

**A Moving Window Analysis of the Granger Causal Relationship  
Between Money and Stock Returns**

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Abstract

The purpose of this paper is to empirically examine whether movements in two important measurements of the aggregates money supply, M1 and M2, help in predicting future movements in the stock market. We use single-equation multivariate autoregressive models, with the optimal lag order selected using the Akaike Information Criterion, and run two types of Granger causality tests across sequences of moving windows of fixed length. The rolling window estimation results indicate that there is a good deal of instability in the lag order of these models when the federal funds rate is used as one of the conditioning variables. The causality test results suggest a rather strong causal link from money to stock prices once data from the 1960's and early-to-mid 1970's are excluded. The evidence in favor of causality from M2 to stock prices is much weaker. Our results suggest caution may be warranted in interpreting "full sample" results on the Granger-causal relationship between money and stock prices.

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## 1. Introduction

Participants in financial markets often focus their attention on actions taken by the Federal Reserve Board. The Fed is responsible for setting monetary policy and overseeing many aspects of the country's banking system. Based upon reports in the business press, it appears that many economic agents believe that Fed policy has strong effects on financial markets. In order to reduce the risk of their financial decisions, many players in financial markets, such as professional money managers, financial analysts, and individual households, condition their actions on expectations of future monetary policy.

Roughly every six weeks, the Fed's Open Market Committee (FOMC) meets to decide the future direction of monetary policy. Under the current monetary policy regime, the outcome of each FOMC meeting is a decision about whether or not to adjust the Fed's target for the federal funds rate. Such decisions have well-understood effects on the growth of the nation's money supply.

The purpose of this paper is to empirically examine whether actions of the Fed, expressed in terms of money supply growth, have predictable effects on stock market behavior. We investigate whether movements in two important measures of the aggregate money supply, M1 and M2, help in predicting future movements in the stock market. Specifically, this paper examines whether money growth rates "Granger-cause" stock returns. One variable is said to Granger-cause another if prediction of the current value of the latter is helped by using past values of the former. This stems from Granger's (1969) argument that if event  $Y$  is the "cause" of event  $X$ , then the event  $Y$  should precede the event  $X$ .

A good deal of earlier research concludes that changes in lagged values of money supply growth have an impact on changes in stock prices; see, for example, Abdullah and

Hayworth (1993), Jones and Uri (1987), and Rogalski and Vinso (1977). In contrast, other researchers have found that stock prices respond only to unanticipated changes in past values of the money supply; see, for example, Pearce and Roley (1983), Sorensen (1982), and Davidson and Froyen (1982).

While such conflicting results can be found throughout the literature on the relationship between stock prices and money, all of this work is subject to the criticism that Swanson (1998) makes of standard causality studies. In particular, Swanson (1998) emphasizes the importance of taking into account the possible time variation in any Granger-causal relationship and argues in favor of using “moving” or “rolling” windows of data in such studies, in contrast to the standard use of “full samples.” Accordingly, the main contribution of this paper is to examine the question of Granger causality from money to stock prices using a sequence of moving windows.

The rest of this paper is organized as follows. Section 2 discusses the theoretical background, presenting two competing hypotheses about the relationship between money supply movements and stock prices. Section 3 describes the stock market data, presents a set of summary statistics, and carries out a univariate time series modeling exercise on stock returns. The data added to make the analysis multivariate are discussed in Section 4, which also presents the econometric framework used for causality testing. Section 5 reports the empirical findings and conclusions are given in Section 6.

## 2. Theoretical Considerations

Empirical results from previous research about the Granger-causal relationship between money and stock returns are related to two competing hypotheses. One is referred to as the “monetary portfolio hypothesis.” According to this argument, the money supply has causal, yet indirect, effects on stock price. The basis of this view is the fact that financial investors hold many kinds of assets in addition to money and are likely to respond to money supply changes by adjusting their portfolio of assets. So, when money supply increases generate short-term interest decreases, driving down the yield on bonds, it’s assumed that investors will shift from bonds to stocks, resulting in an increase in stock prices; the reverse holds for money supply decreases.

The “efficient markets hypothesis” offers an alternative view about the relationship between money supply movements and stock prices. In this framework the current stock price reflects all publicly available information about future economic fundamentals affecting the stock’s value. Since such information includes lagged values of the money supply, the marginal effect of lagged values of money in helping predict future stock movements should be zero. That is, the efficient markets hypothesis implies that money does not Granger-cause stock prices.

The existence of these competing and arguably well-reasoned hypotheses about the Granger-causal relationship between money and stock prices implies that an empirical investigation of this question has substantive importance. First, such an exercise has the potential to establish whether the data favor one of these theories over the other. Second, it may help shed light on whether profit-making opportunities are systematically left unexploited in the stock market.

### 3. The Stock Market Data

The Standard & Poor's 500 Composite Index (S&P500) is one of the most commonly used indicators of stock market activity. It is a weighted average of the prices of stocks selected from two major national stock exchanges and the over-the-counter market. This stock price index is expected to reflect current stock market conditions and a special committee of the Standard and Poor's Corporation is responsible for deciding which specific stocks to include.

The S&P500 index is the measure of stock market activity used in this paper. Granger-causality tests were also computed, however, for both the Dow Jones Industrial Average and the New York Stock Exchange Index. But since these findings were quite similar, not surprisingly, to those for the S&P500, only the S&P500 results are reported.

The S&P500 data used are monthly and cover the 1960:01-1999:10 sample period. Monthly returns in the S&P500 index are used in estimation of the models considered in this paper. The stock returns series for observation  $t$ ,  $s_t$ , is measured by the first difference of the natural logarithm of the S&P500 index

$$s_t = (1 - L) \ln(\text{S\&P500}_t), \quad (1)$$

where  $L$  is the lag operator.

While this transformation is standard in the literature, it also has the benefit of eliminating the trend behavior in this time series. Removal of this nonstationarity is crucial for this paper's analysis, since it is well known that use of nonstationary series in time series regressions can generate spurious correlation and induce bias in the OLS estimators of model parameters.

The top graph in Figure 1 is a time series plot of the general tendencies of the natural logarithm of the S&P500 over the 1960:01-1999:10 sample period. This graph shows that the series increases slowly from 1960 to 1980 and increases quickly from 1981 to 1999. That is, the slope of the series is positive all the time and is steeper during last 20 years. The bottom graph in Figure 1 presents monthly returns series of the S&P500 for the same sample period. The monthly stock returns appear to be stationary. There is no apparent trend and the variance of the series seems roughly constant.

Figure 2 shows a histogram and some summary statistics for the monthly stock returns series. The histogram looks asymmetric and negatively skewed, as the skewness statistic of -0.63 indicates. Compared against a value of 3 for the normal distribution, the sample kurtosis of 5.05 indicates the distribution of monthly stock returns has fat tails. Jointly, the skewness and kurtosis results cause the Jarque-Bera test to reject the normality null hypothesis with a  $p$ -value of less than  $1 \times 10^{-6}$ . The sample mean of the monthly S&P500 index returns is 0.65 percent, which implies an annual return of approximately 8.1 percent.

The sample autocorrelation function (acf) and sample partial autocorrelation function (pacf) are helpful diagnostic tools used to identify time series models for a given time series. The sample autocorrelation at lag  $k$  for a time series  $\{x_t\}$  with zero mean is estimated by

$$r_k = \frac{c_k}{c_0}, \quad (2)$$

where  $c_k$ , defined as

$$c_k = \frac{1}{T} \sum_{t=1+k}^T x_t x_{t-k}, \quad k \geq 0, \quad (3)$$

is the estimate of the autocovariance at lag  $k$ . It is assumed that  $\{x_t\}$  is stationary, so that the autocorrelation coefficient at lag  $k$  is the correlation coefficient between values of  $\{x_t\}$   $k$  periods apart. The sample partial autocorrelations are calculated from the solution of the Yule-Walker equations, expressing the partial autocorrelations as a function of the autocorrelations. The pacf at lag  $k$  gives a measure of the correlation between  $x_t$  and  $x_{t-k}$ , conditional on the values of  $x_{t-1}, x_{t-2}, \dots, x_{t-k-1}$ .

The estimated correlogram for the stock return series is shown in Figure 3. The left panel shows the estimated acf, which cuts off after lag 1. This is the classic pattern of a univariate moving average model of order 1 (MA(1)). An MA(1) model is given by

$$x_t = \varepsilon_t + \theta \cdot \varepsilon_{t-1}, \quad (4)$$

where  $\varepsilon_t \sim WN(0, \sigma^2)$ , i.e.,  $\varepsilon_{t-1}$  is a white-noise process.

The right panel in Figure 3 presents the estimated pacf, which cuts off after lag 1. This is the classic pattern of a univariate pure autoregressive model of order 1 (AR(1)). An AR(1) model is given by

$$x_t = \alpha \cdot x_{t-1} + \varepsilon_t, \quad (5)$$

where  $\varepsilon_t \sim WN(0, \sigma^2)$ .

If either the MA(1) parameter  $\theta$  or the AR(1) parameter  $\alpha$  is sufficiently small, then both the sample acf and pacf for the stock returns series are consistent with either an MA(1) or AR(1) univariate data generating process. Since at lag 1 both the estimated autocorrelation and partial autocorrelation exceed the 95% confidence bounds, it is clear that the stock returns is not a white-noise process. This suggests that there is some predictability of the 1-step-ahead values of stock returns.

Given the dynamics characterized by Figure 3, an AR(1) model was estimated for the stock returns series. The estimated equation for the 1960:02-1999:10 sample period is

$$\hat{s}_t = 0.47 + \underset{(0.04)}{0.26} \cdot s_{t-1}, \quad (6)$$

where the standard error of the AR(1) coefficient appears in parentheses. The adjusted  $R^2$  for this model is 0.068. The  $p$ -value for the  $t$ -test that the AR(1) coefficient equals zero is less than  $10^{-4}$  and the  $p$ -value for the  $F$ -test of the same null hypothesis is less than  $10^{-6}$ . These extremely small  $p$  values are consistent with the correlogram results in Figure 3. The point estimate for the AR(1) coefficient, 0.26, implies that the stock returns series is stationary.

The Durbin-Watson statistic is 1.85, a value which is consistent with the residuals of the estimated AR(1) model being white-noise. As a further check, the sample acf for these AR(1) residuals is presented in Figure 4. The estimated acf at each displacement is quite close to zero and falls within the 95 percent confidence interval for the null hypothesis that the series is white-noise.

These results suggest that an AR(1) model provides a good fit to the stock returns series, capturing the relatively small departure from white-noise in the series. Since the AR(1) residuals are white-noise, it would appear that augmenting equation (6) with lagged values of other variables, including money growth, would not improve the fit obtained. This issue is explored in the next section.

#### **4. Model Specification and Granger Causality Testing**

The two measures of the money supply used in this paper are M1 and M2. M1 equals currency plus all checkable deposits. M2 includes everything in M1 plus funds in some interest-bearing accounts. These two variables are graphed in Figure 5, which shows that these

two series tend to trend upwards in a similar pattern. The difference between them appears to be stationary, suggesting that M1 and M2 are cointegrated. That is, there is a linear combination of these two nonstationary series which is stationary, suggesting that there is a long-run stable relationship between M1 and M2.

As mentioned above, use of nonstationary time series in OLS regressions can induce serious bias and spurious correlation. Since the M1 and M2 series are clearly nonstationary, the growth rates of these two series are used for the causality regressions. These money supply growth rates are graphed in Figure 6.

To run the causality tests, the univariate autoregressive stock returns model is augmented by adding lags of either M1 or M2. But since these variables could possibly serve as a proxy for some omitted variable, several other variables are also included in the causality regressions. First, additional lags of stock returns are used.

Second, lags of an interest rate variable are also included. Since, on many grounds, interest rate movements have important implications for construction of optimal financial asset portfolios, it is reasonable to include interest rates in the analysis. In the causality test regressions, lags of either the Moody's Aaa corporate bond rate or the federal funds rate are also added to the model. The Moody's Aaa rate is the average interest rate on the long-term bonds of top-rated corporations. The federal funds rate is the interest rate charged to banks which borrow reserves from other member banks of the Federal Reserve system.

The two interest rates used are graphed in Figure 7. The Aaa rate is generally above the federal funds rate from 1960:01 to 1999:10. There were exceptions to this, especially during the Federal Reserve Board's announced shift to a monetary stock targeting regime in the late

1979 to late 1982 period. Since there is no clear trending behavior in these series, it is presumed that these time series are stationary.

Third, we also include the monthly growth rates in the Consumer Price Index (CPI) in the causality regressions. These CPI growth rates are a measure of inflation. This series is graphed in Figure 8 and also appears to be stationary.

To run a test for Granger causality from money to stock prices, two regressions are run. The unrestricted model, in which lags of money growth help predict future values of the stock returns, is given by

$$s_t = \alpha_0 + \sum_{i=1}^{\lambda} (\alpha_i \cdot s_{t-i} + \beta_i \cdot m_{t-i} + \delta_i \cdot r_{t-i} + \gamma_i \cdot p_{t-i}) + e_{1,t}, \quad (7)$$

$t = t_1, \dots, T$ , and where  $s_t$  is the monthly growth rate of stock price for period  $t$ ,  $m_t$  is the money growth rate for period  $t$ ,  $r_t$  is the interest rate for period  $t$ ,  $p_t$  is the monthly growth rate of the CPI in period  $t$ ,  $\alpha_0$ ,  $\alpha_i$ ,  $\beta_i$ ,  $\delta_i$  and  $\gamma_i$  (for  $i = 1, 2, \dots, \lambda$ ) are coefficients to be estimated, and  $e_{1,t}$  is a white-noise error term. The parameter  $\lambda$  is the lag order of the model and is determined by the Akaike Information Criterion (AIC)

$$AIC = \exp\{2k/T\} \cdot \hat{\sigma}^2, \quad (8)$$

where  $\hat{\sigma}^2$  is the estimated residual variance of the model.

The restricted model, in which lags of money growth do not help predict future movements in stock returns, is specified as follows

$$s_t = \alpha_0 + \sum_{i=1}^{\lambda} (\alpha_i \cdot s_{t-i} + \delta_i \cdot r_{t-i} + \gamma_i \cdot p_{t-i}) + e_{2,t}, \quad (9)$$

$t = t_1, \dots, T$ , and where  $e_{2,t}$  is a white-noise error term.

To run the standard test of Granger causality from money growth rates to stock returns, an  $F$ -test is run to see if the restrictions imposed in equation (9) can be rejected against the unrestricted model given by equation (7). If these restrictions can be rejected, then it is concluded that “money Granger-causes stock returns.” This test is one of the tests used in this paper. Following Swanson (1998), another test of Granger causality used is based on a comparison of AIC values for estimated versions of equations (7) and equation (9). In particular, if the model “with money” (i.e., equation (7)) has a lower AIC value than the equation “without money” (i.e., equation (9)), it is concluded that “money Granger-causes stock returns.”

Following Swanson (1998), we use rolling fixed-length windows of data, to allow for the possibility that the relationships modeled by equations (7) and (9) may be evolving over time. This allows us to examine how sensitive the Granger causality tests are to the particular sample used.

We use both 10-year and 15-year fixed-length moving windows and they are constructed as follows. The first 10-year window covers the 1960:01-1969:12 sample period. To form the second 10-year window we move one observation ahead for both the initial and last observations, i.e., the second 10-year window covers the 1960:02-1970:01 sample period. We continue in this manner until we obtain the last 10-year window, i.e., the last 10-year window covers the 1989:11-1999:10 sample period. This yields 359 10-year windows. Using a similar strategy in the 15-year window case generates 299 15-year windows.

For each window we impose the same lag length  $\lambda$  in models (7) and (9). This lag length is determined by the AIC as follows. For each window we estimate 12 versions of the

unrestricted model (7) by allowing  $\lambda$  to range from 1,2,...,12. We then use the value of  $\lambda$  which generates the lowest AIC values across the 12 estimated models.

Given that we use two measures of the money supply, M1 and M 2, and two measures of the interest rate, there are four versions of equations (7) and (9) to estimate for each fixed-length window. Given that we use both 10-year and 15-year fixed-length windows, this gives us eight cases, four for each type of fixed-length window. These cases are listed in the first column of Table 1.

## 5. Empirical Results

Choosing the optimal lag order is important for time series modeling. If too small a lag is chosen, the misspecification will cause the OLS point estimates to be biased and can leave a good deal of serial correlation remaining in the residuals. If too large a lag is chosen, OLS estimation is inefficient. As noted above, in this paper we select the lag order for our models using the AIC.

Figure 9 shows the lag order  $\lambda$  selected for each model across all moving windows. Each point in the time series plots shows the lag order selected for the window ending in the observation corresponding to that point. For example, for the 10 year windows the first data point of 1969:12 represents the last observation of the first window, 1960:01-1969:12.

The left-side set of graphs in Figure 9 cover the cases for which M1 is used as the money stock measure and the right-side set of graphs cover the cases for which M2 is used as the money stock measure. The upper four graphs cover the cases in which the Aaa rate is used as the interest rate variable, and the bottom four graphs cover the cases in which the federal funds rate is used.

The results in Figure 9 show that the AIC-specified models are more stable across the windows using the Aaa rate relative to using the federal funds rate. Further, the Aaa models (models using the Aaa rate as the interest rate variable) estimated with 15-year moving windows appear to be a bit more stable than those estimated with 10-year moving windows, especially for Aaa models using M2 as the money measure. Given the small degree of serial correlation present in the stock returns data for the full-sample period (see Figure 3), though, it is a bit surprising that the lag order  $\lambda$  selected by the AIC is so often so high; for example, the bottom two graphs in Figure 9 show that the value of  $\lambda$  selected by the AIC for the Aaa models in the 15-year case is almost always greater than or equal to 10.

In contrast to the Aaa case, there is no clear evidence that the FF models (models using the federal fund rate as the interest rate measure) estimated with 15-year windows are more stable than those estimated with 10-year windows. The two most stable cases for the FF models are represented by the set of windows with final observation past 1985:12 in the first two graphs on the left side of Figure 9, i.e., for (roughly) the second set of windows for the FF models using M1 as the money supply measure. The FF models using M2 as the money stock measure appear to be the most unstable over time.

A standard check of model accuracy in time series modeling is to examine if the residuals from the estimated model appear to be white-noise. Failure to obtain white-noise residuals is an indicator that the model is misspecified. The Ljung-Box  $Q$ -statistic can be used to test the null hypothesis that the residual series is white noise. More specifically, the  $Q$ -statistic can be used to test the null hypothesis that the first  $m$  residual autocorrelations are jointly equal to zero. The Ljung-Box  $Q$ -statistic is computed as follows

$$Q = T(T+2) \sum_{k=1}^m \frac{r_k^2}{T-k}, \quad (10)$$

where  $T$  is the sample size of the residual series and  $r_k$  is the estimated residual autocorrelation at lag  $k$  as defined in equation (2). Under the null hypothesis of white noise, the  $Q$ -statistic is distributed as a Chi-squared random variable with  $m$  degrees of freedom. The second column of Table 1 reports the number of windows across the eight cases of interest for which the null hypothesis of white-noise residuals for equation (7) is rejected via the  $Q$ -test at the 10% significance level. The results show that the white-noise null is not rejected for any out of the 658 windows examined (recall that there are a total of 359 10-year windows and 299 15-year windows). Thus, we conclude that model selection via the AIC yields estimated models that capture well the serial correlation in the stock returns series for each fixed-length window.

The third column of Table 1 reports the results of the AIC-based Granger causality tests. There are three interesting results which stand out. First, for four out of the eight specifications of equations (7) and (9), it is found that money Granger-causes stock returns for more than half of the fixed-length windows examined. Second, these four specifications are those in which M1 is used as the measure of the money supply. Third, the results do not appear to be sensitive to use of a 10-year versus 15-year fixed-length window and seem to be robust across the two different interest rate measures. On the whole, then, the AIC-based results provide a good deal of evidence that prediction of future movements in stock returns is helped by conditioning on lagged values of money growth.

The last three columns of Table 1 report the results from the more standard  $F$ -test of Granger causality. These results are not directly comparable to the AIC-based results, since there is no threshold significance level at which it is in some sense “optimal” to examine the results. As must be the case, the rejection frequencies of the no-causality null hypothesis increase as the nominal significance level increases. At the 10% significance level the  $F$ -test

results appear to match quite well those obtained using the AIC. Accordingly, the evidence in favor of causality from money growth rates to stock returns once again is strongest using M1 and is arguably robust across the length of the fixed-length window and interest rate measure employed.

The graphs in Figure 10 show time series plots of the Granger causality  $F$ -test  $p$ -value for each class of model across the fixed-length window samples. Since the null hypothesis is that money does not Granger-cause stock returns, low  $p$ -values imply that there is strong evidence that money Granger-causes stock returns.

These graphs allow us to examine how the degree of Granger causality documented in Table 1 varies across time. We see that  $p$ -values in the left-side graphs, representing the cases in which M1 is used as the money supply measure, tend to be much lower than those in the right-side graphs. But this fact just mirrors the results reported in Table 1. The new information provided by these graphs is that we are able, in several cases, to identify a rather an apparent shift over time in the nature of the Granger-causal relationship between money growth rates and stock returns. In particular, for three out of the four cases using M1 (i.e., for all except the M1 FF model with 10-year rolling fixed windows), the  $p$ -values for the no Granger-causality null hypothesis are generally quite low once the fixed-length windows end at a data point in the relatively late 1980's and beyond.

## 6. Conclusions

In an important paper, Swanson (1998) documented a good deal of time variation in the Granger-causal relationship between money and output. Following Swanson's (1988) lead, we have used a moving fixed-length window approach in examining the question of whether there is a Granger-causal link between money and stock prices. On the whole our results suggest

that such a strategy is warranted, since we have detected a good deal of movement over time in the nature of this relationship. Accordingly, “full sample” results reported earlier in the literature may not be robust when subjected to a rolling fixed-window analysis of the type carried out in this paper.

In addition to documenting the existence of this time variation, our results suggest the choice of the monetary measure used matters a good deal. In particular, we have found that the evidence in favor of money Granger-causing stock prices is much stronger when M1, as opposed to M2, is used. Further, we have documented that the evidence in favor of M1 Granger-causing stock returns is much stronger once windows of data from the 1960’s and early-to-mid 1970’s are excluded from the analysis.

Topics for future study include an investigation into exactly why the Granger causality results are sensitive to use of data from the earlier part of this dataset. In addition, in light of the fact that this paper’s analysis has been all “in-sample,” it would be interesting to examine whether inclusion of lagged values of money supply growth rates help in “out-of-sample” forecasting. While in-sample comparisons of models with and without money indeed are standard in the literature on Granger causality, it is important to note Granger’s argument that the notion of Granger causality is inherently a statement about out-of-sample predictability; see, for example, his interview in Phillips (1997).

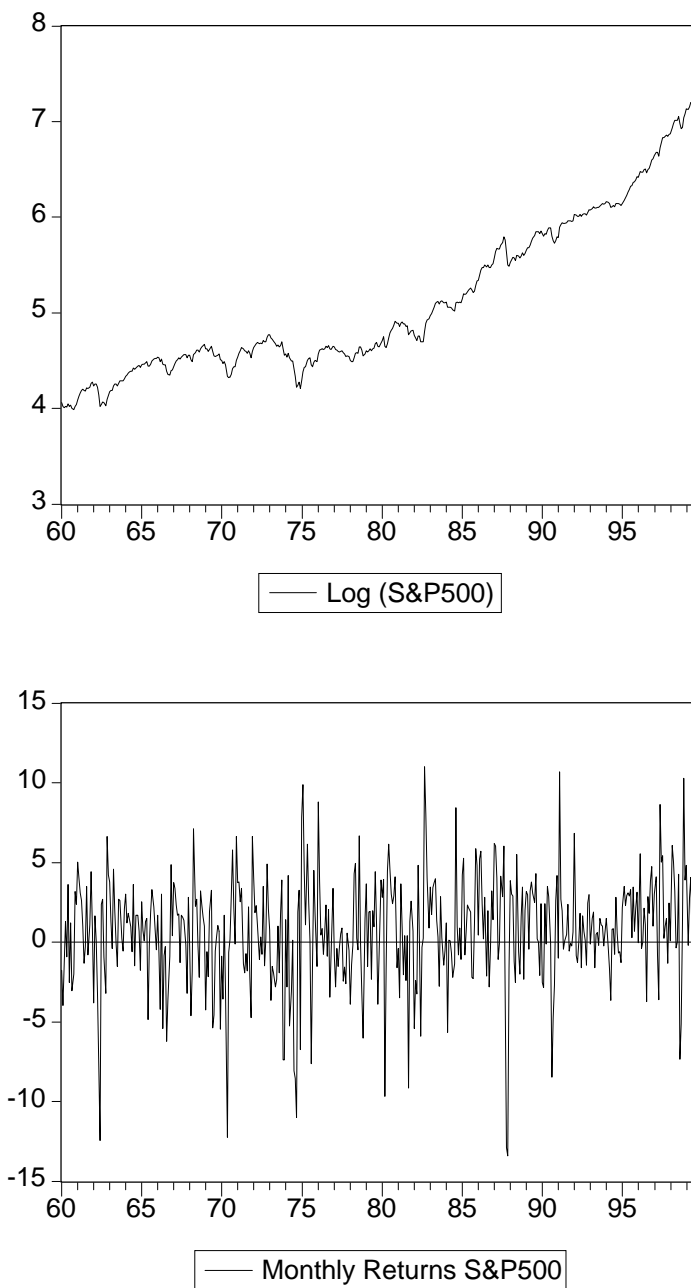
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Table 1  
**Residual White Noise and Granger Causality Tests**

Cases	Residual White noise test	Causality Tests			
		AIC Test	F01	F05	F10
1. M1, FF, 10	0	0.63	0.04	0.25	0.47
2. M1, FF, 15	0	0.62	0.22	0.46	0.61
3. M2, FF, 10	0	0.40	0.06	0.11	0.19
4. M2, FF, 15	0	0.11	0.00	0.06	0.09
5. M1,AAA, 10	0	0.64	0.20	0.50	0.57
6. M1,AAA, 15	0	0.55	0.35	0.52	0.54
7. M2, AAA, 10	0	0.27	0.08	0.12	0.14
8. M2, AAA, 15	0	0.14	0.00	0.07	0.12

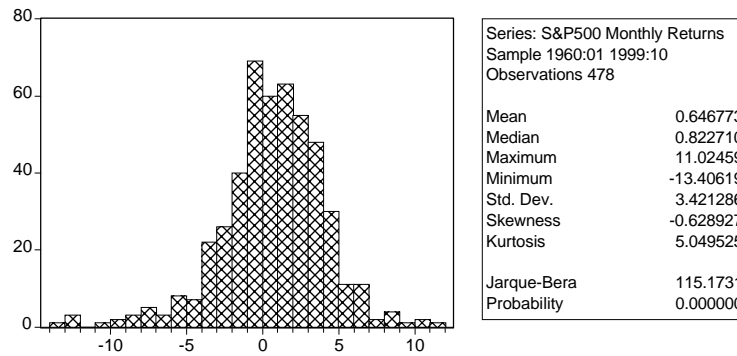
Notes: This table presents the results of carrying out the Granger causality tests using moving fixed-length windows over the 1960:01-1999:10 period. The dependent variable in each model estimated is the 1-month return of the S&P500 index. The first column indicates the money stock measure, interest rate, and fixed window length used for the 8 cases studied. For each model lags of both stock returns and the CPI inflation rate were also included as explanatory variables. The second column shows the number of windows for each the white-noise null hypothesis was rejected at the 10% significance level using the Ljung-Box test on the equation (7) residual acf evaluated at the first 12 lags. The third column presents the fraction of fixed-length windows for which the “model with money” (equation (7) in the text) has a lower AIC value than the “model without money” (equation (9) in the text). The last three columns report the fraction of windows for which the non-causality null hypothesis was rejected via the  $F$ -test at the 1%, 5%, and 10% significance levels.

Figure 1**Time Series Plots of (Log) S&P500 Index and S&P500 Monthly Returns, 1960:01-1999:10**

Notes: The top panel shows a time series plot of the (natural) log of the S&P500 stock market index. The bottom panel shows a time series plot of the monthly returns, defined as (100 times) the log-first difference, of the S&P500 index.

Figure 2

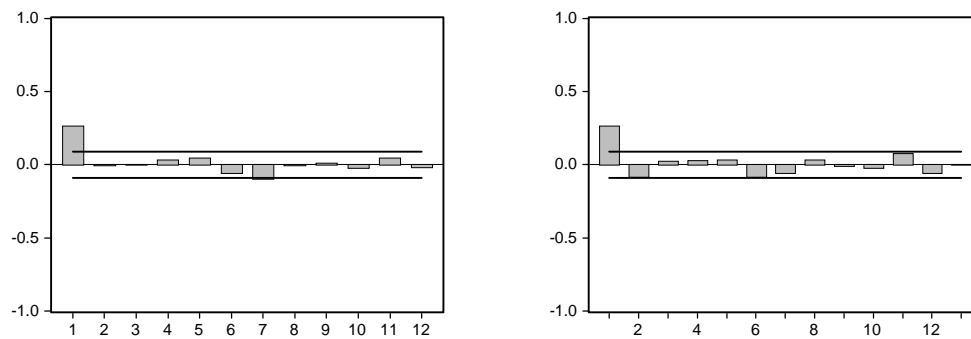
### Histogram and Summary Statistics for Monthly Returns of S&P500 Index, 1960:01-1999:10



Notes: The left panel shows the histogram of the monthly returns of the S&P500 stock market index. Some summary statistics are given in the right panel. The distribution of stock returns is skewed and leptokurtotic, leading to a strong rejection of the null hypothesis that the returns are normally distributed.

Figure 3

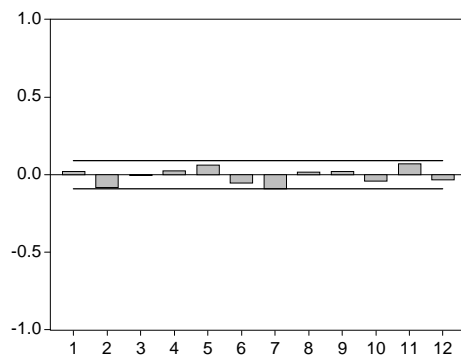
### Estimated Correlogram for Monthly Returns of S&P500 Index, 1960:01-1999:10



Notes: The left graph shows the estimated autocorrelation function (acf) of the monthly stock returns of the S&P500 index, 1960:01-1999:10. The right graph shows the estimated partial autocorrelation function (pacf) of the same series. The unbroken lines give, for each lag, an asymptotic 95% confidence interval for the null hypothesis that the series is white noise. Both the estimated acf and pacf imply that this stock returns series is not white noise. This estimated correlogram is consistent with both an AR(1) data generating process, with a relatively small AR(1) coefficient, and an MA(1) data generating process.

Figure 4

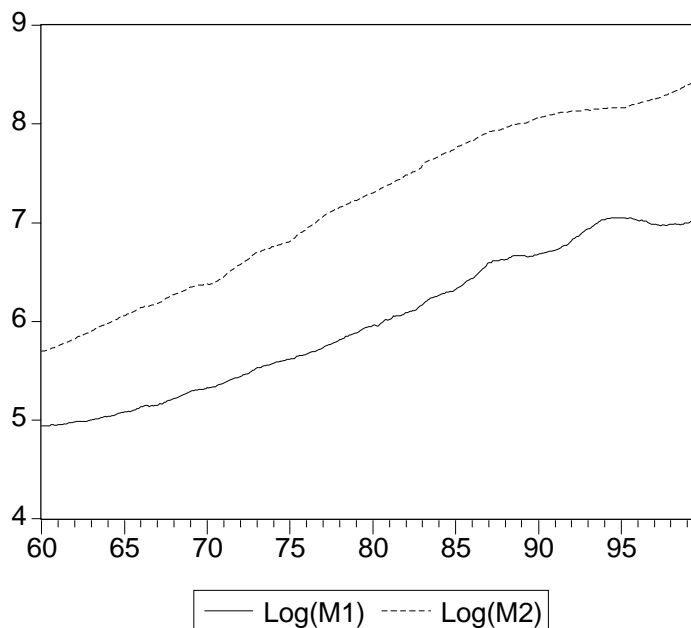
**Estimated Autocorrelation Function for Residuals of AR(1) Model Fitted to S&P500 Monthly Returns, 1960:01-1999:10**



Notes: This graph shows the estimated autocorrelation function of the residuals for an AR(1) model fitted to the monthly stock returns of the S&P500 index, 1960:01-1999:10. The unbroken lines give, for each lag, an asymptotic 95% confidence interval for the null hypothesis that the series is white noise.

Figure 5

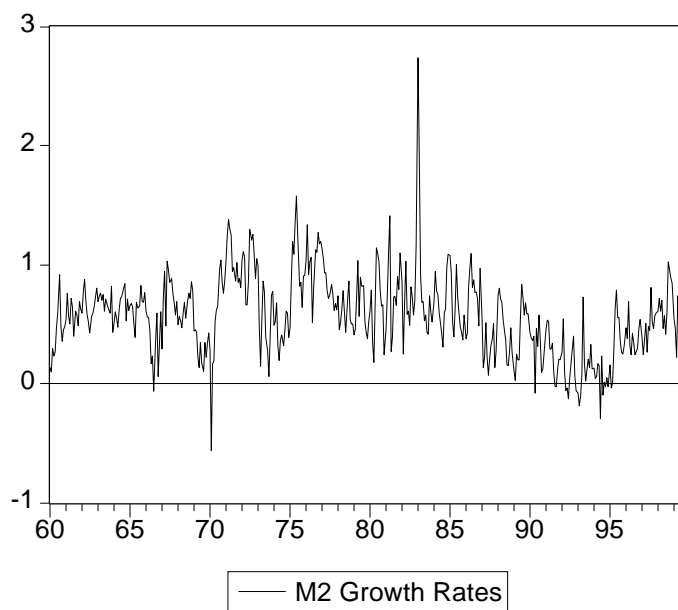
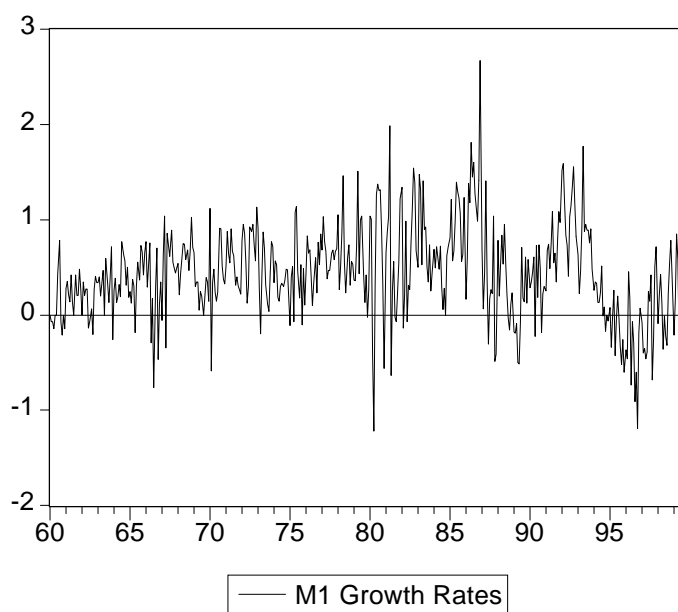
**Time Series Plots of (Log) M1 and M2, 1960.01-1999:10**



Note: This graph shows the time series plot for the (natural) logarithm of the M1 and M2 monetary aggregates over the sample period 1960:01-1999:10. The general trending behavior in these series appear to be quite similar. Also, the difference between them appears to be stationary, suggesting that the two series are cointegrated, as is expected.

Figure 6

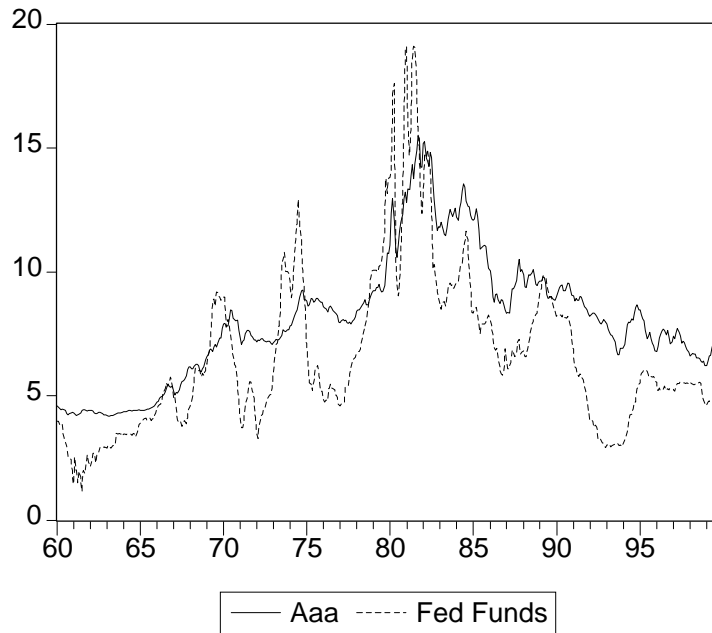
## Time Series Plots of M1 and M2 Growth Rates, 1960:01-1999:10



Notes: These two graphs present time series plots of the M1 (upper graph) and M2 (lower graph) growth rates, computed as (100 times) the log-first difference of M1 and M2, respectively, for the sample period 1960:01-1999:10.

Figure 7

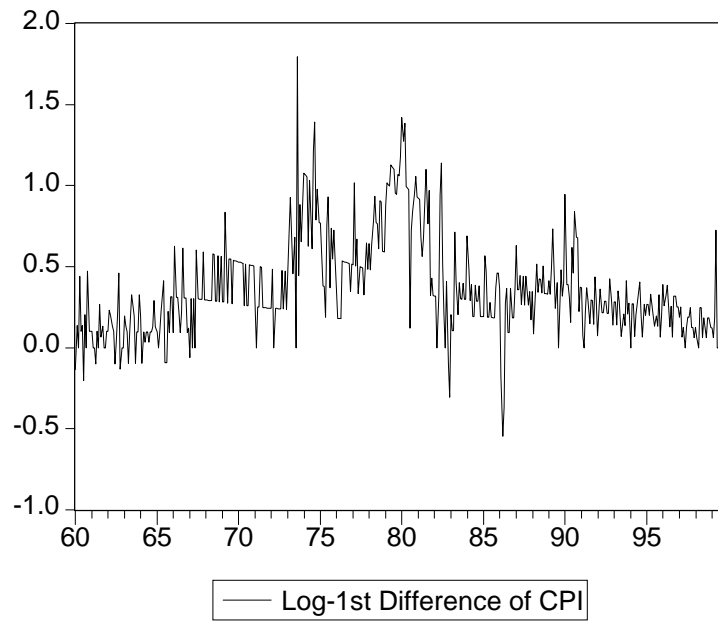
**Time Series Plots of the Aaa Rate and Federal Funds Rate, 1960:01-1999:10**



Notes: This graph shows time series plots of the Moody's Aaa rate (the average interest rate on the bonds of top-rated corporations) and the federal funds rate, 1960:01-1999:10. While the Aaa rate is generally above the federal funds rate, there were several periods in which the reverse was true, especially during the Federal Reserve Board's announced shift to a monetary stock targeting regime in the late 1979 to late 1982 period.

Figure 8

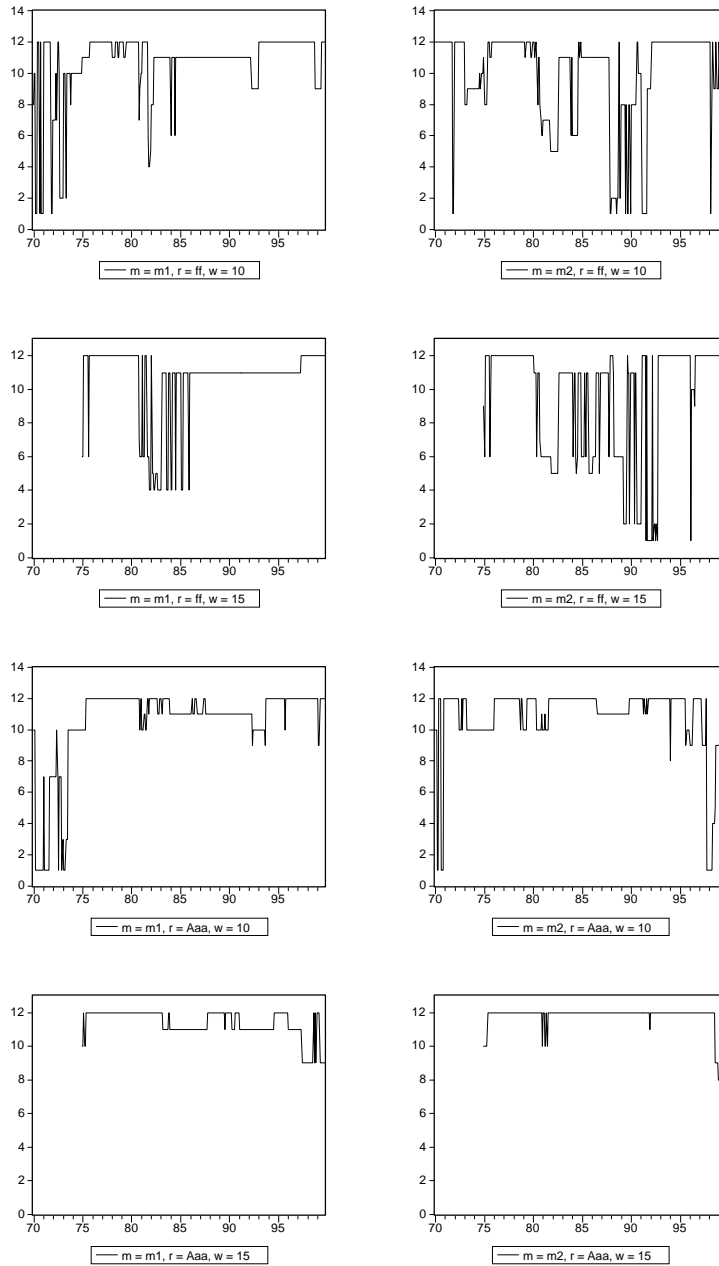
**Time Series Plot of Monthly Growth Rates in the CPI**



Notes: This is a time series plot of the monthly growth rates, calculated as (100 times) the log-first differences, of the CPI. These values need to be compounded to impute the implied annual inflation rate.

Figure 9

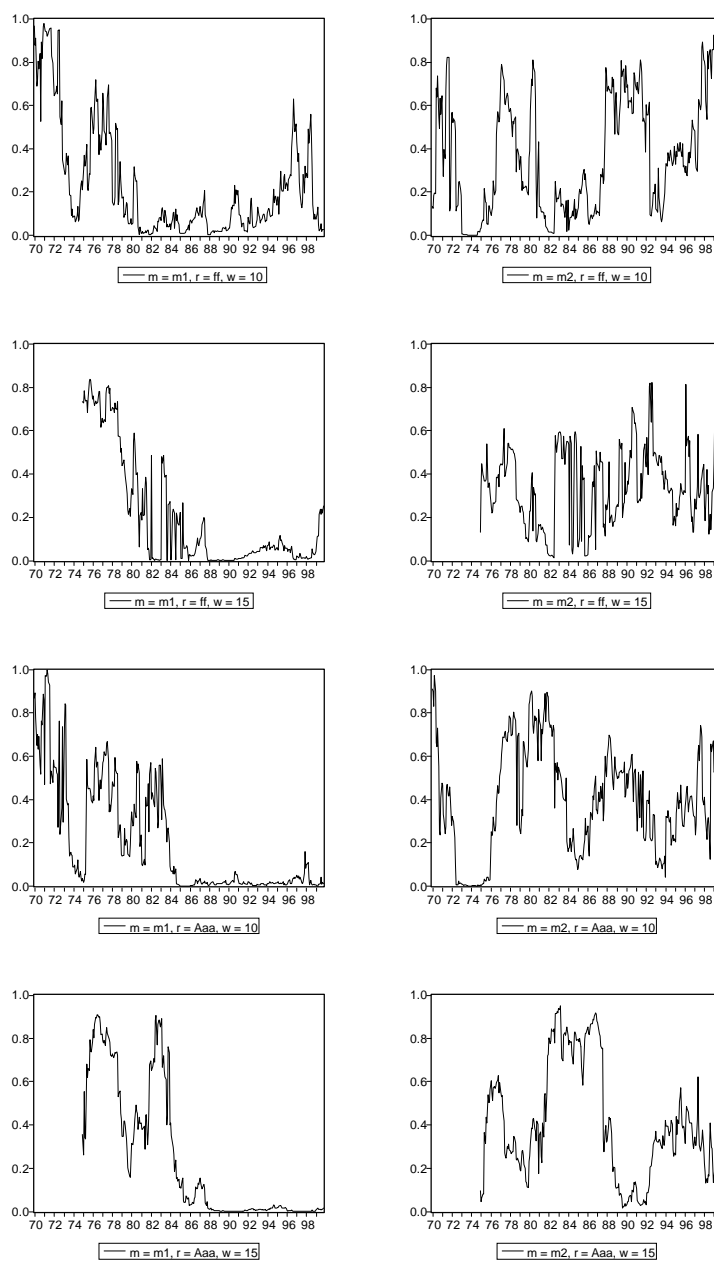
**Time Series Plots of the AIC-Selected Lag Order Across Different Models and Across Sample Windows of Length 10 and 15 Years**



Notes: These graphs for the lag order  $\lambda$  for equation (7) for each model estimated for each sample window. The models vary according to the monetary stock measure (M1 or M2), the interest rate (the Aaa or federal funds rate), and the window length (10 years or 15 years). Each point in each time series plot shows the lag order selected for the window ending in the particular period indicated, e.g., for the 10-year windows, the first data point of 1969:12 represents the last observation of the first window, 1960:01-1969:12. The results show that the models AIC-specified models are more stable across the windows using the Aaa rate compared to using the federal funds rate.

Figure 10

**Time Series Plots of Granger Causality  $F$ -test  $p$ -values Across Different Models and Across Sample Windows of Length 10 and 15 Years**



Notes: These graphs show time series plots of the  $p$ -value of an  $F$ -test of the restrictions in equation (7) implied by equation (9) for each model estimated for each sample period. Since for each model equation (9) implies that lags of money growth do not help predict future values of stock returns, this  $F$ -test is a test of the null hypothesis that money does not Granger-cause stock returns, so that low  $p$ -values imply that there is strong evidence that money does Granger-cause stock returns. Each point in each time series plot shows the  $p$ -value for the null hypothesis of no Granger causality for the sample window ending in the particular period indicated, e.g., for the 10-year windows, the first data point of 1969:12 represents the last observation of the first window, 1960:01-1969:12.