Stock Returns, Money Supply and the Direction of Causality

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For many years, the economic impact of changes in the money supply has been debated in academic discussions. The research of Brunner (3), Friedman and Schwartz (8), Tobin (28) and others have established that a relationship exists between changes in the supply of money and changes in the prices of other assets held in an investors's portfolio.[1] It is generally agreed that an unexpected increase or decrease in the growth rate of money results in a change in the equilibrium position of money with respect to other assets in the portfolio of investors. As a result individual investors try to adjust the proportion of their asset portfolios represented by money balances. Although individual investors can adjust, the system cannot since all money balances must be held. As a result, equilibrium is reestablished by changes in the price levels of the various asset categories.[2]

An important component in the asset portfolio of investors is the value of financial assets, including common stocks. It can be expected that adjustments in portfolios caused by changes in the monetary component will occur in this account as well as those accounts representing real goods and services. Since it also can be expected that the time response of investors will be delayed, it has been hypothesized that changes in the money supply cause changes in stock prices. If the hypothesis is true, then changes in stock prices should respond to monetary disturbances with a lag. If such a lagged relationship were to exist, that information could be used to formulate trading rules to allow greater returns than from a buy and hold strategy.

Non-econometric tests of this model have been performed by Sprinkel (26) and Palmer (17). The thrust of these studies concluded that changes in stock prices resulted from changes in monetary variables.

These studies were followed by econometric studies by Homa and Jaffe (10), Keran (13), Reilly and Lewis (21), Hamburger and Kochin (10), Malkiel and Quandt (15), and Meigs (16).[3] The results of these studies purport to confirm that not only is there a strong linkage between money supply and stock prices but also that monetary changes lead stock prices.

The conclusion which must follow from such results, however, is that if one can forecast changes in money supply, one can determine at least in part future prices and returns of stocks. Such a conclusion contradicts a body of knowledge recently developed which demonstrates that the stock market is efficient with regard to information. That is, new information received by the market is so rapidly incorporated into prices that <u>current</u> prices reflect <u>all</u> currently available information.[4]

This conflict between the monetary portfolio and efficient market models has been recognized. Cooper (4) analyzes the theoretical impact in detail. He then suggests that the lead/lag and cross spectra of stock returns and changes in money supply rates are consistent with the efficient market model and the monetary portfolio models in that stock returns anticipate changes in monetary returns. He interprets his lead/lag spectrum as being consistent with either the monetary portfolio model <u>or</u> the efficient market model (4, p. 899). Cooper also attempts to analyze the relationship between the monetary base and stock returns without any satisfactory outcome. Such a result is not surprising as Rutner (23) found no relationship in the short run between money supply and the monetary base using spectral analysis.

Rozeff (22) questioned Cooper's work and identified the relevant queries to be investigated. 1) Do changes in monetary growth rates affect stock returns? (2) Do changes in monetary growth rates affect stock returns with a lag? A positive finding to the first question does not conflict with the efficient market model but a positive finding for the second question would. He also discusses the problem with publication lag. Stock returns may show a lag relation with changes in the rate of growth of the money supply if there is a lag in publication; that is, stock returns at a point in time reflect information available at that time.

In all of the work to date several data problems reoccur. The first involves money supply data. For example, Sprinkel, Keran, Homa-Jaffe, etc., look at the high correlation between movements in the two series and ignore the fact that part of the relationship involves the serial correlation in the monetary series.[5] Furthermore, although Cooper and Rozeff recognize this point by detrending the money supply series and removing some of the seasonality, they apparently do not remove all of the seasonality.

Another aspect involves the stock price series. Generally, researchers have chosen a money supply series and related that series to some index of returns to investigate the interrelationship, usually the Standard and Poor 500 (SP 500) or Fisher's Link Relative Series (FIS). This approach implies that any series is adequate to represent returns on the market portfolio of common stocks. It also assumed that any index of stock returns is a substitute for any other.[6] This may not be the case.

Finally, the question of information lag has not been adequately treated. While Rozeff recognizes the problem of this lag, he uses money supply data generated at times different from that of the stock index. Other authors ignore the information lag totally. To adequately treat the relationship of money supply and stock returns, it is necessary to use data gathered over the same span of time.

Because of these problems, the results of previous research must be questioned. It is the purpose of this paper to re-investigate the relationship between money supply and stock prices to ascertain whether dependence can be established and in which direction the causality is manifested. The next section discusses the methodology and is followed by an analysis of the data series. A discussion of results follows. The paper closes with a summary and conclusions.

METHODOLOGY

In order to investigate the causal relationship between stock returns and the money supply, one must determine the existance and direction of causality between unexplained variations in both series. The method of studying this causality is now reviewed.

The generally accepted definition of causality is due to Granger (9) and is based on the time series notion of predictability. A variable X causes another variable Y with respect to a given information set (including X and Y), if present Y can be predicted better by using only past values of X than by using all values (past and future) available in the information set. Granger's definition shall be adopted in what follows as it is a suitable definition for empirical testing.

Even accepting this definition, however, the question still remains: How does one in practice test for causality? For this study a procedure developed by Haugh (11)is used in which the series X and Y are first transformed by a filtering procedure into white noise series.[7] The resulting residuals are then cross correlated. If the cross correlation coefficients at particular lags are inferred to be significantly different from zero, one may proceed to build an appropriate model to describe the relationship

Asymptotically, Haugh (11)has shown that these residual cross correlations have a simple structure. Building upon this structure, a chi-square measure can be formulated and serves as an overall test of the size of the cross correlations.

More formally, consider two variables X and Y which have been suitably transformed into the jointly covariant pair of stochastic processes x(t) and y(t) ($1 \leq t \leq N$) so that x and y are related in the same manner as X and Y.[8]

Also assume that the information set consists of only these two variables. Now suppose that x(t) and y(t) may be modeled as mixed autoregressive-moving average processes (ARMA) such that:

$$\varepsilon(x:t) = \phi_{x1}\varepsilon(x:t-1) + \ldots + \phi_{xp}\varepsilon(x:t-px) \tag{1.1}$$

$$+ x(t) - \theta_{x1}x(t-1) - \ldots - \theta_{xq}x(t-qx)$$

$$\varepsilon(y:t) = \phi_{y1}\varepsilon(y:t-1) + \ldots + \phi_{yp}\varepsilon(y:t-py)$$

$$+ y(t) - \theta_{y1}y(t-1) - \ldots - \theta_{yq}y(t-qy)$$

where for either series, $\varepsilon(\cdot:t)$ is the residual of each series at time t, $\phi\cdot p$ is the autoregressive parameter for lag t=p, and $\theta\cdot q$ is the moving average parameter for lag t-q.[9]

Using an iterative least squares procedure one can estimate the parameters in (1.1) to obtain the two residual series $\hat{\varepsilon}(x:t)$ and $\hat{\varepsilon}(y:t)$.[10] These estimated residual series may then be cross correlated to obtain the residual cross correlations:

$$\hat{r}_k = r_k\left[\hat{\varepsilon}(x:t);\ \hat{\varepsilon}(y:t)\right] = \frac{c_k\left[\hat{\varepsilon}(x:t);\ \hat{\varepsilon}(y:t)\right]}{\sqrt{c_0\left[\hat{\varepsilon}(x:t)\right]\ c_0\left[\hat{\varepsilon}(y:t)\right]}} \qquad (1.2)$$

where if $\hat{\varepsilon}(\overline{x})$ and $\hat{\varepsilon}(\overline{y})$ are the sample means for each of the series $\hat{\varepsilon}(x:t)$, $\hat{\varepsilon}(y:t)$ then an estimate of the cross covariance function is

$$c_k\left[\hat{\varepsilon}(x:t);\ \hat{\varepsilon}(y:t)\right] = \begin{cases} \dfrac{1}{N}\displaystyle\sum_{t=1}^{N-k}\left[\hat{\varepsilon}(x:t) - \hat{\varepsilon}(\overline{x})\right]\left[\hat{\varepsilon}(y:t+k) - \hat{\varepsilon}(\overline{y})\right] \\ \qquad k = 0,\ 1,\ 2,\ \ldots \\ \dfrac{1}{N}\displaystyle\sum_{t=1}^{N-k}\left[\hat{\varepsilon}(y:t) - \hat{\varepsilon}(\overline{y})\right]\left[\hat{\varepsilon}(x:t-k) - \hat{\varepsilon}(\overline{x})\right] \\ \qquad k = 0,\ -1,\ -2,\ \ldots \end{cases} \qquad (1.3)$$

Haugh (11) has shown that if the two series $\hat{\varepsilon}(x:t)$ and $\hat{\varepsilon}(y:t)$ are really white noise series after filtering and if the two series are independent, then the set of cross correlation estimators are asymptotically uncorrelated with one another and would be normally distributed with zero mean and constant variance $1/N$. Haugh (11) showed by using Monte Carlo methods that when using his two stage procedure, the fitting process does not perturb the nice asymptotic distribution of white noise corss correlations. In other words, as long as the model fitted to each individual series produces white noise residuals, it appears that there is no appreciable model effect (because of the form of the ARMA model fitted) in differentiating cross correlation patterns. In addition, Haugh (11) has shown that for purposes of cross correlation identification samples as small as size fifty are adequate for the asymptotic results to hold.

Given these asymptotic results under the null hypothesis of series independence, one can derive the statistic S^*:

$$S^* = N^2 \sum_{k=-L_1}^{L_2} (N-|k|)^{-1}\ \hat{r}_k^{\,2} \qquad (1.4)$$

which is chi-square distributed with ($L_1 + L_2 + 1$) degrees of freedom where N is the number of sample observations, L_1 represents the number of future lags, and L_2 the number of past lags. Once L_1 and L_2 are chosen, the statistic S* can be computed and by referring to χ^2 distribution with ($L_1 + L_2 + 1$) degrees of freedom significance can be tested.

Hence we have a practical statistical test for independence and/or causality: compute the cross correlation function between x and y after prefiltering each series by an ARMA model. Then employ the chi-square test to determine if the series are independent by setting L_1 and L_2 equal to lags appropriate for the series under consideration. In a similar fashion if causality runs from x to y, future lags of x should have coefficients insignificantly different from zero, as a group. This relationship can be tested by choosing both L_1 and L_2 to be negative numbers when computing S*. Similarly, one can determine if causality runs from y to x.

In applying these χ^2 tests, one should bear in mind that the absolute size of the individual correlations is also important regardless of the χ^2 value. The fact that future lags of the independent variable have coefficients as a whole insignificantly different from zero only shows that unidirectional causality is possible. If the estimated correlations on future values are large or larger than those on past lags, bidirectional causality may be important despite the insignificant χ^2's.

It is also noteworthy to distinguish causality detection via Haugh's procedure outlined above from the well known scheme of Sims (22). Haugh's approach uses (a) separate filters on x(t) and y(t) which are empirically determined from the sample data and (b) cross correlation analysis rather than regression analysis on the filtered data.[11]

Separate filters are preferred to Sims' ad hoc filters, especially when the regression residuals. In fact, Haugh (11) shows that if filtering procedures are not geared to the individual series, spurious regressions can result leading to an upward bias. Even if the estimated residuals from separate filters are used, spurious independence may occur. However, the resulting bias in significance is downward and of a smaller order of magnitude than the upward bias arising from the failure to adequately treat the invariate serial correlation.

On the second point, Pierce and Haugh (20) have reemphasized the point that causality testing based on regression analysis (the usual F-test) is asymptotically equivalent to testing based on cross correlation analysis (the χ^2 test). Which procedure to use thus becomes one of individual preference. After reviewing the data, the procedure of Haugh outlined above is employed to investigate causality between money supply and alternative stock price indexes.

ANALYSIS OF THE DATA SERIES

A critical part of this investigation is development of correct and consistent data. Several measures of the market return are available--some of which are broad and some of which are narrow. The four most common are the SP500, Fisher's Link Relative Index (FIS), Dow-Jones Industrials (DJIA), and New York Stock Exchange Index (NYSE).[12]

Table 1 provides the sample autocorrelations for each of the four major stock price indexes.[13] All series used are percentage changes based on monthly closing prices (excluding dividends) over the twelve year period, 1963-1974. Sharpe and Cooper (24) suggests that the autocorrelation function estimated will not in general differ if one excludes dividends.

Table 1

ESTIMATED AUTOCORRELATIONS OF PRICE INDEX SERIES

Series (144 obs.)	Lags	Autocorrelations ($N^{-\frac{1}{2}} = .08$) 1	2	3	4	5	6	7	8	9	10	11	12	Q
A. NYSE	1-12	.03	-.04	.02	.09	.08	-.01	-.01	-.14	.13	.01	-.02	.01	7.9
	13-24	.02	-.07	.10	.08	.04	.07	-.09	-.04	-.15	.08	-.04	-.05	18.1
	25-36	-.10	-.05	.02	-.01	-.04	-.11	-.06	-.02	.03	.05	-.05	.01	23.4
B. S&P 500	1-12	.01	-.02	.04	.09	.11	.03	-.05	-.09	.12	-.02	-.01	-.01	7.0
	13-24	.03	-.07	.06	.07	.10	.04	-.08	-.08	-.04	-.01	-.03	-.02	13.0
	25-36	-.12	-.02	.04	-.04	-.06	-.05	-.07	.01	-.02	.02	.01	-.02	17.4
C. DJIA	1-12	-.01	-.06	.05	.12	.08	.03	-.08	-.08	.15	-.06	-.03	-.03	9.9
	13-24	.06	-.08	.04	.03	.06	.09	-.06	-.01	-.04	.01	-.02	-.01	14.2
	25-36	-.07	-.05	-.01	.01	-.05	-.08	-.05	-.02	-.04	.01	.02	.01	17.3
D. FISHER	1-12	.20	-.04	.01	.08	.08	.09	-.05	-.14	.07	-.01	.09	.01	15.4
	13-24	.03	-.02	.12	.10	.10	.03	-.09	-.06	-.03	.04	-.02	-.08	23.7
	25-36	-.10	-.01	.01	.03	-.06	-.06	-.01	.04	.09	.03	-.02	.06	28.5

Notes: All series used are percentage changes based on monthly closing data (excluding dividends) over the twelve year period, 1963-1974.

Results are presented for lags 1 to 36. First row contains autocorrelations for lags 1 to 12 second row for lags 13 to 24, and the third row for lags 25-36. The Q statistic for 12, 24, and 36 are at the end of the first, second and third rows respectively.

To gain some insight as to whether the magnitude of these sample autocorrelations is sufficiently large, one can consider the hypothesis that the series are white noise and hence the price indices follow a random walk. With the white noise hypothesis, the autocorrelations should be approximately normally distributed about zero with a standard error of about 0.08. Inspection of the individual autocorrelations in Table 1 for series A, B, and C and comparing the Q-statistic[14] to a chi-square table with twelve degrees of freedom show the autocorrelations of series A, B and C to be about the magnitude expected on the white noise hypothesis.

These results naturally lead to a discussion of why some researchers reportedly find autocorrelation at lag one for these return series. One possibility could be that one is not using on index of market value or, alternatively, a value-weighted price index.[15] More likely, however, is that one is using an average of daily returns as the monthly return series. Working (29) shows that this inherent averaging will induce the observed autocorrelation at lag one. To illustrate this point more clearly, we estimated the autocorrelation function for the S&P500 series reported in the *Federal Reserve Bulletin*. The data exclude dividends and were converted to percentage changes. The time period covered is the same as reported in Table 1. As expected we observed a spike at lag one (the correlation at lag one was .21 and should be compared with the correlation at lag one of .01 in Table 1). The reason for these contradictary autocorrelations is that the *Bulletin* data represents monthly S&P500 values which were computed as an *average of daily* index values whereas the data in Table 1 are percentage changes based on monthly closes.

With respect to the FIS index, the low order autocorrelation is probably the Fisher effect (7), although after filtering the FIS series the residuals appear to be white noise (see Table 3). This result is important as Rozeff (22) used the Fisher Link Relative Series for his analyses but did not filter the series. Without such filtering, his results must be viewed with suspicion.

Thus, to determine the sensitivity of money supply to the index used all four indices have been prefiltered in the analyses to follow.

Next, the money supply series must be specified. The Federal Reserve defines the money supply as demand deposits and currency in private circulation (M_1) while others have used broader definitions such as M_1 plus time deposits at commercial banks (M_2), M_2 plus savings and loan shares, and others. In this study as in previous ones, the narrowly-defined money supply, M_1, is used.

While the Federal Reserve publishes the money supply data, there is no unique series available. There are monthly average, last Wednesday of the month, or last day of the month all of which are seasonally or unseasonally adjusted.[16] Each of these series are also subject to revision.[17] The Federal Reserve Board of Governors was kind enough to provide the end of month seasonally adjusted money supply data on a revised basis. Likewise, the New York Federal Reserve kindly supplied us with the money supply data for the last Wednesday of the month on a revised basis both seasonally and unseasonally adjusted.

Table 2 gives the sample autocorrelation function for the percentage changes for each money supply series. Q-statistics are not reported but are obviously very large for each of the series. It is interesting that series A, B, and C which are based on closing values display similar patterns. The conspicuous correlations every six lags (i.e. 6, 12, 18, etc) are to be expected because June and December of each year represent call dates. That means that the data on

Table 2

ESTIMATED AUTOCORRELATIONS OF MONEY SUPPLY SERIES

Series (144 obs.)	Lags	1	2	3	4	5	6	7	8	9	10	11	12
		Autocorrelations ($N^{-\frac{1}{2}}$ = .08)											
A. M1 (End of Month-	1-12	-.20	-.15	.04	-.10	-.19	.35	-.20	-.09	.02	-.20	-.17	.83
seasonally adjusted)	13-24	-.17	-.10	.04	-.13	-.14	.30	-.20	-.04	.02	-.23	-.11	.72
	25-36	-.16	-.08	.04	-.12	-.12	.30	-.21	-.01	-.01	-.20	-.09	.65
B. M1--Last Wednesday	1-12	-.39	-.18	.29	-.16	-.13	.33	-.14	-.18	.35	-.21	-.33	.69
(Not Seasonally	13-24	-.34	-.11	.29	-.22	-.07	.28	-.09	-.15	.31	-.30	-.20	.56
Adjusted)	25-36	-.30	-.11	.28	-.17	-.06	.21	-.14	-.06	.30	-.26	-.14	.49
C. M1--Last Wednesday	1-12	-.22	-.16	-.03	-.05	-.15	.37	-.17	-.02	-.04	-.20	-.19	.86
(Seasonally Adjusted)	13-24	-.21	-.13	-.03	-.07	-.12	.34	-.17	-.01	-.04	-.23	-.13	.77
	25-36	-.20	-.11	-.02	-.07	-.08	.29	-.18	.04	-.06	-.20	-.11	.68
D. M1--Daily Average	1-12	-.07	-.32	.26	-.20	-.19	.26	-.21	-.19	.23	-.34	-.06	.74
(Not Seasonally	13-24	-.08	-.28	.23	-.20	-.17	.25	-.18	-.14	.20	-.32	-.04	.70
Adjusted)	25-36	-.08	-.24	.23	-.17	-.14	.22	-.15	-.11	.18	-.28	-.03	.61
E. M1--Daily Average	1-12	.25	.09	.07	.05	.09	.03	-.18	-.04	-.09	.03	.04	-.01
(Seasonally Adjusted)	13-24	-.05	.05	-.01	.09	.09	-.04	-.05	-.07	-.02	-.04	.06	-.02
	25-36	-.03	-.05	-.01	.02	-.08	-.11	-.02	.16	.13	.16	.06	.03

Notes: All series used are percentage changes over the twelve year period, 1963-1974.

See Table 1 for explanation of format.

these dates reflects deposits of nonmember banks. In contrast series D and E have quite different autocorrelation patterns because of the daily averaging over the month. In general, the correlogram of the first four series is most notable for the repetitive correlation every twelve lags suggesting that seasonal differencing is necessary.[18]

Perhaps more surprising is that none of the series display autocorrelations consistent with a third order autoregressive representation, as both Cooper (4) and Rozeff (22) found. One reason for this discrepancy could be that they used none of these series in their analysis. Another may be the difference in time periods used in the studies. This study utilized the period 1963-74 while Cooper and Rozeff used the 1947-70 period.

Recall that the objective of this paper is to investigate the causal relationship between unexplained variations in the growth rate of the money supply and stock returns. Thus, it is necessary to fit models to these raw data series to produce the needed white noise series.

Table 3 reports the univariate models fitted by an iterative least square procedure. As expected, a random walk model is appropriate for the NYSE, SP500, and DJIA series. For the FIS index a low order moving average model is identified and fitted. An adequate representation of the money supply series is a multiplicative model with moving average parameters after applying a twelve month differencing to account for the yearly seasonal pattern indicated by the autocorrelations.[19]

Model fit appears to be good in all cases. Parameter estimates are all large compared with their standard errors thus indicating a high level of significance. For none of the fitted models do the residual autocorrelations indicate autocorrelation. The Q-statistic for the first twenty-four lags are displayed in the last column of Table 3. Comparison of these with χ^2 tables (5 percent of

Table 3

SUMMARY OF FITTED MODELS

Series (144 obs.)	Fitted Models	Residual Variance	Q
New York Stock Exchange (Composite Index)	$NYSE(t) = \epsilon(NYSE: t)$	.1848E-02 (144 d of f)	18.1 (36.4)
Standard & Poor 500 (Composite Index)	$SP(t) = \epsilon(SP: t)$	.1543E-02 (144 d of f)	13.0 (36.4)
Dow Jones Industrial Index	$DJIA(t) = \epsilon(DJIA: t)$	.1528E-02) (144 d of f)	14.2 (36.4)
Fisher Link Relative Index	$FIS(t) = (1 + \underset{(.081)}{.231}B)\epsilon(FIS: t)$	.2617E-02 (143 d of f)	18.9 (35.2)
Money Supply (M1(Fed))	$(1-B^{12})MS(t) = (1 - \underset{(.060)}{.536}B + \underset{(.053)}{.231}B^3)(1 - \underset{(.048)}{.422}B^{12})\epsilon(MS: t)$	.5897E-04 (129 d of f)	27.6 (32.7)

Notes: All Series used all percentage changes based on monthly closing data over the twelve year period, 1963-1974.

Standard errors are shown in parentheses below parameter estimates.

Residual variances are reported in exponential form, i.e. .1848E-02 = .001848, with degrees of freedom given in parentheses on the line below.

The Q statistic is approximately chi-square distributed with (N-n) degrees of freedom where N is the number of sample observations and n is the number of parameters estimated. In parentheses below the Q value is the χ^2 value for the appropriate degrees of freedom at the 5% level of significance under the null hypothesis of zero serial correlation in the residuals of the model.

provide no grounds for questioning the models.

Finally, the time period to be studied is critical. Some studies have attempted to review these series from 1918 to the present. Rozeff found, however, that the period 1948 to 1960 appeared to indicate that the stock market was inefficient with respect to monetary data. He attributed this result to publication lag for the money supply data but a more fundamental explanation appears more likely. Several researchers have noted that although the Federal Reserve stopped supporting the Treasury offerings in March 1951, it took over a decade for the traditional relationship between the bond and stock markets to be reestablished. Thus, money supply changes by the Fed could have had a greater impact than when equilibrium returned to the bond and stock markets.[20] Previous studies (such as those of Cooper (4) and Rozeff (22) may have been influenced by this phenomenon. Likewise, certain of the data series used here such as the NYSE index and month-end money supply series were not available prior to 1962.

For the purposes of this paper, therefore, the series are investigated from January, 1963 to December, 1974. Besides assuring complete data series, this time period avoids the market equilibrium problem previously discussed i.e., prior to 1960 equilibrium relationships between securities markets may have been affected by the accord between the Treasury and the Federal Reserve. Such a time period is considered adequate as several episodes in the business cycle have occurred over that period. In fact, results using this time period would be of even more contemporary interest than results which purport to study market structures no longer current.

CROSS CORRELATION ANALYSIS

Now that the various series have been adjusted to obtain the unexplained variations or white noise series, the direction of causality, if any, can be investigated. Table 4 reports the cross correlation function computed between the residual money supply series and each of the residual price index series obtained using the fitted models in Table 3. One can observe for all the indexes significant positive coefficients at future lag five, and there is a moderate degree of positive association at past lag one for all but the DJIA. The NYSE and SP500 have additional correlation at zero lag while the DJIA has some correlation at future lag two.

Now if the indexes and money supply are independent, one should expect the estimated cross correlations to be zero for all lags. As seen in Table 4, this situation clearly is not the case. It appears instead that in general a feedback situation exists because some of the estimated cross correlations are significant for past lags and some are significant for future lags. These results tend to suggest a bi-directional theory of causality. It should be noted that the significant correlation at lag 1 indicates an information lag not that changes in money supply lead changes in stock returns. The raw data used in this study is the level of money supply at a given point in time. However, it takes the Federal Reserve nearly a month to gather all of the information. So it estimates what the final figure will be and publishes it as a preliminary estimate. Then one month later it publishes the actual value. Thus the significant correlation at lag 0 indicates the incorporation of the estimated or preliminary value of money supply into stock returns as soon as it is published (the estimated value is very nearly identical to the actual). The significant correlation at

Table 4

ESTIMATED CROSS CORRELATIONS BETWEEN MONEY SUPPLY AND PRICE INDEXES

Series (132 obs.)	Lags	Cross Correlations 0	1	2	3	4	5	6	7	8	9	10	11	12
(MS:t) on ε(NYSE:t)	0 to 12	.17	.16	.01	-.03	-.11	.05	-.13	-.02	-.01	-.06	.10	.02	.01
	-1 to -12		.09	.11	.02	.00	.22	.05	-.01	.01	-.09	-.10	-.03	.12
(MS:t) on ε(SP:t)	0 to 12	.16	.21	-.01	-.02	-.06	.03	-.09	-.07	.02	-.11	.13	.02	.03
	-1 to -12		.06	.10	.05	.00	.20	.06	-.05	.05	-.04	-.10	-.01	.06
(MS:t) on ε(DJIA:t)	0 to 12	.13	.12	.04	.01	-.01	.03	-.08	-.10	-.04	-.07	.08	-.08	.07
	-1 to -12		.06	.14	.05	-.02	.23	.01	-.04	.03	-.07	-.13	.01	.02
MS:t) on ε(FIS:t)	0 to 12	.10	.24	-.02	-.03	-.13	.01	-.10	.03	-.02	-.02	.04	-.02	.00
	-1 to -12		.10	.10	.11	-.05	.21	.06	-.07	.01	-.04	-.08	-.03	.06

ote: Results are presented for lag 0 which **is** concurrent and 1 to 12 periods in the past and -1 to -12 which are actually 1 to 12 periods in the future.

lag 1 indicates the incorporation of the information of the actual value of the previous month's money supply by current stock returns also as soon as it is published. None of the other past lags are significant at the 90% confidence level.

The results of applying the chi-square test for different lags is shown in Table 5. It should be noted that the test for independence is for lags -5 to +5 while the tests using other lag lengths are to investigate the direction of causality. The tests of independence indicate that one can reject the null hypothesis of stochastic independence between stock prices and money supply. The results of the tests of the hypothesis that causality goes from money supply to stock returns can be rejected for all series except FIS while testing the hypothesis that causality goes from past changes in stock returns to future changes in money supply can be accepted. These results allow firm rejection of the hypothesis that causality runs unidirectionally from past values of money to equity returns. They are consistent with the hypothesis that stock returns are not purely passive but perhaps influence money supply in some complicated fashion.[21]

It should be noted that these results conflict with a large body of work which suggests that causality goes from money supply to stock prices which was thoroughly discussed in the introduction of this paper. More recently some evidence, particularly the work of Cooper (4) and Rozeff (22) has appeared suggesting that under an efficient market hypothesis (EMM) this situation should not be true and perhaps causality may run the opposite way. Our empirical results, however, suggest that a bi-directional theory may be more appropriate. That is, changes in money supply cause contemporaneous changes in stock returns but likewise current changes in stock returns lead changes in money supply. This outcome would be consistent

Table 5

$$S^* = N^2 \sum_{k=L_1}^{L_2} (N - k)^{-1} \hat{r}_k^2$$

Test	(132 obs.) L_1	L_2	ϵ(MS:t) on ϵ(NYSE:t)	ϵ(MS:t) on ϵ(SP:t)	ϵ(MS:t) on ϵ(DJIA:t)	ϵ(MS:t) on ϵ(FIS:t)
Independence	-5	+ 5	18.7*	17.4*	15.7	21.6*
Causality	0	+ 6	11.5	10.9	5.6	12.6*
	-3	- 1	2.8	2.3	3.5	4.0
	-3	+ 6	14.3	13.2	9.1	16.6*
	0	+12	13.5	16.1	10.5	13.1
	-6	- 1	9.9	8.1	10.9	10.9
	-6	+12	23.5	24.1	21.5	24.0
Test	**(132 obs.) L_1**	**L_2**	**ϵ(NYSE:t) on ϵ(MS:t)**	**ϵ(SP:t) on ϵ(MS:t)**	**ϵ(DJIA:t) on ϵ(MS:t)**	**ϵ(FIS:t) on ϵ(MS:t**
Independence	-5	+ 5	18.7*	17.4*	15.7	21.6*
Causality	0	+ 6	13.7*	11.4	13.2*	12.2*
	-3	- 1	3.4	5.7	2.3	7.8
	-3	+ 6	17.2*	17.1*	15.5	19.9*
	0	+12	18.1	14.2	16.8	14.8
	-6	- 1	7.7	7.5	3.4	11.3
	-6	+12	25.9	21.8	20.1	26.1

Notes: The statistic S^* is approximately chi-square distributed with $(|L_1| + |L_2| + 1)$ degrees of freedom where L_1 is the number of future lags and L_2 is the number of past lags.

*Asterisks indicate significance at the 10% level under the null hypothesis of independence between the two series.

In contrast to these results, Cooper (4) finds that money supply lags the Standard and Poor 500 index over the period 1947-70 by about one to three months. His analysis shows significant correlations only at future lags two and three and past lag eight. Rozeff (22), on the other hand, runs his tests between money supply and Fishers index over the period 1947-72 and finds significant future lags one, two, and four and significant past lags zero, eight and twelve.

Although the time period of their results differs from ours and the money supply series used here is unique to this study, these discrepancies may also be due to the methodology employed. Neither of the previous authors prefilered their series before preforming the regression analysis. In the case of Rozeff's study, no prefiltering was done on the return series. From our investigations in the previous section one should expect some autocorrelation for the Fisher index and particularly for the SP500 series taken from the Bulletin. Although Cooper fits a third-order autoregressive model to the money supply series, his regressions are not made on the resulting residual series. Failure to remove this serial correlation in the univariate series results in the "spurious" regression phenomenon. This means that least square estimates will be consistent but there will be bias in the estimates of their variance. If this bias is upward, it will produce inflated t- and F- statistics and R^2 values.

While these results are interesting, it is instructive to examine whether investors are actually using forecasts of money supply in making investment decisions. To investigate this question, an ARIMA model was identified and fitted to the first half of the original money supply growth series. Using this model, one-step ahead forecasts were generated for the next quarter of the period. Then we used the first three-quarters of the original money supply growth series to identify and fit a model to generate one-step ahead forecasts for the last quarter of the period.

observations for the stock price index series (of percentage changes) were filtered to generate white noise series. The NYSE, SP, and DJIA series were random walk series as before while the FIS series was again identified and estimated to be a first-order moving average process. Finally, the cross correlation function was extimated between the resulting residuals of the money supply growth forecast series and each of the stock index series for the last half of the observations.

The results of the cross correlation analysis are highlighted in Table 6. It should be noted that there are no significant correlations at lags zero or past lag one which implies that the informational context of money supply has probably been captured by the forecasting models. In addition, significant positive correlations are again exhibited at future lag five. In sum, this additional validation substantiates our earlier contentions and indicates that investors may be using money supply information in their decision-making process.[22]

Thus, our results are consistent with the hypothesis that money supply is important in determining market rates of return but that changes in returns may actually lead money changes. These results have been generalized to include all major stock indexes whether broad based or narrowly constructed. This conclusion lends support to the concept of market efficiency and implies that future money supply changes are incorporated into current returns. In other words, if one chooses to include money supply changes into the information set, this additional information cannot be used to better predict stock prices.

These statements concerning efficiency can be further interpreted in light of Cooper's (4) work. Using Cooper's combined quantity theory/efficient capital market model, one would expect returns to lead money supply for long term movements in money changes and possibly lag for the short term movements. In fact, however,

Table 6

ESTIMATED CROSS CORRELATIONS BETWEEN MONEY SUPPLY FORECASTS AND PRICE INDEXES

Series (72 obs.)	Lags	Cross Correlations 0	1	2	3	4	5	6	7	8	9	10	11	12
MS_f:t) on ε(NYSE:t)	0 to 12	.01	.06	-.12	-.05	.02	-.11	-.11	-.04	-.17	-.15	-.07	-.02	.12
	-1 to -12		.03	.19	-.03	-.05	.33	-.05	.06	-.03	.10	-.04	.02	.19
MS_f:t) on ε(SP:t)	0 to 12	-.03	.09	-.11	-.06	.09	-.17	.12	.04	.05	-.15	.00	.00	.08
	-1 to -12		.02	.16	-.02	-.04	.30	.00	.00	.04	.15	.06	.02	.17
S_f:t) on ε(DJIA:t)	0 to 12	.05	.08	-.11	-.09	.04	-.10	.05	-.03	.09	-.12	-.01	-.05	.07
	-12		-.05	.20	-.01	.08	.40	.02	.03	-.01	.14	-.06	.05	.15
S_f:t) on ε(FIS:t)	0 to 12	-.06	.03	-.10	-.02	.13	-.14	.06	-.01	-.02	-.14	.07	-.03	.04
	-1 to -12		-.05	.18	.18	.10	.34	-.06	.00	-.03	.19	-.11	-.04	.20

te: See note on Table 4 for explanation of format.

the strict form of the efficient market hypothesis would suggest a bi-directional theory of causality in the form of say simultaneity rather than a lag one way or the other. The results obtained here support this stricter view of efficiency.

SUMMARY AND CONCLUSIONS

The results of this study are consistent with the proposition that the rate of growth of the money supply has an impact on stock returns as proported by various monetary portfolio theorists. It also supports the notion that the stock market is efficient with respect to monetary information as the efficient market theory would suggest. In other words, causality does not go from money supply to stock prices but rather from stock prices to money supply and back again. What we therefore propose based on our results is a bi-directional theory of causality between money supply and stock returns.

Finally, these results have implications for monetary policy in that changes in the money supply as effected by changes in Federal Reserve policies will have a direct impact on r-turns from common stocks. While monetary policy should not be guided by the impact on the stock market, such influences should not be ignored due to the influence of the stock market on economic activity.

FOOTNOTES

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[1] This theory of monetary impact has usually been called the quantity theory of money or "Simple Quantity" model as Cooper (4) refers to it. Rozeff (22) suggests that this model has advanced beyond the simple quantity theory of the early economists so that he uses the term "Monetary Portfolio" model. The model is reviewed by Patinkin (18). In this paper, the term monetary portfolio model will be used when referring to this portfolio adjustment theory.

[2] Although there is general agreement among economists that changes in money supply cause certain changes in asset values, there is disagreement over the importance of money in economic activity. Friedman and the monetarists argue that autonomous shifts in the money supply independently influence the money value of assets. On the other hand, Tobin and other non-monetarists suggest that disturbances in the financial markets can be generated by other sources besides shifts in the money supply. Investigation of this conflict is beyond the scope of this paper, but it should be kept in mind. Likewise, it is argued that changes in the money supply can be offset by changes in the "velocity" of money or the frequency with which money is transferred by the economy. Although investigation of this factor is also beyond the scope of this paper, velocity effects might prove an interesting avenue for future research.

[3] A discussion of the Keran, Hamburger-Kochin, and Homa-Jaffee models is presented by Pesando (19).

[4] For a complete review of the efficient market model see Fama (5).

[5] Of course, a far more serious problem with these studies is the failure to relate changes in money growth rates to changes in stock returns. Pesando (19) discusses this problem in detail.

[6] For example, Cooper (4) suggests that analysis of the Dow-Jones Industrial, SP500, and Fisher's indices indicate similarity of characteristics. It is shown later that this assertion cannot be supported.

[7] A white noise series is a random sequence which is independent, normally distributed with zero mean and constant variance.

[8] This transformation may consist for example, of simple differencing, percentage changes, or trend removal.

[9] The notation used here is that developed by Box and Jenkins (2).

[10] Because no discussion of the th

[11]An example of this approach is found in the work of Feige and Pearch (6) where they analyzed the relationship between money and income.

[12]For example, Sprinkel and Cooper used the SP500 while Rozeff used Fisher's Index. Although the American Stock Exchange calculates an index, it is ignored as it is based on price changes rather than returns.

[13]A complete description of Fisher's index can be found in Fisher (7). Likewise, a complete discussion of the methods of construction for all the other series can be found in Lorie and Hamilton (14).

[14]The Q-statistic is explained in Box and Jenkins (2, chapter 8).

[15]An equally-weighted index presents average price changes of all stocks under consideration. When listings appear the divisor used to obtain the average net change is increased correspondingly.

[16]See Axilrod and Beck (1) for a complete description of the preparation of the various money supply series.

[17]Although Rozeff recognized that the revisions published in the Federal Reserve Bulletin were monthly averages of daily figures when discussing data, he ignored this fact when performing his analyses (Tables 4 and 5 in particular). Thus the averaging problem experience with stock return series also biased his results when using the revised money supply data.

[18]There is no indication from the Rozeff or Cooper work that they adjust the series for these seasonal components.

[19]Several different models were identified and fitted for the money supply series before deciding on the form displayed in Table 3.

[20]For a discussion of the Accord, see Sproul (27).

[21]This result suggests that money supply is expected to change when the economy changes and since stock prices are a leading indicator for changes in the economy, future changes in money supply are correlated with past changes in stock prices. Investigation of these directions of causality are beyond the scope of this paper but could prove a direction for future research.

[22]Ideally, one would like to use say, the first half of the money supply growth series to identify and estimate an appropriate model for forecasting next month's growth in money supply. Then once next month's actual money supply figure was available, one would incorporate the new growth observation to re-identify and re-estimate another model to forecast the following month's growth rate. As each actual money supply figure was obtained one could re-iterate this procedure to obtain forecasts for the following month. In this manner the difference between the forecasts generated and actual growth rates would probably result in a minimum forecast error on average. To do this, however, would require producing up to seventy two seperate forecasting models. It should be noted, moreover, that the sign of the estimated cross correlation coefficients will be effected by the form of the moving average process used to filter the growth forecast series.

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