23}^{1}=0$	1	7.14601**

Table 1 (continued)—Likelihood Ratio Tests

Hypothesis	Degrees of Freedom	χ^2 Statistic
Panel B Causality Directions		
22. $\phi_{24}^{6} = 0$	6	41.25925*
23. $\phi_{31}^{6} = 0$	6	30.11424*
24. $\phi_{41}^{3} = 0$	3	21.35758*
25. $\phi_{42}^{4} = 0$	5	39.12251*
26. $\phi_{43}^{3} = 0$	3	25.46118*
27. $\phi_{45}^{7} = 0$	7	28.04636*
28. $\phi_{51}^{2} = 0$	2	12.82314*
29. $\phi_{52}^{8} = 0$	8	21.81041**
30. $\phi_{54}^{2} = 0$	2	13.21833*

Tests 18 through 30 test the statistical significance of the nonzero polynomials in equation (20)

* Statistically significant at the 1 percent level
** Statisticaly significant at the 5 percent level

Notes: Polynomials in the table are based on equation (20). Subscripts represent matrix ordering and superscripts represent the number of lag terms. Data sources are listed in the appendix

in each row are increased by 2 and tested for their nonsigificance (overfitting the model). These are tests 8 through 12 of Table 1. The coefficients of the additional lags are not statistically significant according to the likelihood ratio statistics. All nonzero polynomials are reduced by 2 or 1 and tested for their significance (underfitting the model). These are tests 13 through 17 of Table 1. The coefficients of the omitted lags are statistically significant according to the likelihood ratio statistics. Thus, the LR tests confirm the adequacy of the VAR model reported in equation (20).

The likelihood ratio tests also are performed to test the significance of the relationships among variables in the model in order to determine the strength and direction of causality. All nonzero off-diagonal polynomials are set equal to zero and tested for their significance. These are tests 18 through 30 in Table 1. Tables 2 and 3 summarize the directions of causality of the varialbes based on the statistical significance of the lags implied by the likelihood ratio statistics. Table 4 reports the results of the variance decomposition, which quantifies the contributions of the system's innovations to the ten-months-step-ahead and the twenty-months-step-ahead forecast errors for each variable in the model.

Table 2—Direct Causal Relationships Implied by the Vector Autoregressive Model

Significant Polynomials	Implications for Direct Causality
$\phi_{12}^{11}(L)$	M1 ==> SP
$\phi_{14}^{3}, \phi_{41}^{4}(L)$	SR <==> SP
$\phi_{15}^{7}(L), \phi_{51}^{2}(L)$	CPI <==> SP
$\phi_{23}^{1}(L)$	IP ==> M1
$\phi_{24}^{6}(L), \phi_{42}^{4}(L)$	SR <==> M1
$\phi_{31}^{6}(L)$	SP ==> IP
$\phi_{43}^{3}(L)$	IP ==> SR
$\phi_{45}^{7}(L),\phi_{54}^{2}(L)$	CPI <==> SR
$\phi_{52}^{8}(L)$	M1 ==> CPI

==> = Direct prima facie cause;
<==> = Direct prima facie feedback;
M1 = Narrowly defined money stock;
IP = Index of Industrial Production;
SR = Three month Treasury bill rate;
CPI = Consumer Price Index

Data sources are listed in the appendix

Table 3—Indirect Causal Relationships Implied by the Vector Autoregressive Model

Summary of Significant Polynomials	Implications for Indirect Causality
$\phi_{12}^{11}(L),\phi_{14}^{3}(L), \phi_{22}^{5}(L), \phi_{42}^{4}(L)$	IP ==> SP via M1 and SR
$\phi_{23}^{1}(L), \phi_{24}^{6}(L), \phi_{31}^{6}(L), \phi_{41}^{3}(L)$	SP ==> M1 via IP and SR
$\phi_{22}^{5}(L), \phi_{45}^{7}(L)$	CPI ==> via SR
$\phi_{31}^{6}(L), \phi_{14}^{3}(L)$	SR ==> IP via SP
$\phi_{31}^{6}(L), \phi_{15}^{7}(L)$	CPI ==> IP via SP
$\phi_{31}^{6}(L), \phi_{12}^{11}(L)$	M1 ==> IP via SP
$\phi_{52}^{8}(L), \phi_{54}^{2}(L), \phi_{23}^{1}(L), \phi_{43}^{3}(L)$	IP ==> CPI via M1 and SR

Notes: Subscripts represent matrix ordering. Superscripts represent the number of lag terms.Other terms are as defined in Table 2. Data for IP are from various issues of *Business Conditions Digest*. All other data are from the International Financial Statistics data tapes

Table 4—Variance Decomposition of the Ten-Step-Ahead and Twenty-Step-Ahead Forecast Errors of the Variables in the Autoregressive Model

Variance of Forecast Error	Steps Ahead	Explained by Innovations in: SP	M1	IP	SR	CPI
SP	10	69.28	7.65	3.90	14.12	5.39
	20	65.18	9.86	3.62	13.73	7.72
M1	10	1.26	75.17	5.82	15.92	1.76
	20	1.28	71.84	6.19	15.21	5.57
IP	10	13.78	0.43	82.27	3.15	0.18
	20	13.56	1.72	80.21	2.62	1.38
SR	10	9.13	13.34	12.68	57.87	6.64
	20	9.74	13.76	12.26	55.84	8.71
CPI	10	2.72	6.73	2.24	3.84	84.54
	20	2.90	9.28	1.63	3.12	83.36

Terms are as defined in Table 2. See the appendix for data sources

The results summarizing the direct causal relationships among the model's variables in Table 2 are consistent with the implications of the quantity theory of money. The polynomial ϕ_{12} measuring the response of the change in share prices (SP) to changes in the money supply is statistically significant. The sum of the parameters in the polynomial is positive.[11] This implies that an increase in the money supply has a direct causal positive impact on share prices.

In Table 3, evidence on the indirect impact of changes in the money supply on share prices is based on the significance of the nonzero polynomials ϕ_{14}, ϕ_{15}, ϕ_{42}, and ϕ_{52}. The significance of the polynomials ϕ_{14} and ϕ_{15} indicates that past changes in the interest rate and the price level are important to the forecast of share prices, which provides support for their causal impacts on these prices. The sum of the parameters in these polynomials is consistent with this paper's expectation. An increase in the interest rate (which is measured by the rate on Treasury bills, a substitute for shares in the portfolio) has a cumulative negative impact on share prices.[12] In contrast, a rise in inflationary expectation has a cumulative positive impact on share prices as investors look for alternative substitutes for money balances in their portfolio.[13] The significance of the polynomials ϕ_{42} and ϕ_{52} suggests that past changes in the money supply are determinants of current changes in the interest rate and the price level and, in turn, that causal relationships exist in these directions. The sum of the parameters in both polynomials is positive. As expected, an increase in the money supply has a cumulative positive impact on the price level.[14] Further, it appears that the Fisher effect operating through inflationary expecta-

[11] The parameters in the ϕ_{12} polynomial according to their lag order are -1.58, 1.68, -0.064, 0.65, -0.24, 1.036, 0.66, 1.00, -0.92, 1.59, and -1.17. The sum of these parameters is 2.64.

[12] The parameters in the ϕ_{14} polynomial according to their lag order are -0.18, -0.046, and 0.054. The sum of these parameters is -0.17.

[13] The parameters in the ϕ_{15} polynomial according to their lag order are -1.79, 0.097, 1.95, -1.25, 2.37, -2.85, and 2.32. The sum of these parameters is 0.85.

[14] The parameters in the ϕ_{52} polynomial according to their lag order are 0.10, -0.054, -0.050, 0.013, -0.00015, 0.055, -0.092, and 0.050. The sum of these parameters is 0.022.

tion dominates the impact of an increase in the money supply on the nominal interest rate which is consistent with the positive sum of the parameters in the polynomial characterizing this relationship.[15] Thus, it appears that changes in the money supply have an indirect significant impact on share prices through changes in the interest rate and the price level, as predicted by theory.

The evidence accumulated from the estimation of the vector autoregression is also useful in examining the validity of the efficient market hypothesis. The order of the ϕ_{12} polynomial suggests that the causal impact that the money supply has on share prices is statistically significant with a lag length of 11. This evidence violates the efficiency hypothesis of the share market. Past changes in the money supply are able to predict future changes in share prices. This implies that share prices did not incorporate all publicly available past information. The most obvious explanation for this inefficiency is that traders in the share market suffer from recognition lag. Although changes in the stock of money are readily available to share market traders, the implications of these changes on the direction of monetary policy may not be readily apparent. As traders try to make inferences about monetary policy from published data on the money stock, they may confuse the direction of monetary policy. Information about the policy change may not be reflected in share prices. The results suggest that 11 months may pass before share market traders recognize the direction of the change in monetary policy and account for this change in their daily transactions.

Table 2 shows that the money supply is not caused directly by share prices. There is evidence of indirect causality from share prices to the money supply, however. The polynomials ϕ_{31} and ϕ_{41} are statistically significant, indicating that changes in share prices are significant in explaining future changes in real output and the short-term interest rate. The sum of the parameters in these polynomials shows that an increase in share prices has a cumulative positive impact on both real industrial output and the interest rate. An increase in share prices improves the financing position of industries issuing these shares which increases their demand for investment and, in turn, industrial output.[16]

On the other hand, an increase in share prices attracts financial investors from government bonds. Bond prices consequently decrease, which is consistent with a rise in the interest rate on these bonds.[17] It appears that changes in real output and the interest rate are important to the design of monetary policy. The polynomials ϕ_{23} and ϕ_{24} are statistically significant which reveals the relevance of past changes in real output and the interest rate to the design of the monetary policy in the current period. The sum of the parameters in these polynomials reflects the direction of monetary policy.[18] While the cumulative

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[15]The parameters in the ϕ_{42} polynomial according to their lag order are 5.39, -0.59, 2.061, and -1.94. The sum of these parameters is 4.92.

[16]The parameters in the ϕ_{31} polynomial according to their lag order are -0.0019, 0.036, 0.019, 0.057, -0.032, and 0.045. The sum of these parameters is 0.12.

[17]The parameters in the ϕ_{41} polynomial according to their lag order are 0.13, 0.51, and -0.12. The sum of these parameters is 0.52.

[18]The polynomial ϕ_{23} has one lag for which the parameter estimate is 0.11. The parameters in the ϕ_{24} polynomial according to their lag order are -0.026, -0.018, -0.0079, -0.012, -0.022, and -0.010. The sum of these parameters is -0.096.

impact of output changes is positive on monetary growth, changes in the interest rate have a cumulative negative impact on this growth.[19] The combined evidence of these observations presents an indirect channel through which changes in share prices may affect monetary growth.

The money supply does not cause industrial production directly in Table 2. The only causal impact on industrial production stems from changes in share prices; the polynomial ϕ_{31} is statistically significant which reveals the importance of past changes in share prices in the forecast of industrial production. Further, the evidence in Table 3 suggests that changes in other variables in the economy are transmitted to real output indirectly through changes in share prices. Changes in the interest rate, the price level, and the money supply affect share prices by altering the equilibrium position among the various assets in the portfolio balance. The polynomials ϕ_{12}, ϕ_{14}, and ϕ_{15} are statistically significant. This creates indirect channels through which changes in the short-term interest rate, the price level, and the money supply affect real output.

On the other hand, changes in the money supply in Table 2 have a direct causal impact on the price level without feedback. The polynomial ϕ_{52} is significant, with a lag order of eight. The polynomial ϕ_{25} is insignificant. This is consistent with the long lasting impact that changes in the money supply have on the price level.

It is not clear, however, that the combined evidence can be used to support the hypothesis of the long-run neutrality of the money supply. According to this hypothesis, changes in the money supply are absorbed fully in the price level in the long run with no impact on real output. The evidence of the direct causal relationships among the variables in the current model is consistent with this hypothesis. Changes in the money supply have a direct causal impact on the price level that lasts for eight months, with no evidence of a similar causal impact of money supply on real output. The validity of this hypothesis is questionable, however, because of the evidence of the indirect causal relationships. Changes in the money supply are transmitted to real output in the long run through their impact on share prices. Thus, changes in the money supply have indirect nonneutral impact on real output in the long run. This long-run impact may last for 17 months according to the orders of the polynomial ϕ_{12} (measuring the duration of the impact of monetary changes on share prices) and the polynomial ϕ_{31} (measuring the duration of the impact of share prices on industrial production).

The primary implication of these relationships is in identifying the significance of each variable to the forecasts of other variables in the model. Table 4 summarizes the results quantifying the magnitudes of this interaction using the variance decomposition of the forecast error. Contrasting the magnitudes reported in each column of the table reveals

[19]Changes in the interest rate and output growth are not induced solely by changes in share prices. The signs of the sum of parameters in the money policy rule are consistent with a monetary policy aimed at stabilizing the interest rate as an intermediate instrument for curbing inflation. To be able to explain these signs, one needs to recall the impact of other factors. Energy price shocks have played an important role in business cycles over the sample period. The inflationary impact of these shocks had a positive impact on the nominal interest rate and a negative impact on real output growth. The monetary authority appears to have chosen to counter the inflationary impact of the supply shocks. Such action is expected, as the sum of the parameters reveals, to stabilize the interest rate at the expense of exacerbating the impact of these shocks on output growth. Further evidence in support of this argument is provided by the variance decomposition results.

the relative contributions of the system's innovations to the variance of the forecast error for all variables in the model.

The contribution of each variable to the variance of the forecast error for other variables indicates the significance of its causal impact. Consider the variance decomposition for the forecast error of share prices. Innovations in share prices explain 69 percent of the total variance of their forecast error. The remaining variance is distributed among other variables in the model: short-term interest rate, 14.12 percent; money supply, 7.65 percent; price level, 5.39 percent; and industrial production, 3.90 percent.

Innovations in the money supply explain a larger share, 75.17 percent, of the variance of its forecast error. Innovations in the interest rate have the second largest share, 15.92 percent, of the total variance of the forecast error for the money supply.

The share of innovations in industrial production of this variance is 5.82 percent. Approximately 3 percent is attributed to innovations in the price level and share prices. The share of innovations in industrial production of the variance of its forecast error is 82.27 percent. The remainder is distributed among other variables in the model, with the shares of innovations in share prices and the short-term interest rate comprising the majority of this remaining variance, approximately 17 percent.

The contribution of innovations in the interest rate to the variance of its forecast error is the smallest, 57.87 percent, of the variables in the model. This is consistent with the high degree of endogeneity of the interest rate, where more than 40 percent of the variance of its forecast error is attributed to innovations in the other variables of the model. The shares of these other variables in the variance of the forecast error of the interest rate range from a high of 13.34 percent for innovations in the money supply to a low of 6.64 percent for innovations in the price level.

The share of innovations in the price level in explaining the variance of the forecast error, 84.54 percent, is the largest of the variables in the model. The remainder of this variance is distributed among other variables, ranging from 6.73 percent attributable to innovations in the money supply to 2.24 percent attributable to innovations in industrial production.

The variance decomposition of the forecast error of share prices provides further evidence concerning the relevance of the direct and indirect channels through which changes in the money supply affect share prices. Approximately 27 percent of the variance of the forecast error in share prices is explained by innovations in the money supply, the short-term interest, rate and the price level. This is consistent with the fact that changes in these variables have a direct causal impact on share prices. In contrast, approximately 91 percent of the variance of the forecast error of M1 is explained by its own innovation and that of the short-term interest rate. These results are consistent with the causality test results. The results suggest that the money supply process is exogenous in general. There is evidence, however, that the Fed may be responding to changes in the interest rate and, to a lesser extent, to changes in real output in the short run. Over a longer horizon (the 20-months-step-ahead horizon), the inflation rate appears to be of concern to Fed officials—approximately 5 percent of the variance of the forecast error of the money supply is explained by innovations in the price level. Finally, innovations in share prices have a negligible impact on the forecast error of the money supply. This suggests that changes in share prices have not been a factor in the design of monetary policy.

Thus, the results of the variance decomposition exercise provide further evidence concerning the direct and indirect causal impact that monetary policy has on share prices. Change in share prices has been a determinant of the rate of growth of real output, but these changes have not had an important impact on the direction of monetary policy.

SUMMARY AND CONCLUSION

This investigation focuses on determinants of changes in share prices in view of the recent volatility of share prices in the United States. A vector autoregressive technique is followed that allows for the simultaneous interaction of variables relevant to the determination of share prices. The model includes share prices, money supply, the short-term interest rate, price level, and real output.

The results are consistent with a direct causal impact of changes in the money supply on share prices. This impact is significant, with a lag that questions the validity of the share market efficiency. It is interesting to note that of the studies cited in this paper, only the evidence of Hashemzadah and Taylor (1988) is consistent with this conclusion. This observation may suggest that, aside from differences in the econometric methodology, the inefficiency of the share market may be a characteristic of the recent years distinguishing the current sample period and that of Hashemzadah and Taylor from other studies.[20]

The direct impact that the money supply has on share prices is reinforced through the indirect channels suggested in theory. Changes in the money supply have causal impacts on the interest rate and the inflation rate that are transmitted to share prices indirectly through the causal impact that these variables have on share prices. Some aspects of this indirect relationship find support in other studies; Pearce and Roley (1985) and Hashemzadah and Taylor (1988) report evidence on the causal impact that the interest rate has on share prices. In addition, Schwert (1981) finds evidence of a significant impact that inflation has on share prices.

On the other hand, the current findings suggest that changes in share prices have a large impact on the rate of growth of industiral real output. This can be explained by the effect of changes in share prices on the financing position of industries comprised by the industrial sector of the economy. This causal relationship qualifies share prices to serve as a leading indicator of economic conditions, as suggested by Fama (1981). A reduction in share prices serves as a signal for a possible future recession through the negative impact that this reduction is expected to have on the rate of growth of real output.

Despite the significant causal impact that monetary growth has on fluctuations in share prices and the significance of these fluctuations on real activity, Fed officials have not considered change in share prices as a factor in their design of monetary policy. Share prices lack a significant direct causal impact on the money supply. The evidence of the paper leads to the following conclusion. There is a clear channel through which the monetary authority can affect the volatility of share prices. Fed officials need to consider these

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[20]This evidence may be interpreted to suggest a higher degree of confusion about the direction of monetary policy in the 1980s as share market traders were trying to guess the direction of monetary policy from data released by the Fed on money supply changes.

fluctuations more formally if the stability of real output growth continues to be a high priority item among the objectives for monetary policy.

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APPENDIX—DATA DESCRIPTION AND SOURCES

1. SP: The Laspeyres Index of Standard & Poors Corporation for 400 industrials on the New York Exchange based on daily closing, 1980=100, series # 62, International Financial Statistics, data tapes

2. CPI: The Consumer Price Index, 1980=100, series # 64, International Financial Statistics, data tapes

3. M1: The money stock, series # 34..b, International Financial Statistics, data tapes

4. SR: Discount on new issues of the three-month Treasury bills, series 60c, International Financial Statistics, data tapes

5. IP: Index of Industrial Production, 1977=100, *Business Conditions Digest*, historical data, p. 100.