# Is Money Useful in the Conduct of Monetary Policy?

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How useful monetary aggregates are for the conduct of monetary policy is a long-standing question. We analyze this question by examining their role as information variables in situations where the monetary authority uses an interest rate instrument. Monetary aggregates may be useful in that context if they contain information about the underlying contemporaneous state of the economy by helping to predict imperfectly observed variables that appear in the policymaker's reaction function. This use of money generally requires that the demand for money be well behaved and that random movements in the money demand function do not severely reduce the signal content of money. Alternatively, if the policy rule involves expectations of future variables, then money may be useful for predicting those variables.[1] Analyzing money's usefulness requires a very different statistical analysis for each of these two roles. The first role deals with the stability of the money demand relationship and the precision with which the money demand curve can be estimated, while the second role deals with the usefulness of money for forecasting.

While in practice monetary authorities do use monetary aggregates as information variables, their use varies over institutions and over time. For example, Hetzel (1981) indicates that the behavior of M1-influenced Federal Reserve policy decisions over part of the 1970s and Dotsey (1996) provides

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[1] For recent discussions of the role of forecasts in monetary policy, see Svensson (1999), Woodford (1999), and Amato and Laubach (2000).

evidence that money played a role during the early 1980s. The behavior of money, however, does not always enter into policy deliberations. Currently, most FOMC participants pay little attention to the growth rate of the monetary aggregates.[2] The time-varying use of money could be related to its time-varying usefulness. We here explore how money's behavior and predictive content have changed over time.

We do this in two ways. First, we analyze both the long-run and short-run behavior of M1 and M2 in Sections 1 and 2. We find that the parameters of the money demand function are time-varying and that our ability to explain money demand also varies over time. In Section 3, we look at how useful money is for forecasting nominal income, real output, and inflation. Our analysis indicates that M1 has been periodically useful in helping to forecast economic activity, but that its usefulness has waned. M2, on the other hand, has fairly consistently helped forecast nominal GDP and on occasion has been useful in improving the forecasts of real GDP. Section 4 concludes.

## 1. LONG-RUN RELATIONSHIP

We first examine the long-run relationship between money, income, prices, and interest rates. This investigation is important because it indicates the correct statistical specifications needed for the analysis in the rest of the article. If money, income, prices, and interest rates are cointegrated, then the empirical work that analyzes the demand for money and the predictive content that money has for future output growth and inflation must take account of the cointegrating relationship. Failure to do so will result in an improper specification of the empirical model.

The first step in any such investigation is to determine the order of integration of the relevant variables. These variables are: nominal M1; nominal M2; nominal GDP; real GDP; inflation as measured by changes in the GDP deflator; the three month Treasury bill rate; and the opportunity cost of holding M2, which is given by the difference between the T-bill rate and the own rate paid on M2 balances, real M1 balances, and real M2 balances. All variables with the exception of inflation and the two interest rate measures are measured in logs, and our sample goes from 1959:II through 2000:I. Other than the opportunity cost, all variables are nonstationary in levels. The stationarity of the opportunity cost reflects the cointegration between the T-bill rate and M2's own rate. It is not surprising that these two variables would exhibit a long-run relationship.

[2] A reading of recent policy discussions summarized in the regularly released minutes of FOMC meetings indicates that very little weight is placed on the behavior of money in the setting of policy.

**Table 1 ADF Test Results**

| variable | test includes constant | test includes trend | test includes trend squared |
|---|---|---|---|
| M1 | −3.07 | | −4.74 |
| M2 | −2.71 | −3.01 | |
| Y | −3.35 | −3.76 | −4.19 |
| y | −6.35 | | −6.02 |
| $\pi$ | −2.34 | | |
| R | −5.52 | | |
| $m1$ | −4.39 | | |
| $m2$ | −4.27 | −4.26 | |
| 5 percent critical value | −2.91 | −3.45 | −3.89 |

We then examine whether first differences of the variables are stationary or if the variables are integrated of order one. The results of augmented Dickey-Fuller (ADF) tests are displayed in Table 1.[3] Values of the test statistic that are less than the critical value indicate rejection of the null hypothesis that the variable is integrated. The lag lengths were chosen by the step-down method advocated in Ng and Perron (1995). When a trend or quadratic trend variable is significant in the regressions, test statistics are included for that specification. With the exception of nominal M2 growth and inflation, all the variables seem to be integrated of order one. Importantly, real M1 ($m1$) and real M2 ($m2$) are integrated of order one, and these variables will be used to investigate cointegration.

The results of our unit root tests, displayed in Table 1, are fairly standard. It is, however, worth presenting them since our sample size is somewhat larger than most reported studies. For example, given the recent move of many monetary authorities to explicitly or implicitly target inflation, one would expect inflation to eventually exhibit stationary behavior. It is worth checking to see if the professed change in emphasis on controlling inflation has shown up in the statistical characterization of nominal variables.

## Cointegration

We now wish to look at the cointegrating relationship between real money balances, real income, and nominal interest rates. The two behavioral equations that inform our investigation are fairly standard specifications of the long-run relationship between real money balances, income, and interest rates:

[3] All unit root and cointegration tests were performed using the ADF, CADF, and PS procedures in the Gauss module, *Coint* written by Ouliaris and Phillips (1994–1995). These procedures produce the value of the relevant test statistic and its critical values.

$$m1_t = a + by_t - cR_t + e_t \tag{1.1}$$

and

$$m2_t = \alpha + \beta y_t - \gamma R_t - \delta(R_t - R_t^{M2}) + \varepsilon_t. \tag{1.2}$$

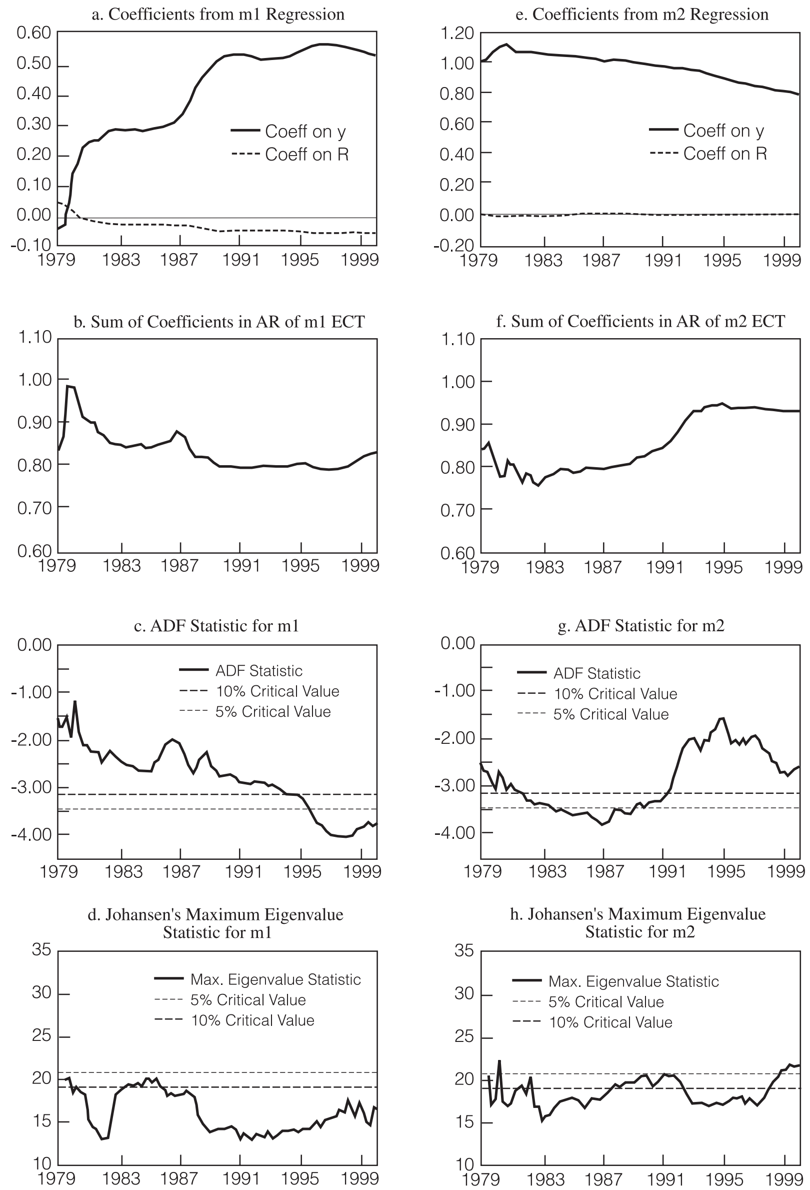
Equation (1.1) displays a simple demand function for real M1 balances as a function of real GDP and the nominal interest rate. Equation (1.2) depicts the demand for real M2 balances as a function of these same variables, as well as the opportunity cost of holding balances that are in M2 but not in M1. As mentioned, the money variables and output are in logs.

Before formally testing for cointegration we perform a heuristic exercise to examine the autoregressive behavior of the series. First, we recursively estimate a dynamic OLS regression of the respective real monetary aggregate on real GDP and the nominal interest rate. We use dynamic OLS, which includes leads and lags of first differences of the explanatory variables, to correct for correlation between the residual in the cointegrating relationship and the residuals in the processes generating the explanatory variables. The errors from the regression are computed as $m_t - \hat{a} - \hat{b}y_t + \hat{c}R_t$ for each definition of money. We then look at the sum of coefficients on a fourth order autoregression of this error; this sum can be thought of as the $\hat{\rho} - 1$ part of the Dickey-Fuller test statistic, $T(\hat{\rho} - 1)$. This sum is plotted in panels b and f of Figure 1. The sum is informative because it indicates the size of $\rho$, although no confidence intervals are calculated. One can see that the autocorrelation of the M1 residual declines over much of the sample, and as the sample size increases, it is likely that M1 will be judged to be cointegrated. The opposite is true of M2.

There are a number of issues involved in the various tests for cointegration proposed in the literature. Because the effect of the interest rate in money demand equations is generally small (as indicated in panels a and e of Figure 1), the presence of cointegration largely involves money's behavior with respect to output. Output is partially governed by a trend and partially governed by a nontrend nonstationary component. The various tests emphasize only one component of output in determining whether money and output are cointegrated. That is, the critical values of the tests are derived based on whether the asymptotic distributions are dominated by a time-trend or a random walk component. In reality both components are important, and for this reason the plots of sum of the coefficients in a fourth order autocorrelation are informative.

When testing for cointegration, one must take a stand on what portion of output is most important. In conducting augmented Dickey-Fuller tests, we assume the trend is the most important portion of output and follow the methodology advocated in Hamilton (1994, p. 597). First we perform auxiliary regressions of the interest rate and money on output. Of these two

**Figure 1 Cointegrating Results**




regressions, we then take the residual from the second (money) regression, and regress it on a constant, the residual from the auxiliary interest rate regression, and a time trend. Using the residual from this regression, we conduct an ADF test (see panels c and g of Figure 1). A test statistic that is less than the critical value indicates rejection of the null of no cointegration. Here we see that as the sample size increases, cointegration cannot be rejected for M1, but M2 appears to be cointegrated only over the first part of our sample. We should point out that the critical values for the tests are not uniform critical values for a sequence of random variables, but instead represent critical values that are appropriate for an individual test with a specific end date. Our tests only show what a researcher testing for cointegration at a specific date would find.

An alternate test for cointegration commonly performed in the literature is the Johansen (1988) maximum eigenvalue test (see panels d and h of Figure 1).[4] Here a test statistic above the critical value indicates that the variables are cointegrated. For both M1 and M2 the test produces results that are somewhat at odds with the ADF tests. For example, the Johansen test indicates that M1 was only cointegrated in the mid-1980s and is not cointegrated at present. It also indicates cointegration in the late 1970s. Given the behavior of the autocorrelation coefficient, the results appear counterintuitive. The autocorrelation coefficient for the error correction term has been relatively low in the 1990s, which should increase the likelihood that no cointegration among the variables will be rejected. Regarding M2, the Johansen test indicates cointegration, but shows that cointegration was not nearly so uniformly present in the 1980s. Both tests do, however, indicate cointegration in the late 1980s and early 1990s.

### Stability

In our analysis of the long-run relationships' stability, the recursive estimates of the coefficients in the dynamic OLS regression on M1 seem to settle down as the sample size increases. More formal tests for parameter stability are conducted using the SupF and MeanF statistical tests developed in Hansen (1992).[5] For both tests the null hypothesis is that the coefficients are constant. The SupF test tests against the alternative of a single structural break at an unknown break date, while the MeanF test tests against the alternative: that the coefficients follow a martingale. The SupF test performs an F test for a structural break at each point on an interior interval of the data sample. The interval is chosen to allow sufficient sample size for constructing the F test. We can calculate the distribution of the supremum of the F test and derive a test statistic. Similarly, we can derive a distribution for the mean of the F-statistics. The SupF test rejects stability at the 1 percent significance level and the MeanF test rejects at the 10 percent significance level. The rejections

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[4] The Johansen tests were conducted using the SJ procedure in the Gauss *Coint* package with a specification of a trend and six lags.

[5] We wish to thank Bruce Hansen for making available the code for performing these tests.

occur largely because of a sharp spike in the F-statistic in late 1980 and early 1981.

The coefficient on income in the M2 specification seems to be drifting downward while the coefficient on the T-bill has been increasing. It currently is positive, which makes little theoretical sense. Stability is, however, only rejected by the MeanF test at the 10 percent significance level.

## Comparability of Results

Our results on cointegration are in agreement with a number of studies in this area. Stock and Watson (1989) reject cointegration for M1 using monthly data over the sample 1960:2 to 1985:12, which is consistent with our results since only after 1996 with the ADF test do we find cointegration at the 5 percent significance level. Our results are also consistent with the findings in Friedman and Kuttner (1992), who do not find that M1 is cointegrated over a sample ending in 1990:4, and with their finding for cointegration for M1 over the sample 1960:2 through 1979:2 if one employs Johansen's procedure, which they do. Miyao (1996), however, indicates that the Johansen test may overstate the finding of cointegration.

Regarding M2, Friedman and Kuttner find cointegration over their shorter sample, but only find evidence for cointegration for M2 at the 10 percent level over their entire sample, which ends in 1990:4. Given that they employ Johansen's method, their results are broadly consistent with ours. Like us, Miyao finds no evidence of cointegration for M2 over his entire sample, 1959:1 to 1993:4, but he also fails to uncover evidence for cointegration over his earlier subsamples when using both ADF and Johansen test statistics. His tests on earlier samples, which end in 1988:4 and 1990:4, are at odds with ours since we fail to reject the null at 10 percent significance levels. Our results are in greater agreement with those of Carlson et al. (2000), who find that M2 is cointegrated until about 1990. Swanson (1998), on the other hand, finds evidence for cointegration for both M1 and M2 over the period 1960:2 through 1985:12 using Johansen's methodology. His results are consistent with our M1 result, but not our M2 result. He uses monthly data, and it could be that sampling frequency is important for the test results, especially those involving M2. Lastly, our results are consistent with those of Feldstein and Stock (1994), who find that M2 velocity is cointegrated with the nominal interest rate. The coefficient on income elasticity is very close to one in the 1980s and early 1990s, so constraining it to be one as they do does not significantly affect the test results.

On the basis of our results and for conciseness, we choose to treat both M1 and M2 as cointegrated and include the estimated error correction term in the empirical work of the next two sections. We realize that the evidence in favor of cointegration is not overwhelming: that the evidence varies with sample periods, methodology, and data frequency. We therefore indicate those instances where our results are sensitive to the presence of an error correction term.

## 2. THE DEMAND FOR MONEY

We next investigate the time-varying behavior of the demand for money in order to shed light on whether the current behavior of money contains information useful to the monetary authority for controlling nominal income or inflation. This question is related to the desirability of monetary targeting. As emphasized by Friedman (1969), a well-defined and stable money demand curve is a necessary condition for monetary targeting to produce desirable economic outcomes, thus his emphasis on understanding the demand for money. Even if one does not wish to use money as an instrument or intermediate target, the current behavior of money may provide useful information about imperfectly observed variables such as current output or inflation. The usefulness of this information is related to understanding the demand for money, and we therefore share the same emphasis.

Lately the literature has moved away from this approach and has instead emphasized the notion of Granger causality. Recent examples include Friedman and Kuttner (1992), Estrella and Mishkin (1997), and Feldstein and Stock (1994). Those papers argue that in order for money to be useful in the conduct of monetary policy, it must have predictive content for some variable that the monetary authority cares about.

### Money as a Signal

We believe the foregoing view is too restrictive. It neglects the signal value that money may have for contemporaneous and lagged values of economic variables that could plausibly be of interest to the central bank.[6] In reality, output and prices are not contemporaneously observable and are at best imperfectly observed with a lag. It may very well be that these variables, like the underlying shocks that impact the economy, may never be fully observed. In this case an optimizing monetary authority may find it desirable to use the economic information contained in money when setting its interest rate instrument. This point is made in Dotsey and Hornstein (2000), who consider the case of optimal time-consistent monetary policy. Their analysis would carry over to the study of optimal policy when the central bank is fully credible, or

[6] Furthermore, the notion of Granger causality involves general equilibrium considerations as pointed out in Dotsey and Otrok (1994). Since we are primarily concerned with money's usefulness when the central bank employs an interest rate rule we do not belabor these earlier points. Instead we concentrate on the contemporaneous signal value of money.

to a situation where the central bank was following a feedback rule that possessed desirable properties across a wide range of models. Using money as a signal of underlying state variables or of endogenous variables that may be part of some feedback rule could be helpful depending on how good a signal money is in practice. The value of that signal is directly related to the behavior of the demand for money.

To be more specific, consider a case where the monetary authority is following a rule in which the nominal interest rate target depends on output whose true value is never fully observed. Also, for simplicity assume that all variables are stationary and that output is the only endogenous variable not observed. That is, the price level, the interest rate, and nominal money are known. Simultaneously observing nominal M1, prices, and the nominal interest rate conveys the following signal,

$$s_m = (\hat{a} - a) + b(y_t - \bar{y}) + (\hat{b} - b)\bar{y} - (\hat{c} - c)\bar{R} + e_t,$$

where a bar over a variable indicates the variable's mean and a hat indicates an estimate of the parameter.[7] The monetary authority would in this case employ the Kalman filter to update its inference of output using the above signal. The precision of that estimate would depend on the variance of the money demand disturbance, which is directly related to how well money demand is behaved. It would also depend on the variance of the parameter estimates in the money demand regression.[8] In a case where the demand for money is stable, the variance of the parameters would get arbitrarily small as the sample size got larger. As more data were acquired, the estimation of the parameters would become more precise. Consequently, the signal content of money would then depend on whether one could well explain its current behavior. In a case where parameter estimates are time varying and unstable, the variance of the parameter estimates would not become arbitrarily small, and variability in the parameters would contaminate the signal value of money with respect to output.

The above explanation also applies to a situation where the variables are nonstationary and where perhaps all variables with the exception of the interest rate are observed with error. Whether money will be a useful signal of the level of income and prices will depend on how precisely it is measured and how precisely the cointegrating relationship is estimated. Thus, the stability properties analyzed in the previous section take on added significance apart from whether or not cointegration exists. The fact that the cointegrating vectors are unstable implies that money may provide a relatively poor signal of prices

[7] The signal is a first order linear approximation of the regression in equation (1).

[8] In the case where ouput is only observed with measurement error, the estimated coefficients will suffer from the effects of that measurement error as well.

and output. However, because the coefficients in the cointegrating relationship for M1 seem to be settling down and the rejection of stability was due to behavior in the early 1980s, the information contained in M1 may be more useful. In any event, how useful either monetary aggregate is will depend on the noise in its signal relative to the noise in other signals, such as reported output, that are available to the monetary authority.

## An Error Correction Representation

The central bank may be interested not only in money as a signal, but also in the growth rate of output and prices, both past and present. Examining an error correction representation of the demand for money is therefore necessary if we are to ascertain money's usefulness in communicating the values of these variables. We now turn to that exercise.

The error correction money-demand equations that we estimate are

$$m1_t = a_0 + b_0(cv_{t-1}) + c(L)\Delta y_{t-1} + d(L)\Delta m1_{t-1} - e(L)\Delta R_{t-1} + u_t \tag{2.1}$$

for $m1$ and

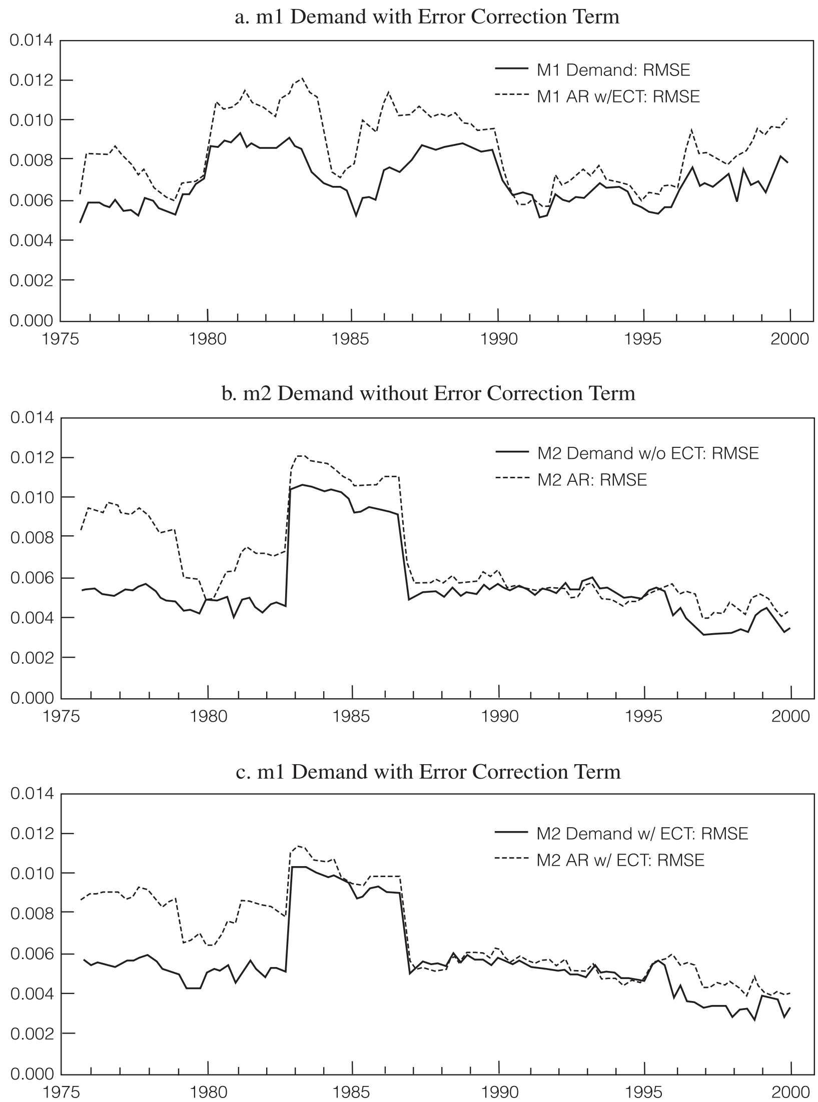
$$\begin{aligned} m2_t \;=\; & \alpha_0 + \beta_0(cv_{t-1}) + \gamma(L)\Delta y_{t-1} + \delta(L)\Delta m1_{t-1} - \epsilon(L)\Delta R_{t-1} \\ & -\zeta(L)(R_t - R_t^{M2}) + u_t \end{aligned} \tag{2.2}$$

for $m2$, where $cv_{t-1}$ is the error correction term. The $m2$ equation includes an additional term capturing the opportunity cost of holding balances in M2 that pay explicit interest. We also looked at the possibility of including polynomials in time, but they were found to be insignificant.

Using these equations we first ask if money demand was well explained at any given point in time. We do this by estimating 15-year rolling windows of money demand regressions and looking at the standard deviation of the residuals of those equations over 4 years.[9] We use rolling windows because of the voluminous amount of research indicating that these regressions are unstable over time. Later we confirm this instability. The results of this exercise are depicted in Figure 2, where the dates on the horizontal axis are the end dates of each sample period. Although we run the error correction models using rolling windows, we arrive at the estimates of the error correction terms, $cv$, recursively; the latter make use of all the available data up to the end date of the sample.

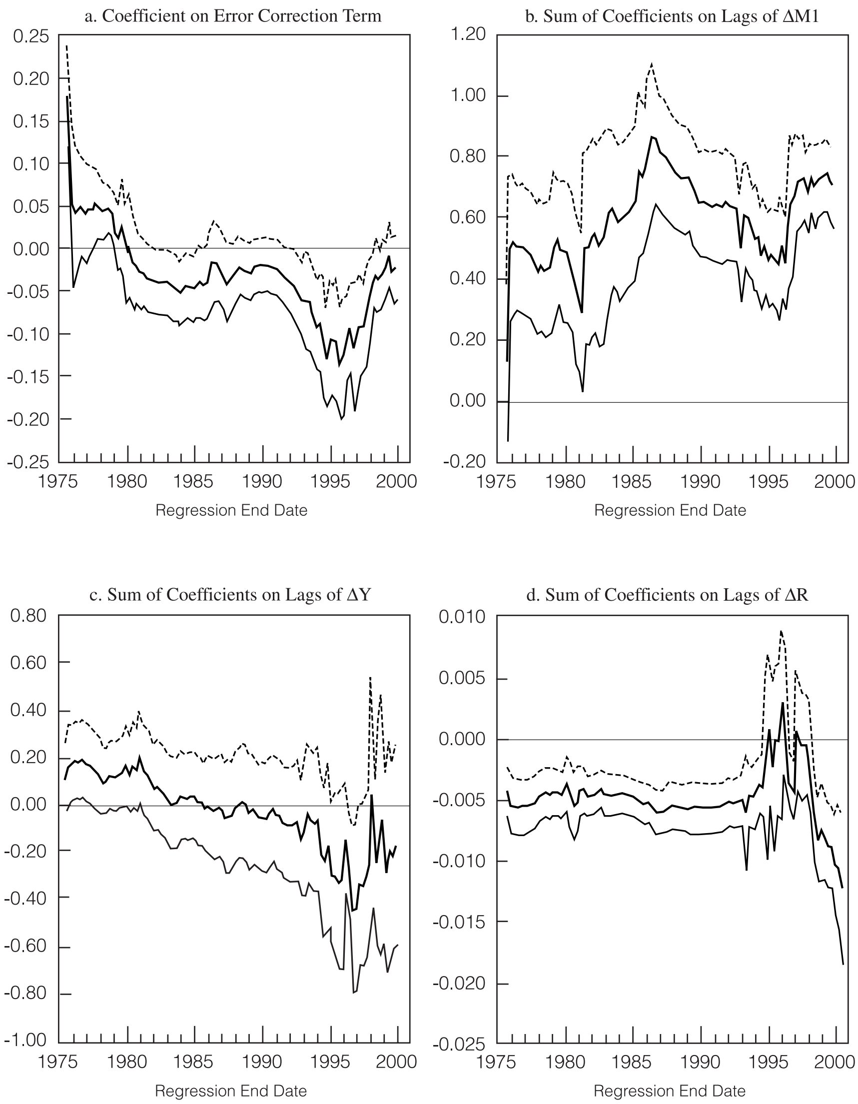
[9] All regressions are run using the robust errors routine in RATS, which corrects the standard errors of the regression coefficient when there is autocorrelation and heteroskedasticity in the errors.

**Figure 2 In-Sample RMSE**




This experiment shows how well the money demand regression explains the recent behavior of money. A benchmark is included that shows the errors occurring in a simple autoregression of money along with the error correction term. It is clear in the top panel that the ability of equation (3) to explain $m1$'s behavior varies over time with standard deviations ranging from approximately 40 basis points to 90 basis points. The early and mid-1970s reflect the best

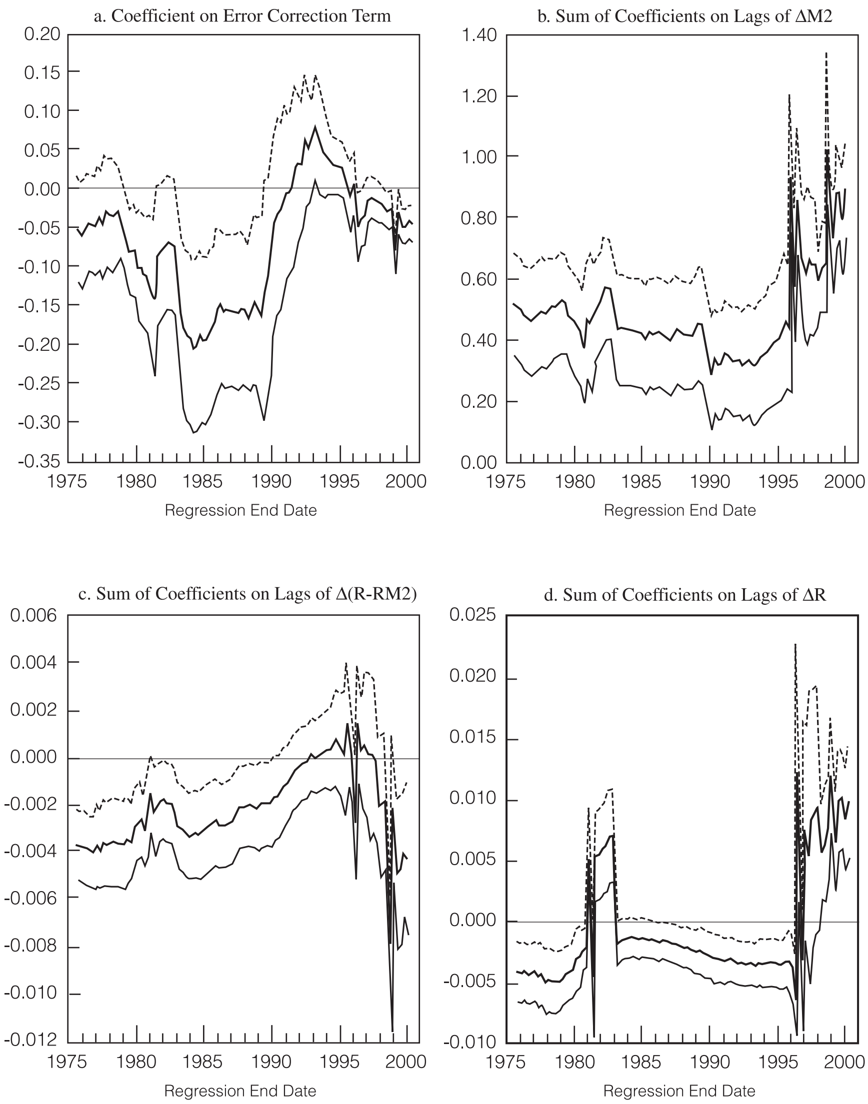
**Figure 3 Coefficients in m1 Rolling Regression**




performance of the regression and it is not surprising that this would be a period when monetary policy responded to M1 (see Hetzel [1981]).

Panel 2 of the figure examines M2's performance. Here the standard errors are slightly higher using $m2$ than $m1$. Also, the standard errors are relatively small at both the beginning and end of the sample, indicating that

**Figure 4 Coefficients in m2 Rolling Regression**




the $m2$ relationship was less variable in the 1970s and is currently fairly well behaved.

As we mention above, the signal content of money is related to the stability and the precision of the various coefficient estimates in the money demand regression. The value of the coefficients and their two standard error bands for the $m1$ regression are displayed in Figure 3. We do not display the constant since its value is small and insignificantly different from zero. If we exclude the end of the sample, the coefficients for the most part appear fairly stable. This stability was largely confirmed by the results of a time-varying parameter regression, but that regression did indicate statistically significant variation in the coefficient on the T-bill rate. We conduct a more formal test for stability in the presence of an unknown sample break using Andrews's (1993) sup Wald test. This test is basically similar to the SupF tests conducted in the previous section. To perform it, one constructs a Wald test for parameter constancy at each point on the interior of the data sample. A test statistic for the supremum of these values can be calculated, as can the statistic's critical values. In Figure 5, we graph the test statistic and the 5 percent critical value. The test rejects stability, with the rejection of stability arising from large values of the Wald statistic in the late 1960s and early 1970s. Between 1974 and 1993, the test statistic is below the 5 percent critical value.[10]

In Figure 4, we examine the behavior of coefficients in the M2 regression. The coefficients on the error correction term, the T-bill, $m2$, and the opportunity cost all show statistically significant variability. The coefficients on the last three variables fluctuate in the 1990s, but this high-frequency volatility did not have much influence on parameter estimates obtained using a time-varying parameter procedure. However, the Andrews test for stability (lower panel of Figure 5) does reject stability of the regression coefficients with the Wald statistic jumping above the 5 percent critical value in 1987.

The implications of this exercise for using money to help implement policy are decidedly mixed. For example, at times the demand for money appears to be well behaved, implying a close link between the behavior of money and the behavior of nominal output. At other times money demand is less predictable and the relationship appears unstable, implying that money may not be providing accurate information about the behavior of nominal income. Given this inconsistency and the desirability of following a simple and transparent rule of behavior, the central bank might reasonably decide not to use money in a feedback rule because the optimal response is likely to be time varying and difficult to explain.

The above findings do not imply that money serves no purpose. A number of economists recommend that the monetary authority respond to expectations of future variables such as expected future inflation.[11] In that regard money may communicate useful information about these variables. It is to this issue that we next turn.

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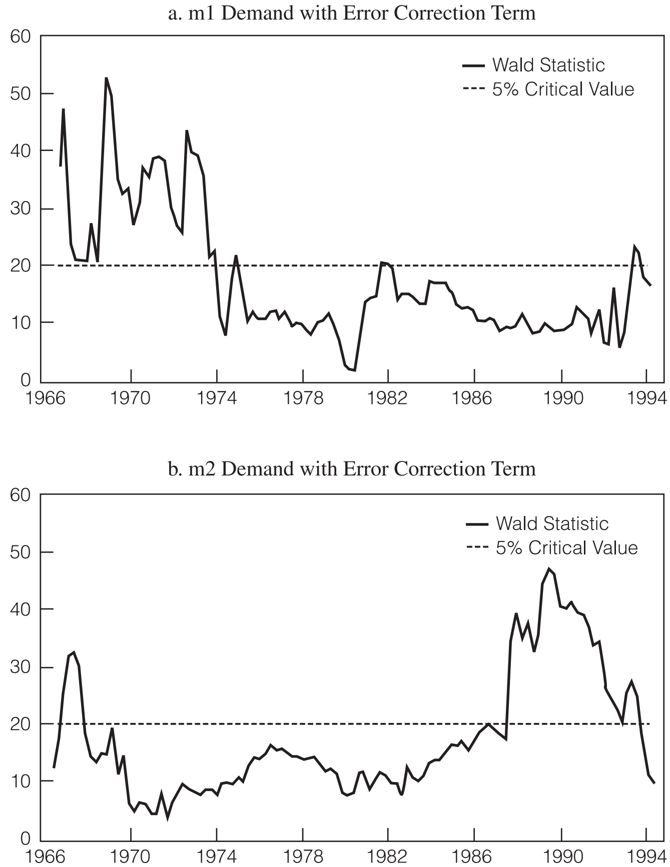
[10] Given instability and lack of significance of time in the full sample regression, we do not report any estimation using recursive procedures. It turns out that the in-sample errors using recursive regressions are similar to those of the rolling window regressions.

[11] Two recent articles that advocate such policies are Svensson (1999) and Amato and Laubach (2000).

**Figure 5 Results of Andrews's Test for Structural Break**




## 3. THE PREDICTIVE CONTENT OF MONEY

In this section we examine whether money has any useful predictive content for real GDP, nominal GDP, and inflation. As discussed in Dotsey and Otrok (1994), when the Fed uses an interest rate instrument that does not feed back on monetary variables, there may be a presumption against finding that money would Granger cause any of these variables. That presumption, however, is based on a number of restrictive assumptions, including the accurate observability of output and prices, that money balances do not serve in some buffer stock capacity, and that money demand shocks do not result from improvements in financial technology having significant effects on resource constraints. If observations on output and prices occur with significant lags and are subject to measurement error, then contemporaneous observation of money will be useful in solving the signal extraction problems faced by economic agents who are not completely informed. Therefore, observations on money will influence both agents' and the monetary authority's decisions and could help predict economic variables. Also, if agents accumulate money balances before engaging in expenditures, then large money balances today will indicate higher output in the future. Similarly, if changes in velocity are due to technological innovations that are persistent and affect resource availability, then observations on money will provide information about these innovations. An optimizing monetary authority should respond to these innovations, and hence money will have predictive content.[12]

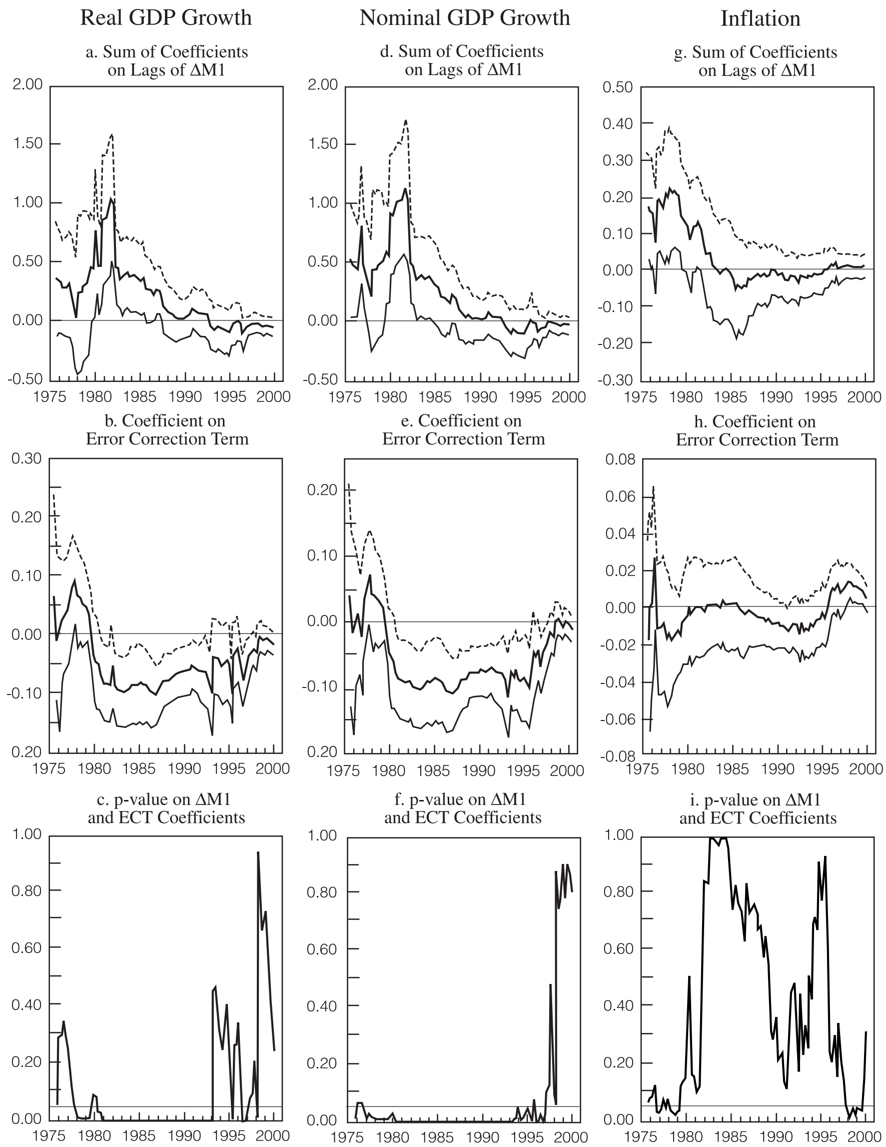
Figures 6 and 7 analyze the predictive content of M1, while Figure 8 investigates the predictive content of M2.[13] We should note that omitting the error correction term does at times worsen M2's forecasting ability. Figure 7 reports the same information regarding M1's predictive content, but also includes a time trend in the specification. This investigation follows from the recommendation of Stock and Watson (1989). The assumption that money is neutral in the long run implies that changes in trend money growth will not have any long-run consequences for output. In the short run the implications for changes in trend money growth could easily be quite different from those for cyclical changes. For example, in a model where firms change their prices only infrequently, the breakdown of how a change in money influences nominal income will in general depend on the persistence of the change in money growth (see Dotsey, King, and Wolman [1999]). If the change was perceived as either permanent or a change in trend, firms would be expected to aggressively change their prices, and the change in money growth would have a largely nominal impact. If the change was temporary or cyclical, the real effect could be significant. By putting a trend term in the forecasting equation, we are able to isolate the forecasting performance of cyclical changes in money growth.

We also conduct the analysis using 15-year rolling windows; as above, standard errors are corrected for the presence of heteroskedasticity and autocorrelation. We choose to use rolling windows based on evidence that the relationships are unstable. Our choice of a 15-year window is based on the results in Swanson (1998), who finds that 10-year rolling windows may be too short to give an accurate measure of the effect of money on industrial production. We also pick optimal lag lengths for each regressor using the Schwarz criteria.

[12] This is at least one of the theoretical messages in recent research by Dotsey and Hornstein (2000). Similarly, if money demand disturbances arise from shocks to preferences, the monetary authority will find it optimal to adjust the nominal interest in reaction to these disturbances or its best guess of these disturbances.

[13] The general forecasting model is an error correction specification where the growth rates of real and nominal GDP, as well as inflation, are regressed on a constant, an error correction term, lags of real GDP grouth, lags of money growth, lags of changes in the treasury bill rate, and lags of inflation.

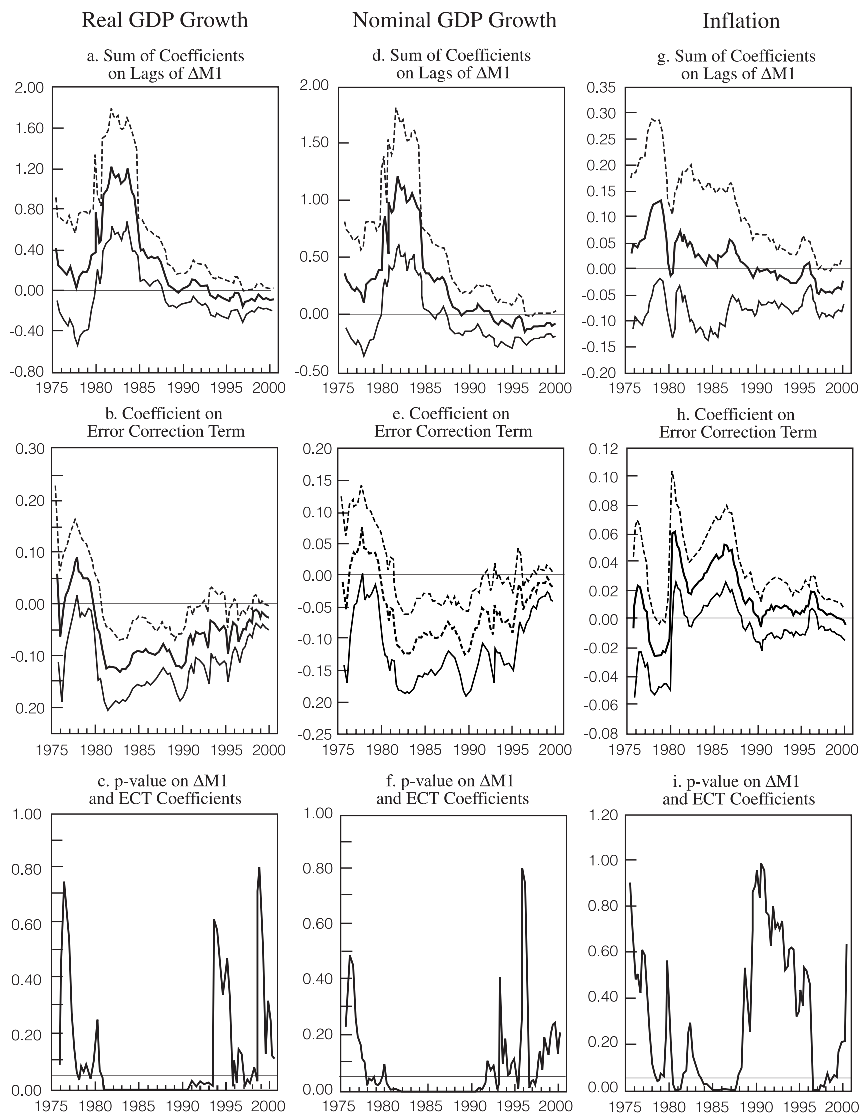
**Figure 6 Predictive Content of M1**




## Results for M1

Figure 6 indicates that M1 had significant predictive content for real GDP and nominal GDP during the late 1970s and 1980s, but that it no longer helps forecast one quarter ahead movements in either of these variables. This

**Figure 7 Predictive Content of M1 with Time Trend**




finding is consistent with those of Estrella and Mishkin (1997) and the 6 lag specification of Stock and Watson (1989), but differs from the latter's 12 lag specification and from the results reported in Friedman and Kuttner (1992). With 12 lags, Stock and Watson do not find that nominal M1 Granger-causes real output over their sample 1960:2 to 1985:12. Friedman and Kuttner do not find evidence of Granger-causality over the sample 1960:2 to 1990:4; however, they do find predictive content for M1 over the subsample that ends in 1979:3. The difference between our results and those of Friedman and Kuttner is largely due to two main differences in our methodologies. One difference is that we find $m1$ and $y$ to be cointegrated, and we therefore include an error correction term in the specification. The other is that we optimally select lag lengths; we generally end up with lags on M1 that are less than three quarters and often pick only one lag. Also, we look at rolling windows, but a recursive procedure produces results that are qualitatively similar. In the early part of the sample, much of the predictive content is coming from M1 growth, the sum of whose coefficients is positive and significantly greater than zero. In the 1980s much of M1's significance comes from the long-run or cointegrating relationship of real $m1$ with real output and interest rates. Interestingly this coefficient has a negative sign, which runs counter to the notion that M1 serves in a buffer stock capacity.

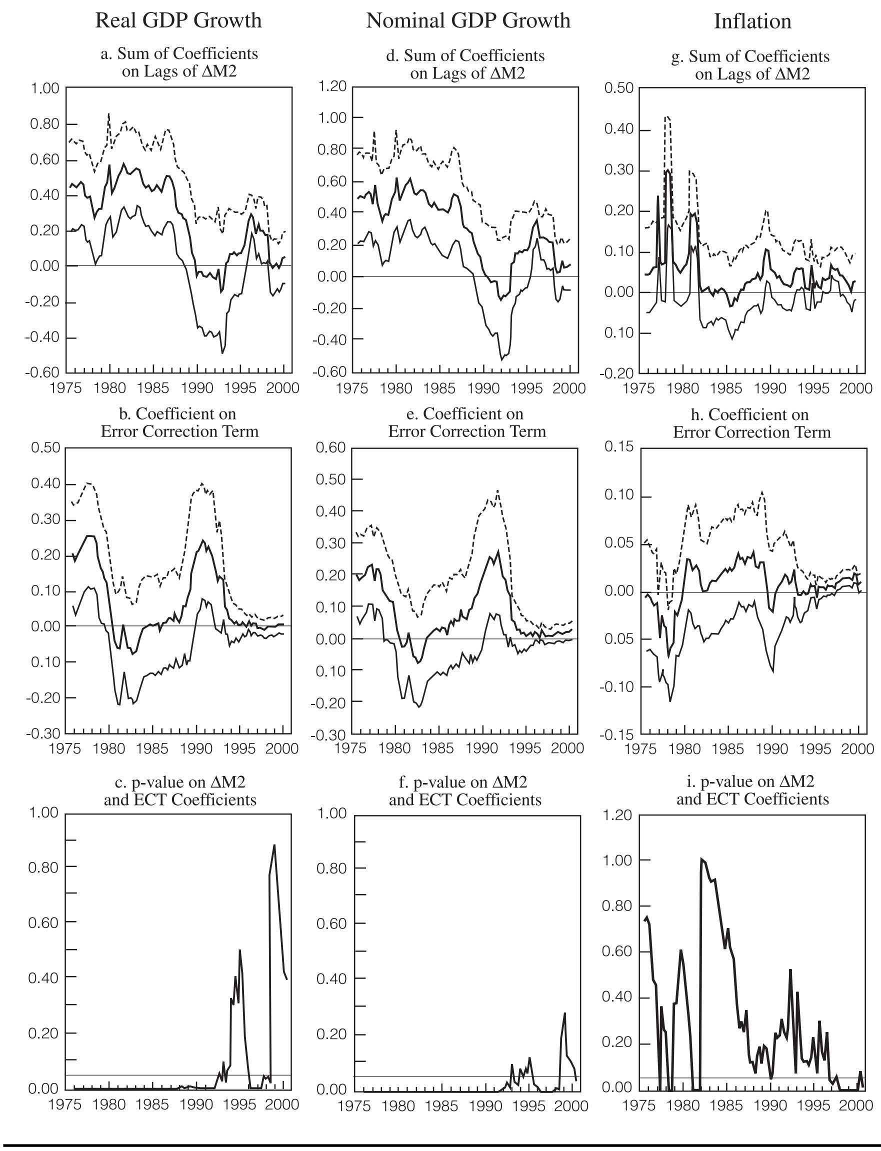
We also find that M1 helps predict nominal output through 1995 (see the middle column in Figure 6). This result is at odds with that reported in Feldstein and Stock (1994). We also observe that the behavior of M1 does not help forecast inflation (see the last column in Figure 6), which is consistent with the result reported in Cecchetti (1995).

Adding a time trend to the specification does not qualitatively have any impact on the results, which contrasts with the main message of Stock and Watson (1989). The contrast, however, could be due to lag length specifications because only Stock and Watson's 12 lag length specification produces the sharp differences in detrended versus raw money growth. Also, we include an error correction term, which would be picking up long-run relationships in both specifications. The inclusion of a trend term, therefore, may not have as much impact. Indeed, the coefficient on the trend term is insignificantly different from zero.

### Results for M2

In Figure 8, M2 appears to have significant explanatory power in forecasting real GDP in the 1970s and 1980s, although it is no longer very helpful in that regard. It does Granger-cause nominal output over most of the sample, but it does not help predict inflation until the very end of the sample (see the last column of Figure 8). Furthermore, in the regressions on all three dependent variables, the sum of the coefficients on lagged M2 growth is positive. The coefficient on the error correction term is often insignificantly different from zero, but it happens to be significant in just those periods when the sum of the coefficients on lagged M2 growth is not. Thus, adding an error correction term provides overall help in predicting the three economic variables of interest. The general lack of statistical significance in the error correction term, however, indicates that there is no compelling evidence that broader money serves

**Figure 8 Predictive Content of M2**




as a buffer stock either. This last result is consistent with that of McPhail (1999), who analyzes Canadian data.

Our result that M2 is helpful in predicting the behavior of real and nominal GDP is consistent with that of Feldstein and Stock (1994), Dotsey and Otrok (1994), and Swanson (1998), but differs from that of Friedman and Kuttner (1992). It is also not consistent with the results in Estrella and Mishkin (1997), who find that M2 does not help predict nominal GDP over the sample 1979:10 to 1995:12 and that M2 does not Granger-cause inflation. They use monthly data, nine monthly lags, and the CPI deflator to measure inflation, while we use quarterly data, the GDP deflator, and varying lag lengths that are optimized for each sample. By looking at a comparable quarterly specification, we find that both the presence of an error correction term and the optimization over lag lengths are responsible for the difference in results.

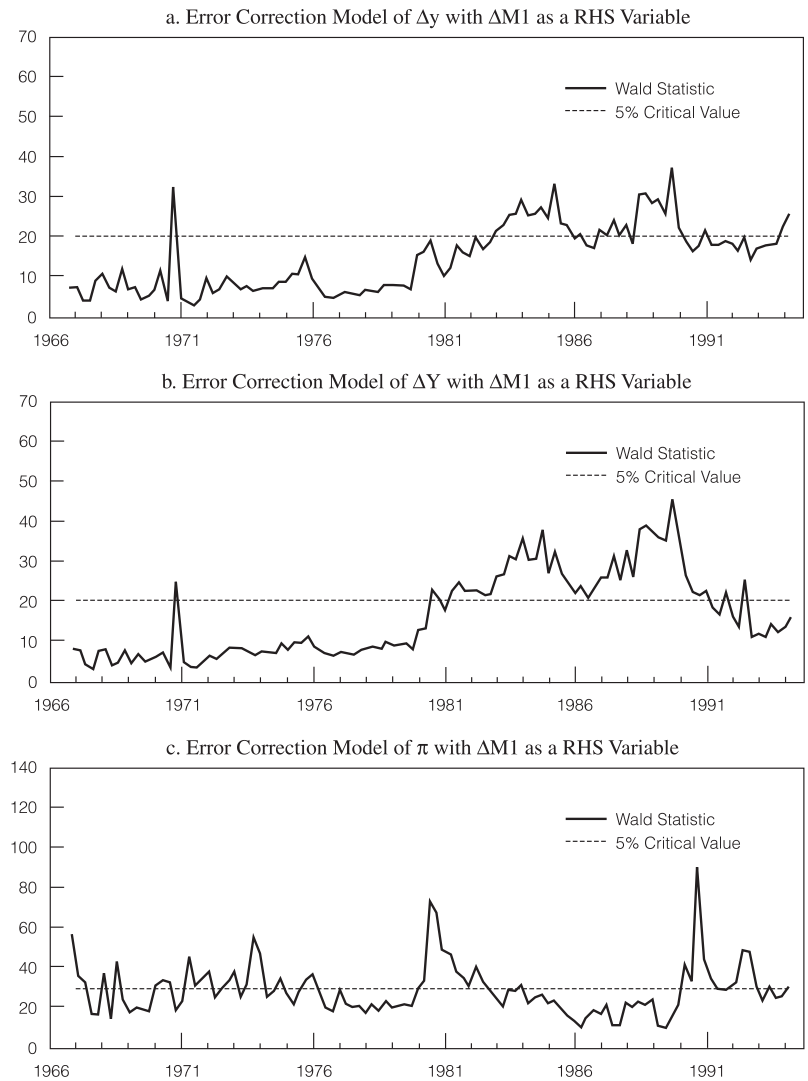
Our result that M2 does not help predict inflation is at first glance in conflict with the results presented by Cecchetti (1995) as well. He primarily looks at forecast horizons of a year and longer using monthly data, and he finds that M2 is significant for predicting inflation. He also finds evidence of instability in the relationship, with the worst predictive performance occurring between 1983 and 1989 although M2 is still significant at the 10 percent confidence level. If, however, we replace the GDP deflator with the PCE deflator, we find that M2 has significant predictive content for inflation over the 1990s, but fails to help predict inflation in the mid-1980s. One major difference between our study and that of Cecchetti is that the latter only includes M2 and lagged inflation in his specification, while the former also includes lagged interest rates and lagged output growth.

As with the results for M1, including a time trend does not appreciably affect the results of our study, so we do not report those results. There is, however, one particular change related to forecast horizon that makes a notable difference in our conclusions: In the context of predicting one-year-ahead nominal income growth using M2, M2 is always significant. The coefficient on the error correction term is large and significant in the late 1980s and early 1990s—just at a time when the coefficients on lagged M2 growth are insignificant. That is the only specification in which a monetary variable is uniformly informative about a potentially important macroeconomic variable. One should not get too excited about this result, however, because the coefficients move around a good deal and the relationship, while having good predictive ability, does not appear to be stable.

## Stability

Feldstein and Stock (1994) use a battery of stability tests and find that the relationship between M2 and nominal income is largely stable, although there may be some parameter instability regarding the constant term. Feldstein and Stock also indicate that the M1–nominal income relationship is unstable; Figure 9 is consistent with that result. We again use the Andrews sup Wald test and graph the $p$-values for the test of a sample break at each date on the chart. Figure 10 indicates a rejection of stability for the relationship between M2 and the three dependent variables, and therefore our results differ from those of Feldstein and Stock.

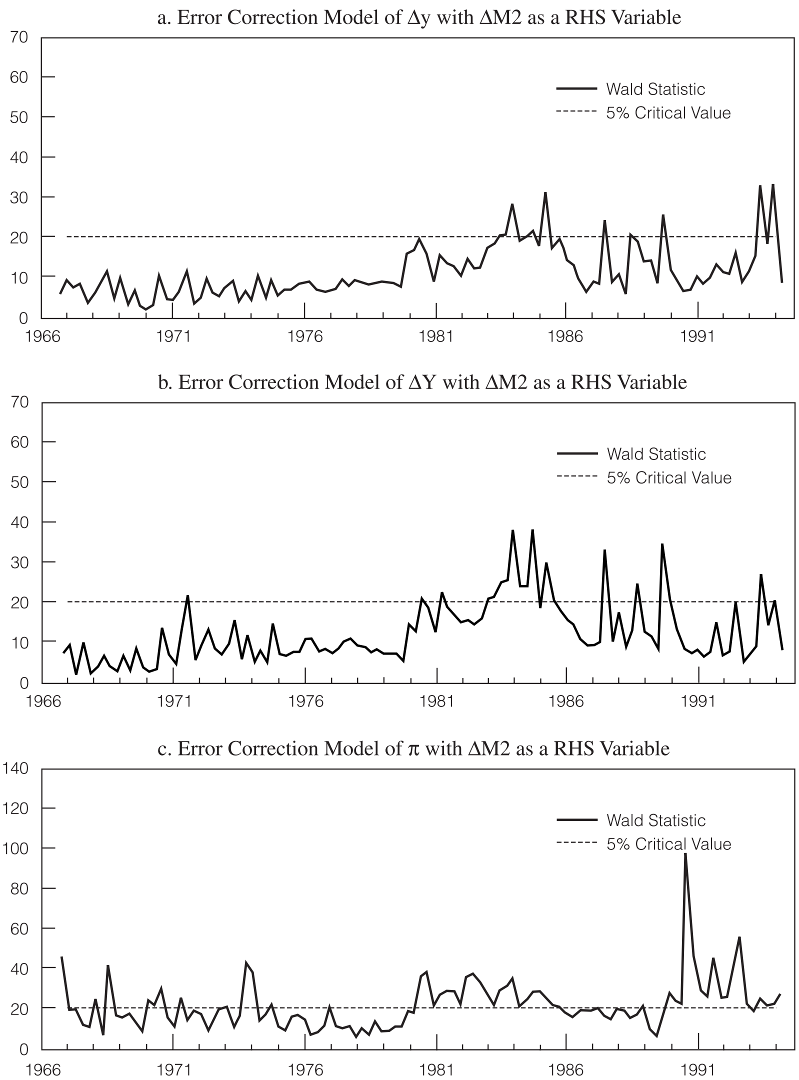
**Figure 9 Results of Andrews's Test for Structural Break**




## 4. SUMMARY

We have examined the behavior of both M1 and M2 with respect to their potential policy usefulness in providing information about contemporaneous but imperfectly observed variables or in helping to forecast future variables that may appear in an interest rate rule. As we show, the two notions are quite different and require different statistical investigations. By and large,

**Figure 10 Results of Andrews's Test for Structural Break**




the behavior of money itself is not reliable enough to advocate targeting either M1 or M2 or including them in a feedback rule. Their predictability varies substantially over time, and the coefficients in the various regressions we run do not appear to be stable. M1 and M2 do, however, seem to be useful in forecasting. Although their forecasting ability varies with time, the periods over which they often have significant predictive content can be prolonged enough to allow one to ascertain when those times occurred.

Even though the relationships we have investigated are not quite stable, much of their instability seems to be evolutionary in nature. That is, the changes in parameters appear to occur gradually. This fact suggests that a modeling strategy allowing the parameters to vary over time rather than holding them constant would better explain the behavior of the aggregates themselves and improve their forecasting ability. The biggest benefit to incorporating time variation might accrue from modeling the cointegrating relationship as evolving slowly over time. Using rolling windows and recursive estimation of the cointegrating relationship probably does not capture the behavior of money adequately. Financial innovations affect the behavior of money; these innovations are seldom radical and their adaptation is usually gradual. They are essentially an unobserved variable in the money demand regressions, and one hopes that future research will help account for their effects more thoroughly.

Furthermore, regulatory changes such as the elimination of regulation Q interest rate ceilings on personal checking accounts in 1981; allowing banks to offer MMDA accounts in 1983; changes in capital requirements that occurred in the late 1980s (see Lown et al. [1999]); and the relaxation of the use of sweep accounts in the 1990s have each had an impact on the demand for money. Some of these regulatory changes were no doubt reactions to technological changes that were taking place outside the banking sector, and thus they may be thought of as part of some endogenous process. Nevertheless, regulatory changes often have a discrete and uncertain impact on the demand for money. Policymakers are well aware of these changes, and modeling strategies can often be devised to incorporate them into the demand for money function; many, then, may view our investigation of money's usefulness as overly harsh. However, incorporating such regulatory changes formally into the behavior of money demand often requires a number of years of subsequent data, reducing the signal value of money during these episodes. For that reason, we refrain from accounting for the many regulatory changes occurring in the last 20 years. Nevertheless, we view our exploration of money's usefulness as a worthy exercise.

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