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ABSTRACT

This paper examines the problem of measuring the growth of a monetary aggregate in the presence of innovations in financial markets and changes in the relationship between individual assets and output. We propose constructing a monetary aggregate so that it is a good leading indicator of nominal GDP; in general the weights on its components vary over time. We investigate two specific procedures: one in which subaggregates discretely switch in and out, and one in which the growth of the aggregate is a time-varying weighted average of the growth of the subaggregates, where the weights follow a random walk. These procedures are used to construct aggregates which potentially augment M2 with stock and/or bond mutual funds. Over 1960-1991, the time-varying aggregates look much like M2, but during 1992-93 the time-varying aggregates outperform M2.

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1. Introduction

This paper addresses the problem of constructing a monetary aggregate when financial innovations change the relative importance of different monetary subaggregates. Our objective is to develop a procedure that automatically adjusts the composition of the monetary aggregate in a way that makes the resulting measure of the money stock a stable leading indicator of nominal GDP and potentially a useful control instrument for altering nominal GDP. Two alternative solutions to this problem are developed and applied to the U.S. experience over the past three decades.

Although we are very much aware that the link between M2 and nominal GDP has been far from perfect, we are nevertheless impressed by the evidence that this link has been sufficiently strong and stable in the past to make the existing M2 series a useful leading indicator of nominal GDP. More specifically, Feldstein and Stock (1994) found that the rate of change of M2 is a statistically significant predictor of the rate of change of nominal GDP over the period 1959-92. When short term interest rates are added to the relation, M2 remains statistically significant although interest rates add marginally to the equation's predictive power. Our earlier analysis also showed that the strength and historical stability of this relationship implies that, if the Federal Reserve were able to control M2 optimally, then both the long-term average rate of inflation and the variance of the annual growth rate of nominal GDP could be reduced. Although there is a danger that attempting to use M2 to control GDP would weaken that relation (the "Goodhart's law" problem), the potential gain appears to be large enough to make further analysis of the control possibility worthwhile.

In practice, the current broad monetary aggregate M2 has been redefined by the Federal Reserve on several occasions. For example, M2 was expanded to include money market deposit accounts and, subsequently, money market mutual funds. The apparent weakening of the relation between the existing M2 measure and nominal GDP that began in 1992, along with the rise in M2 velocity since 1990 in the face of low and falling interest rates, has caused some analysts to conclude that M2 should be expanded again to incorporate bond and stock funds (see Duca (1993) and Orphanides, Reid and Small (1993) for discussions of this proposal). Such changes in the definition of the monetary aggregate are potentially appropriate when households and businesses substitute existing or new financial instruments for previous components of the monetary aggregate. Money market deposit accounts and money market mutual funds were new financial instruments that households could easily substitute for small time deposits. More recently, households have begun to substitute highly liquid bond and stock funds for shorter maturity money market funds. Since the substitutions are never complete or perfect, the desirability of expanding or redefining the monetary aggregate is an empirical issue.

The decision to redefine the monetary aggregate involves three questions. First, does the proposed new aggregate have a stronger and more stable leading relation with nominal GDP than the existing monetary aggregate? Second, would a decision by the Federal Reserve to shift from the old aggregate to the new alternative weaken public confidence in the Federal Reserve's determination to control the money stock and thereby to limit the rate of inflation? And third, would the new monetary aggregate be more difficult to control than the old one?

The methods described in this paper revise the definition of the monetary aggregate when the rate of growth of the resulting new aggregate would have a stronger relation to the rate of growth of nominal GDP. More specifically, the analysis relates the quarterly rate of growth of nominal GDP to distributed lags of past growth of nominal GDP and the monetary aggregate. The monetary aggregate is changed when the new monetary aggregate improves the ability of that relation to explain changes in nominal GDP.[1]

The timing procedures that we discuss are non-judgmental. Given a list of possible monetary subaggregates (e.g., the existing M1, small denomination time deposits, overnight repurchase agreements, money market deposit accounts, money market mutual funds, bond funds, etc.), the procedure would automatically decide which ones should be included in "the" monetary aggregate or how much weight should be assigned to each. This inclusion or weighting decision varies with time. If the list of possible subaggregates is specified in advance, the fact that these changes in the definition of the monetary aggregate are generated by a pre-established rule should reduce suspicion that the redefinition of the aggregate reflects an attempt by the Federal Reserve to avoid a previous commitment to control the growth of the monetary aggregate and thus the future rate of inflation. Indeed, even if the procedure that we develop produced the same redefinitions of the monetary aggregate as the Federal Reserve would choose judgementally, the ability to arrive at those changes by a prespecified set of rules would be desirable. Alternatively, these procedures can provide a framework for initiating Federal Reserve discussions about changing the monetary aggregate and a standard by which to evaluate judgmental decisions about including or excluding a particular subaggregate.

There is frequently a tradeoff between the controllability of a monetary aggregate and the strength of its link to nominal GDP. Advocates of controlling the monetary base (e.g., McCallum (1988, 1990)) emphasize that it is directly controlled by the Federal Reserve, unlike any of the broader monetary aggregates. Similarly, the Federal Reserve has been much better able to control M1 than any broader aggregate because reserve requirements are based on the non-currency components of M1 while the components of M2 that are not in M1 are no longer subject to reserve requirements. This may explain why the Shadow Open Market Committee and others have focused on the growth of M1. While it is true that the monetary base and M1 are now more controllable by the Federal Reserve than M2, the evidence that we have examined (Feldstein and Stock, 1994, section 6) indicates that the predictive content of these narrower aggregates is much less than the predictive content of M2. Expanding reserve requirements to all of M2 would make it possible for the Federal Reserve to control M2 over any period of more than one or two months (Feldstein (1993)).

In designing our current procedures for redefining the monetary aggregates we have not given explicit attention to the controllability of the resulting aggregate. Indeed, one set of experiments in the current paper considers aggregates which include bond and stock mutual funds. Direct control of the size of these funds is well outside the range of current policy options facing the Fed. This raises the question of how one should interpret the shift by one of our automatic procedures to a monetary aggregate which includes bond and stock funds, since a switch from M2 to M2 plus stock and bond funds is a move away from controllability. One interpretation of such an automatic switch is that this is signalling to the Fed that control of M2 should be deemphasized and replaced with an alternative rule or judgmental procedure, perhaps one based on interest rates. In this sense, the composition of the appropriate aggregate can be interpreted as an indicator of when a monetary aggregate rule may or may not be appropriate. We provide evidence on the magnitude of the improvement in predictability that is achieved by using a less controllable index than M2. However, we do not examine systematically the relative degree of controllability (using interest rates as well as reserves) of M2 and the broader aggregates considered here.

The current paper considers two quite different approaches to redefining the monetary aggregate. The first approach regards the appropriate aggregate as an unweighted sum of certain monetary subaggregates and considers once each quarter whether the set of those subaggregates that is defined to constitute the monetary aggregate should be expanded or reduced in order to improve the predictive link between that overall aggregate monetary stock and nominal GDP. For example, before 1983 the broad M2 money stock did not include money market mutual funds. The "switching regressions" procedure presented in secnon 2 considers the possibility of adding the money market mutual funds to the narrower pre-1983 aggregate each quarter until the procedure indicates that it is desirable to do so. The results of this approach, presented in section 3, are quite similar to the actual timing decision of the Federal Reserve in expanding the definirion of M2 to include the money market mutual funds. These results also indicate that expanding the aggregate further to include bond and stock funds would now improve its predictive content but would not have done so in 1989.

The second approach models the growth of the monetary aggregate as a weighted sum of the growth of certain monetary subaggregates and reestimates optimal weights each quarter. This "time varying parameter" procedure, described in section 4, changes the relative importance of different subaggregates over time and allows new subaggregates to be introduced. Although previous researchers have constructed monetary aggregates with time varying weights (e.g., Barnett (1980), Spindt (1985), Driscoll, Rotemberg and Poterba (1991), and Barnett, Fisher and Serletis (1992); also see Friedman and Schwartz (1970, ch. 4.1) for a discussion of unequal weighting schemes), those weights were based on a priori theoretical considerations. Despite this virtue, these alternative aggregates have met with limited empirical success and have not been widely adopted by practitioners; see for example Lindsey and Spindt (1986) and Fisher, Hudson and Pradhan (1993). In contrast, the present paper constructs the aggregate to optimize a prediction function that causes the weights to vary over time. The results of this analysis are presented and discussed in section 5.

Notably, we find empirically that the TVP monetary aggregate is similar to the unweighted inclusion-exclusion aggregate derived by the switching regressions method. Despite the differences in the two techniques, the quantitative similarity of the resulting series suggests that this approach is robust to changes in its implementation.

2. Switching Regression Model of a Monetary Indicator

The switching regression model provides a framework for making discrete additions of a new component to an existing monetary indicator. The implementation here assumes that there is a natural order in which to introduce subaggregates into the indicator. For example, in the first empirical application we consider the mutually exclusive subaggregates M1, those subaggregates in M2 excluding M1 and money market mutual funds (MMMF's), and MMMF's. Consequently the decisions modeled are when (if ever) to switch from M1 to an aggregate which is M2 excluding MMMF's, and subsequently when (if ever) to include MMMF's in M2. This assumption could be relaxed but only at considerable computational cost (each additional switching option increases the number of regressions by approximately a factor of the sample size).

Let Z_{it}, $i = 1,\ldots,I$ denote the level of the i-th monetary subaggregate, and suppose that Z_{it} are mutually exclusive. Let S_{it} be the sum of the first through i-th monetary subaggregates, so $S_{it} = \Sigma_{j=1}^{i} Z_{jt}$, and let $s_{it} = \Delta \ln S_{it}$. The growth rate of the monetary indicator is defined by

$$m_t(\tau_1,\ldots,\tau_{I-1}) = s_{1t}1(t<\tau_1) + s_{2t}1(\tau_1 \leq t < \tau_2) + \ldots + s_{IT}1(\tau_{I-1} \leq t) \tag{2.1}$$

where $1(t<\tau_1)$ takes on a value of one if $t<\tau_1$ and is zero otherwise, etc. Thus the monetary indicator is defined in terms of the growth rates of the increasing family of aggregates S_{it}, where the indicator switches from the (i-1)-th to the i-th aggregate at date τ_{i-1}.[2]

The switching dates are estimated by selecting those dates which produce the aggregate with the greatest ability to forecast GDP growth in a stable forecasting relation. Let $x_t = \Delta \ln GDP_t$. Here, we consider the bivariate forecasting equation,

$$x_t = \mu + \alpha(L)x_{t-1} + \gamma(L)m_{t-1}(\tau_1,\ldots,\tau_{I-1}) + \epsilon_t. \tag{2.2}$$

Thus the forecasting relation between the monetary indicator $m_{t-1}(\tau_1,\ldots,\tau_{I-1})$ and GDP growth, conditional on lagged GDP growth, is assumed to be stable. The standard switching regression model has the same set of regressors, with coefficients that change at an unknown date. In contrast, in (2.2) the coefficients are stable and the only time-varying feature is the monetary aggregate itself.

The switch dates are estimated by least squares. Let $SSR(\tau_1,\ldots,\tau_{I-1})$ denote the sum of squared residuals from estimating (2.2) by OLS, given $\tau_1,\ldots, \tau_{I-1}$. The switch date estimator solves,

$$\min_{\tau_1<\ldots<\tau_{I-1}} SSR(\tau_1,\ldots,\tau_{I-1}). \tag{2.3}$$

If $\{Z_{it}\}$ are strictly exogenous and the errors are i.i.d. Gaussian, then this procedure would yield the maximum likelihood estimators of the switch dates. More plausibly, $\{Z_{it}\}$ are predetermined but not exogenous and there is no reason to believe the errors to be Gaussian, in which case one might consider other estimators. An alternative would be to choose $\tau_1, \ldots, \tau_{I-1}$ to minimize a multistep ahead forecast error.

One would of course like to be able to perform statistical inference on the estimated switch dates, in particular testing the hypothesis that there is no switch and constructing confidence intervals for the switch dates in the event that there has been a switch. These questions have been studied in the related change-point problem. In the change-point model, statistical significance can be studied using maximal Wald or likelihood ratio statistics, or using related tests with explicit break dates; see for example Andrews and Ploberger (1992). Also, nonstandard techniques can be used to construct confidence intervals for a break date (Picard (1985), Bai (1993)). However, the structure of the problem at hand is sufficiently different that these results do not apply directly (here, the coefficients are constant and the series itself is changing, while the reverse is true in the change point literature). We hope to be able to provide results about inference in this model at a later date.

3. Empirical Results: Switching Regression Model

The switching regression procedure is examined by performing two experiments. Following Orphanides and Porter (1993), we first examine the switch from M1 to M2 (excluding MMMF's) and the subsequent decision to incorporate MMMF's into M2. The second examines whether M2 might usefully be extended to include bond, or bond and stock, mutual funds. The data are quarterly, 1959:1 to 1993:4. Quarterly money quantities are the monthly average for the final month in the quarter. Our data on MMMF's begin in 1975:2, and the stock and bond mutual fund data begin in 1976:1; these are the first dates at which the instruments are permitted to enter the switching regression aggregate.[3] All regressions are executed for samples starting in 1960:2, with earlier observations used for initial conditions for lagged variables.

A. Results for M1, M2 ex MMMF, and M2

For this experiment we set S_1 = M1, S_2 = M2 excluding MMMF's, and S_3 = M2. Using data through 93:4, the least-squares estimator of the break dates, based on two lags each of x_t and the monetary aggregate in (2.2), are $\hat{\tau}_1$ = 71:3 and $\hat{\tau}_2$ > 93:4. Thus, through 1969:4 the selected monetary aggregate is M1 and thereafter it is M2 excluding MMMF's. The growth rates of the resulting series and M2 are plotted in figure 1.

These results are based on all the data through 1993:4. A natural question is what aggregate this procedure would produce were it run in real time. This question is addressed by using this algorithm to estimate the break dates for samples with terminal dates running from 1978 to 1993. The results are summarized in table 1. For example, using data from 1959:1 to 1978:4, the best indicator would have switched from M1 to M2 ex MMMF's in 1971:3, then would have included MMMF's starting in 1975:4. During 1982, the best indicator would have excluded MMMF's, and subsequently MMMF's reenter only after the recovery from the second early-80's recession is under way. From 1983:3 through 1993:3, the aggregate would have included MMMF's, although MMMF's would have been dropped in 1993:4. However, it should be noted that the objective function is very flat in 1993:4 and the full-sample estimates $\hat{\tau}_1$ = 71:3 and $\hat{\tau}_2$ > 93:4 produce a sum of squared residuals which is less than 0.02% smaller than for $\hat{\tau}_1$ = 71:3 and $\hat{\tau}_2$ = 83:1, the optimal choice for the subsample through 89:4. Thus, with even a very small penalty for switching (which one might plausibly introduce), the real-time aggregate would not have switched and instead would have continued to include MMMF's since 83:1. Mechanically, the reason the procedure drops MMMF in 1993:4 is that during the 1990's M2exMMMF was growing more rapidly than M2 (see figure 1) so the increase in M2exMMMF velocity was not as sharp as for M2 velocity. Thus M2exMMMF was a better predictor than M2 over this episode.

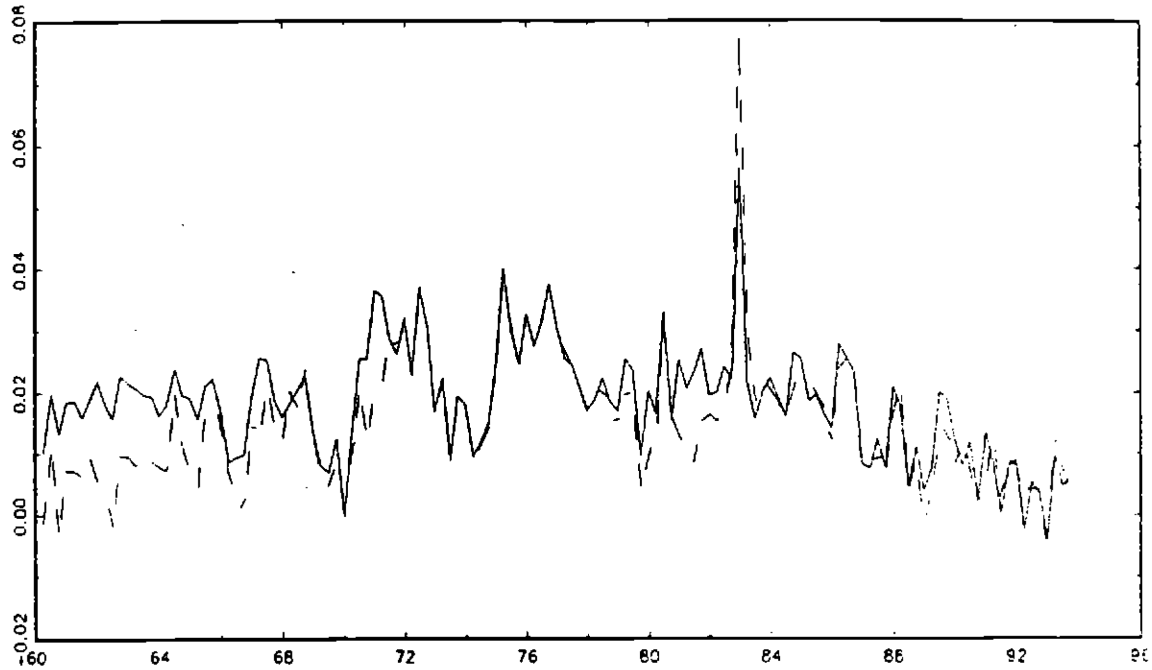


Figure 1
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Historical series produced by switching regression model.

Full-sample estimates, 1960:2 - 1993:4

Subaggregates: M1, M2 ex MMMF, M2

Table 1
Recursive Estimation of Switching Model of Monetary Aggregate

Aggregates: M1, M2exMMMF, M2

End of Sample	Switch from M1 to M2exMMMF	Switch from M2exMMMF to M2
78:4	71:3	75:4
79:4	71:3	75:4
80:4	71:3	80:2
81:4	71:3	80:1
82:4	71:3	--
83:4	71:3	83:1
84:4	71:3	83:1
85:4	71:3	83:1
86:4	60:4	83:1
87:4	71:3	83:1
88:4	71:3	83:1
89:4	71:3	83:1
90:4	60:4	83:1
91:4	60:4	83:1
92:4	60:4	83:1
93:1	60:4	83:1
93:2	60:4	83:1
93:3	60:4	83:1
93:4	71:3	--

Notes: Each row presents results from estimating the switching regression procedure summarized in (2.1) - (2.3) using data from 1960:2 to the date in the first column. The two estimated switch dates for the regressions with that final date are reported in the next two columns. A dashed line indicates that the switch did not occur during the sample.

The growth rate of the monetary aggregate produced by this recursive procedure is plotted in figure 2. This aggregate was computed supposing that it is redefined quarterly; for example, the aggregate reported in 1978:4 would have been M2 because the recursive estimate of the break dates would have placed both M2exMMMF's and MMMF's in the aggregate prior to 1978:4, as indicated in the first row of table 1. Evidently, the simulated real time aggregate is very similar to M2 itself, with the main exception being 1982, when MMMF's would not have been included and when the aggregate would have grown more slowly than did M2.

B. Results for Bond and Stock Mutual Funds

The second experiment examines whether an alternative aggregate based on M2 and stock and bond mutual funds could be a better economic indicator than M2 alone. Specifically, we consider results based on the subaggregates M2, bond mutual funds (MFB), and stock mutual funds (MFS), added sequentially, so that S_1=M2, S_2=M2+MFB, and S_3=M2+MFB+MFS. The full-sample OLS estimates of the break dates are $\hat{\tau}_1$=89:1 and $\hat{\tau}_2$=89:3. Historical values of this series are plotted in figure 3. Evidently, the only substantial difference between M2 and the switching-regression aggregate is the higher growth rate of the alternative aggregate since 1991.

The results of the recursive simulation, in which the break dates were estimated over subsamples with increasing terminal dates, are summarized in table 2. The results indicate more revisions of the historical series than in the experiment with MMMF's. Through the mid-1980's, the simulated real-time series would have included both bond and stock funds. Not surprisingly, both bond and stock funds would have been dropped after the stock market crash in the final quarter of 1987. This is evident in the plot in figure 4 of the simulated real-time monetary aggregate which this procedure would produce. The stock market crash resulted in a large decline in this monetary aggregate; the decline was not associated with subsequent reductions in output, so stock funds were automatically dropped from the series in 1988:2 and were not reintroduced until 1990:1.

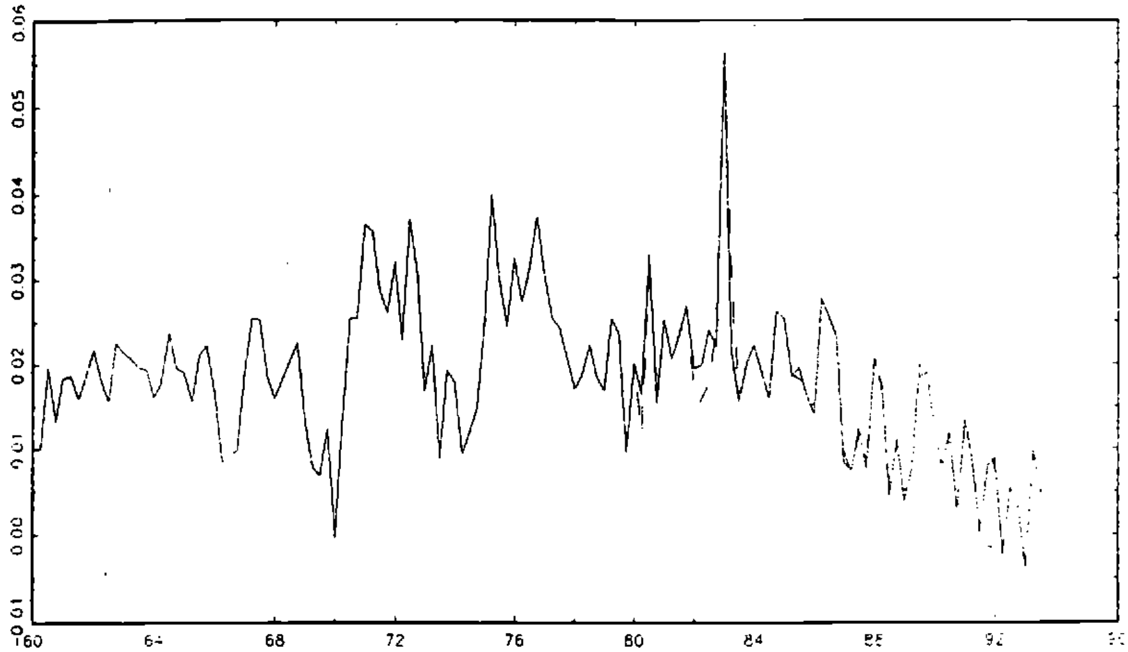


Figure 2
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Simulated real-time series produced by switching regression model.

Recursive estimates for samples from 1960:2 - 1978:4 through 1960:2 - 1993:4

Subaggregates: M1, M2 ex MMMF, M2

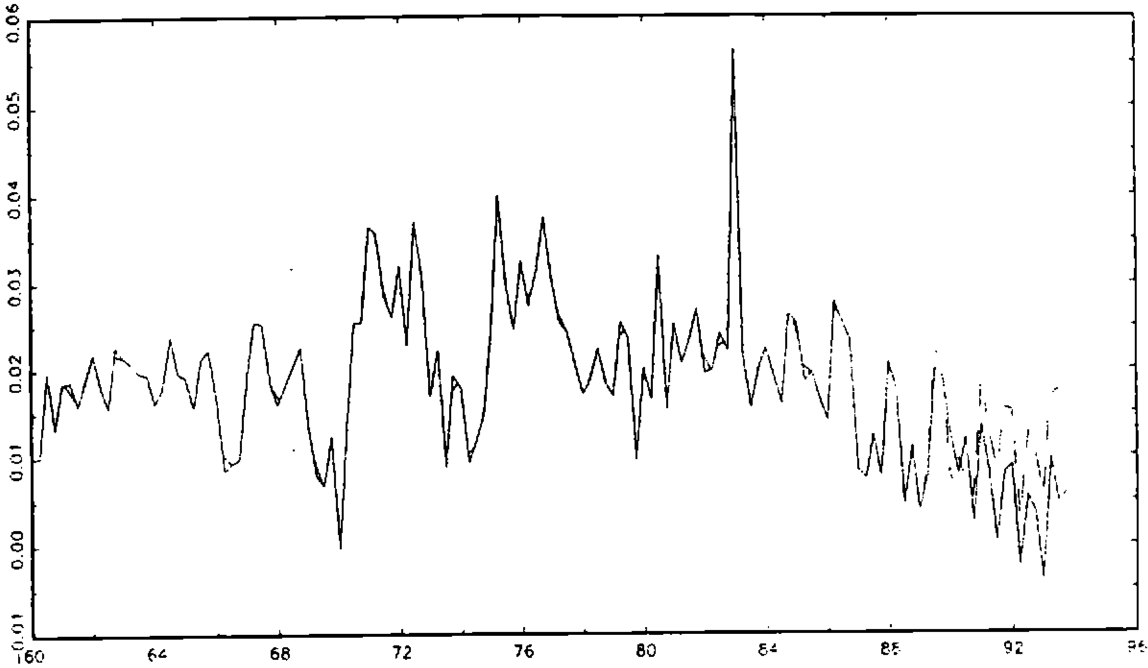


Figure 3
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Historical series produced by switching regression model.

Full-sample estimates, 1960:2 - 1993:4

Subaggregates: M2, M2+MFB, M2+MFB+MFS

Table 2
Recursive Estimation of Switching Model of Monetary Aggregate

Aggregates: M2, M2+MFB, M2+MFB+MFS

End of Sample	Switch from M2 to M2+MFB	Switch from M2+MFB to M2+MFB+MFS
78:4	77:4	78:2
79:4	77:4	78:2
80:4	77:4	78:2
81:4	77:4	78:2
82:4	77:4	78:2
83:4	77:4	78:2
84:4	77:4	78:2
85:4	77:4	78:2
86:4	--	--
87:4	87:1	87:2
88:4	--	--
89:4	89:3	--
90:4	89:1	89:3
91:4	89:1	89:3
92:4	89:1	89:3
93:1	89:1	89:3
93:2	89:1	89:3
93:3	89:1	89:3
93:4	89:1	89:3

Notes: see the notes to table 1.

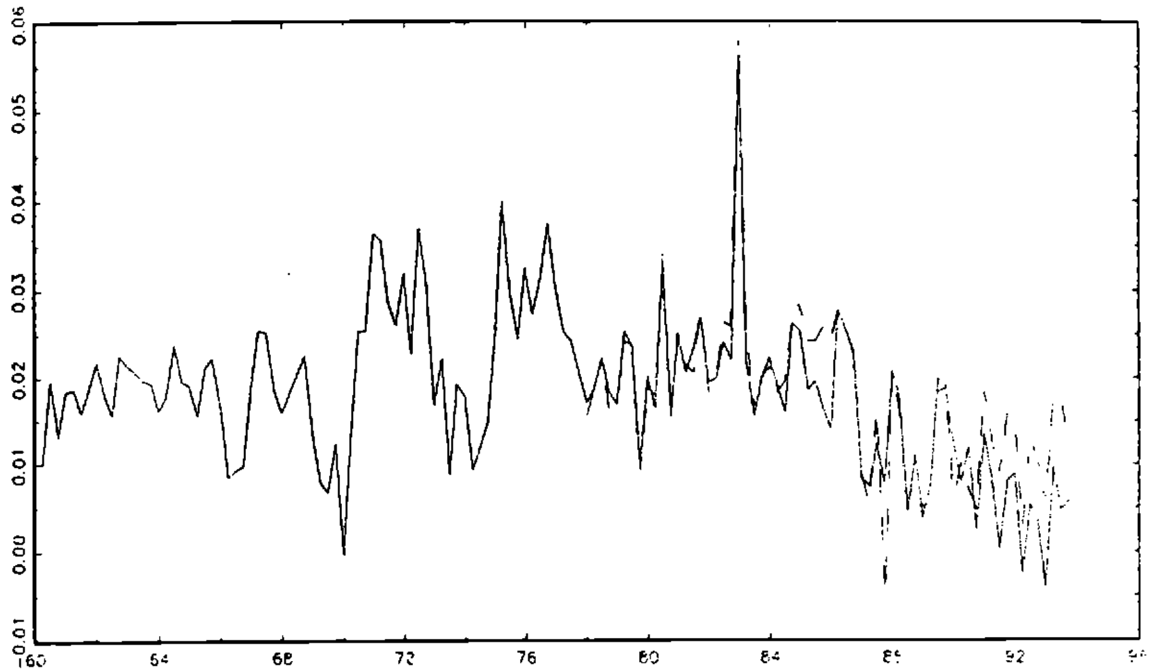


Figure 4
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Simulated real-time series produced by switching regression model.

Recursive estimates for samples from 1960:2 - 1978:4 through 1960:2 - 1993:4

Subaggregates: M2, M2+MFB, M2+MFB+MFS

4. Time-Varying Parameter Model of a Monetary Indicator

The time varying parameter (TVP) model provides an alternative framework for measuring the rate of change of a monetary aggregate with stable indicator properties. In contrast to the switching model of section 2, the TVP model produces a series in which the weights on the subaggregates vary over time but in general are neither zero nor one. The growth rate of the aggregate is constructed as a weighted average of the growth rates of the subaggregates. To a first order, the growth rate of a conventional aggregate such as M2 can be approximated as a weighted average of the growth rates of its components, where the weights are the time-varying shares of the components in the total aggregate. Weighted averages of growth rates are also used in the monetary services and transaction cost index approaches. For example, Barnett's (1980) Divisia monetary aggregate is constructed in growth rates as a time-varying weighted average of the growth rates of the subaggregates, where the weights depend on the subaggregate's expenditure share based on user costs. Our TVP approach allows the weights on the components to differ from their shares by choosing them to produce an aggregate with a stable predictive relationship to GDP. The use of growth rates here is mainly for computational convenience, since this produces a model which is linear in the (unrestricted) parameters. An advantage of the TVP model over the switching model of the previous section is that there is a well-developed theory of inference in the model, and in particular the Kalman filter produces estimates of standard errors on the time-varying weights.

The standard time-varying parameter model proposed by Cooley and Prescott (1973a, 1973b, 1976), Rosenberg (1972, 1973) and Sarris (1973) has time variation in all of the regression coefficients. In contrast, the statistical model considered here presumes a stable relation between the monetary aggregate and output, so only the weights used to construct the aggregate vary over time. The model is, (4.1a) $\quad \Delta x_t = \alpha_0 + \alpha(L)\Delta x_{t-1} + \gamma(L)(\beta_t' z_{t-1}) + \epsilon_t, \ \epsilon_t$ i.i.d. $N(0, \sigma_\epsilon^2)$

where x_t is the logarithm of nominal GDP and z_t is the vector of first differences of logarithms of the various mutually exclusive subaggregates. The weights β_t are assumed to evolve as,

(4.1b) $\quad \beta_t = \beta_{t-1} + \eta_t, \ \eta_t$ i.i.d. $N(0, \sigma_\eta^2 I)$

where ϵ_t and η_t are independent. The monetary aggregate is $m_t^* = \beta_{t+1}' z_t$. The subaggregates z_t are specified in growth rates. Thus the growth rate of the aggregate is a weighted average of the growth rate of the subaggregates, with weight vector β_{t+1}.

In this model, β_t is an unobserved random variable so the monetary aggregate m_t^* technically is not observable. However, β_t can be estimated using the full data set. Let $\beta_{t|T}$ denote the estimate of β_t given data through time T (that is, given all the available data). Then the estimated monetary aggregate is,

(4.2) $$m_{t|T}^* = \beta_{t+1|T}' z_t.$$

Note that $\beta_{T+1|T} = \beta_{T|T}$, so for the final observation $m_{T|T}^* = \beta_{T|T}' z_T$.

If all the subaggregates exist over the entire time period, then the dimension of z_t is constant. In practice, however, over time new financial instruments become available. This is handled by permitting the dimension of z_t and β_t to expand when a new instrument is introduced, a modification which is conceptually straightforward using the Kalman filter.

Econometric implementation of (4.1) and (4.2) entails the estimation of the parameters of the model and then, given the parameters, obtaining the estimates $\beta_{t+1|t}$ and $\beta_{t+1|T}$ and thereby constructing the aggregate (4.2). It is convenient first to discuss the second of these problems, the construction of $\beta_{t+1|t}$ and $\beta_{t+1|T}$ given the parameters.

The parameters of the model consist of $\theta = (\alpha_0, \alpha(L), \gamma(L), \beta_0, \sigma_\epsilon^2, \sigma_\eta^2)$. Given θ, $\beta_{t+1|t}$ and $\beta_{t+1|T}$ respectively can be estimated using the Kalman filter and the Kalman smoother for the TVP model. The state vector consists of $(\beta_t', \beta_{t-1}', \ldots, \beta_{t-p}')'$, where p is the order of $\gamma(L)$. The state transition equation is (4.1b), augmented to handle the lags of β_t. The measurement equation is (4.1a). This constitutes a standard state space model so the Kalman filter and smoother can be applied directly to yield estimates of β_t and its standard error; see for example Harvey (1989). The only remaining issue is the choice of initial conditions for the filter. The convention adopted here depends on the subaggregate. For subaggregates which exist at the beginning of the sample, $\beta_{0|0}$ is set to the share of each subaggregate in the total, so that the first-period growth rate equals the growth rate of an aggregate which is equally weighted in levels. For subaggregates introduced after the beginning of the sample, the initial weight on a new aggregate is set to zero. In both cases the element of the state covariance matrix corresponding to this weight is set to zero in its initial period. The choice of initial conditions has only transitory startup effects, and unreported experiments indicated that our empirical results are insensitive to these initial condition assumptions. Also, for producing the aggregate, the weights are normalized to add to one in each period; that is, the weights used are $\beta_{t|T}/\Sigma_{i=1}^{I}\beta_{it|T}$, where $\beta_{t|T}$ are the weights produced by the Kalman smoother.

For our main results, θ is estimated by maximum likelihood. The Kalman filter as just described produces as a byproduct the value of the Gaussian likelihood given θ, and the MLE is obtained by maximizing this likelihood. The likelihood was optimized using a simulated annealing algorithm, modified with a local quadratic search routine.

One part of the analysis, the construction of a simulated real time monetary aggregate, does not use the MLE's. The simulated real time monetary aggregate is produced by reestimating the parameters every quarter, so that each quarter the data set increases by one observation; the weights on the subaggregates for the final period of the subsample, based on these reestimated parameters, is then used to construct the simulated real-time monetary aggregate. In the empirical work, the simulated real time period extends for more than a decade, entailing numerous parameter reestimations. The computationally intensive Kalman filter MLE's are therefore impractical. Instead θ was reestimated by nonlinear generalized least squares (NGLS). In brief, if the regressors are strictly exogenous, the NGLS estimator would be approximately equivalent to the MLE, where the approximation arises by setting for numerical convenience $\gamma(L)(\beta_t'z_{t-1}) = \beta_t'(\gamma(L)z_{t-1})$. This introduces approximation error into the model, but this error will be small if $\gamma_j^2\sigma_\eta^2\mathrm{var}(z_{it})/\mathrm{var}(\epsilon_t) << 1$ for $j \geq 2$, $i = 1,\ldots, I$. This condition is satisfied in the empirical work where this ratio is typically less than 1%. With this assumption and the identity $\beta_t = \beta_0 + \Sigma_{s=1}^t \eta_s$, the model (4.1a) and (4.1b) can be rewritten,

$$\Delta x_t = \alpha_0 + \alpha(L)\Delta x_{t-1} + \gamma(L)(\beta_0' z_{t-1}) + u_t, \tag{4.3}$$

where $u_t = (\Sigma_{s=1}^t \eta_s)'(\gamma(L)z_{t-1}) + \epsilon_t$. The nonlinearities come through two restrictions: the restriction $\gamma(L)\beta_0'$ places on the unrestricted coefficients on the lags of z_t, and the restriction that $\gamma(L)$ appears in both the mean and the conditional covariance matrix of $(u_1,\ldots,u_T)$. If $\{x_t, z_t\}$ were strictly exogenous, then feasible nonlinear GLS would yield the Gaussian MLE. This is readily implemented numerically by (i) obtaining preliminary estimates of $\alpha(L)$, $\gamma(L)$ and β_0; (ii) computing the $T \times T$ variance-covariance matrix of $(u_1,\ldots,u_t)$ and inverting it; (iii) using this to compute the one-step NGLS estimator, imposing the conditional mean restrictions implied by $\gamma(L)\beta_0'$; and (iv) iterating on this until convergence. This NGLS algorithm was used to produce the subsample estimates in the simulated real time experiment. Because $\{x_t, z_t\}$ are only predetermined but not strictly exogenous, this algorithm does not produce the MLE here. However, using the full sample the point estimates from the NGLS algorithm are similar to the MLE's, as are the implied historical monetary aggregates; this suggests that the simulated real time results are insensitive to the use of the NGLS estimator rather than the MLE.

5. Empirical Results: TVP Model

A. Results for M1, M2 ex MMMF and M1, and MMMF's

The first experiment considers an aggregate, the growth of which is a time-varying linear combination of the growth rates of M1, M2R = M2 excluding MMMF and M1, and MMMF. For the initial years after their introduction, the value of MMMF's was small so small changes in their value resulted in large changes in their growth rates and hence the growth rate of MMMF's has a large variance in these early years. We therefore chose 80:1 as the first quarter in which MMMF's could enter the monetary aggregate m_t^*; that is, through 79:4, we set the weight on MMMF's in m_t^* to zero.

Three sets of MLE's, computed over the full sample, are given in table 3. In the first two columns σ_η was restricted to .025 and .05, respectively; in the third column, σ_η was estimated along with the other parameters. Notably, the point estimate of σ_η is very small, so that the estimated weights vary trivially over the sample. However, the values of the likelihood are relatively close, suggesting that nonzero values of σ_η are also plausible. (Formal distribution theory of the likelihood ratio test statistic when the true value of σ_η is nearly zero appears to be unavailable so we are unable to produce formal confidence intervals for σ_η.) The subsequent results therefore focus on the cases with nontrivial movements in β_t in the first two columns.

Results for the case $\sigma_\eta = .025$ are presented in figures 5 and 6. Figure 5a presents the smoothed estimates of the weights, $\beta_{t|T}$. Because these weights are on growth rates, they are not immediately comparable to the unit weights on the dollar-valued levels of the various components actually used to construct M2. To provide a basis of comparison, figure 5b plots the effective weights on the growth rates of the components in M2 based on the first order approximation $\Delta \ln M2_t \doteq \sum_{i=1}^{3} \bar{\beta}_{it} z_{it}$, where $\bar{\beta}_{it} = Z_{it-1}/\sum_{i=1}^{3} Z_{it-1}$. The smoothed estimate of the resulting monetary aggregate, $m_{t|T}^*$, is plotted in figure 6. The results for σ_η = .05 are presented in figures 7 (weights) and 8 (the monetary aggregate). The smoothed weights and their standard errors are tabulated in appendix table A-1 for σ_η = .025.

Table 3

MLE Parameter estimates: TVP model

Three subaggregates: M1, MMMF, and M2R = M2-M1-MMMF

Estimation period: Quarterly, 60:2 - 93:4

Notation: $\alpha(L) = \sum_{i=1}^{k}\alpha_i L^i$, $\gamma(L) = \sum_{i=1}^{k}\gamma_i L^i$

Parameter	(1)	(2)	(3)
α_0	0.0066 (0.0026)	0.0079 (0.0027)	0.0049 (0.0025)
α_1	0.118 (0.091)	0.104 (0.097)	0.141 (0.085)
α_2	0.040 (0.089)	0.053 (0.091)	0.043 (0.085)
α_3	0.039 (0.081)	0.019 (0.081)	0.065 (0.079)
γ_1	0.190 (0.083)	0.142 (0.065)	0.233 (0.110)
γ_2	0.173 (0.110)	0.130 (0.103)	0.191 (0.112)
γ_3	0.079 (0.093)	0.052 (0.074)	0.111 (0.108)
σ_ϵ	0.00852 (0.00054)	0.00837 (0.00058)	0.00869 (0.00054)
σ_η	0.025[a]	0.05[a]	0.00008 (0.00784)
2xlog likelihood	1144.115	1143.214	1146.144

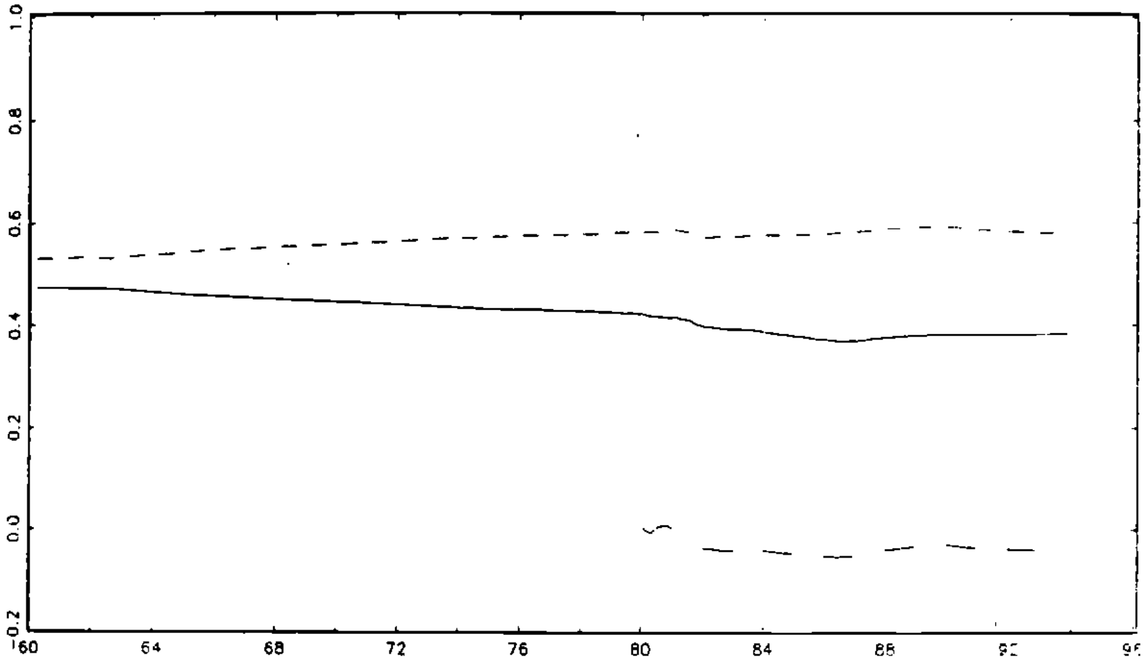
Notes: Parameters were estimated by maximum likelihood using the Kalman filter. The likelihood was maximized by simulated annealing with a minimum of 10,000 evaluations for each optimiziation.

[a]value imposed.

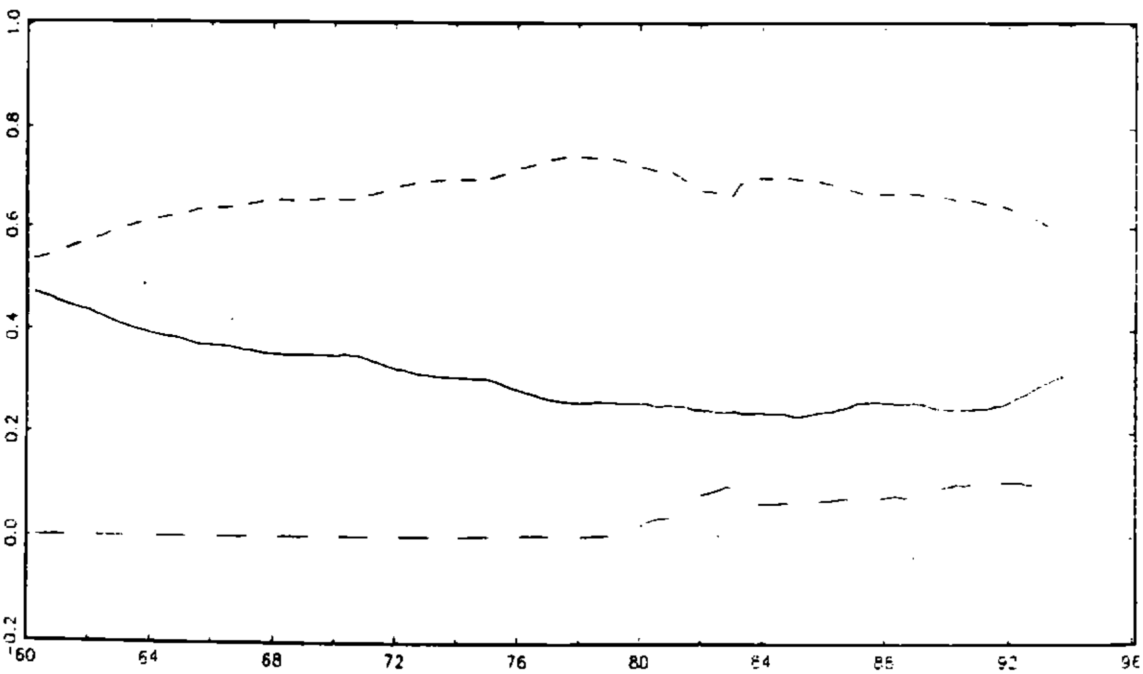
Figure 5
Weights on Alternative Monetary Aggregate and M2
Subaggregates: (i) M1, (ii) M2 ex M1, MMMF (iii) MMMF (80:1 start); σ_η = .025; 3 lags

Key: (i) solid line; (ii) short-dashed line; (iii) long-dashed line

(a) Time-varying weights, alternative monetary aggregate



(b) Implicit weights on growth rate, M2 (current definition)



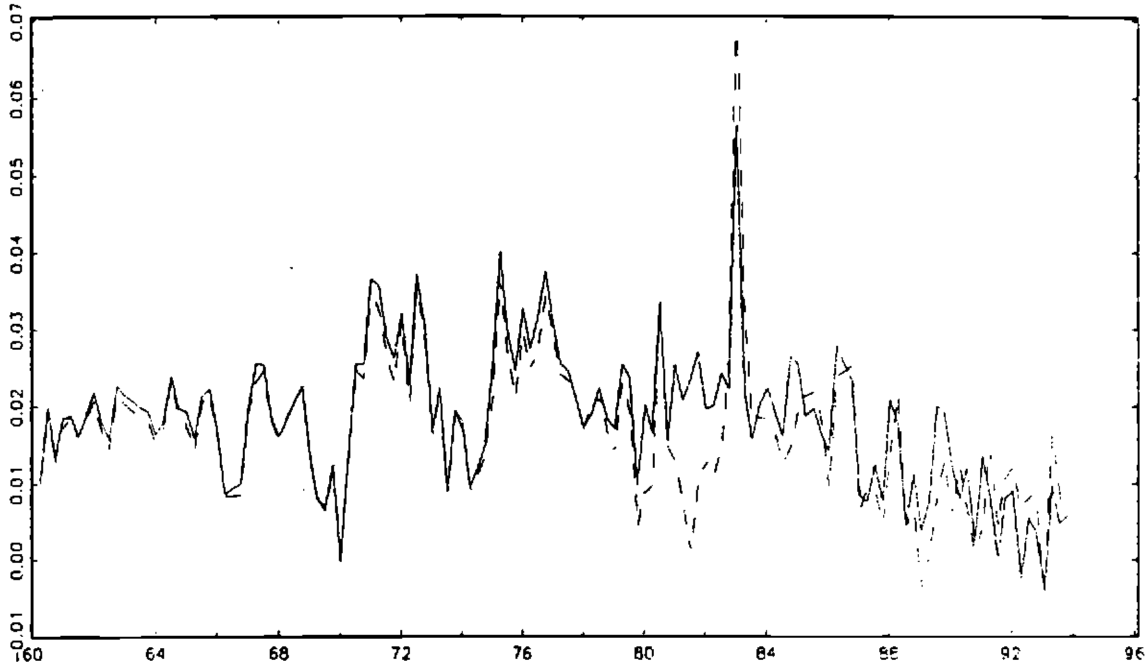


Figure 6
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Historical series produced by TVP model.

Full-sample estimates, 1960:2 - 1993:4

Subaggregates: M1, M2 ex M1 and MMMF, MMMF; σ_{η} = .025, 3 lags

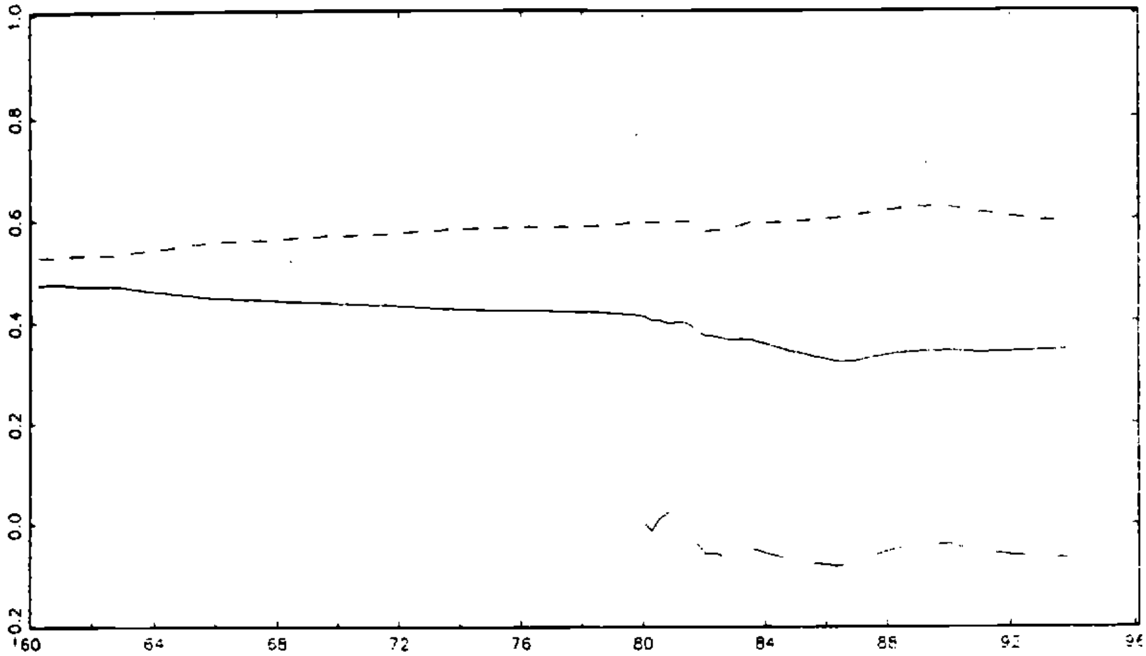
Figure 7

Weights on Alternative Monetary Aggregate and M2

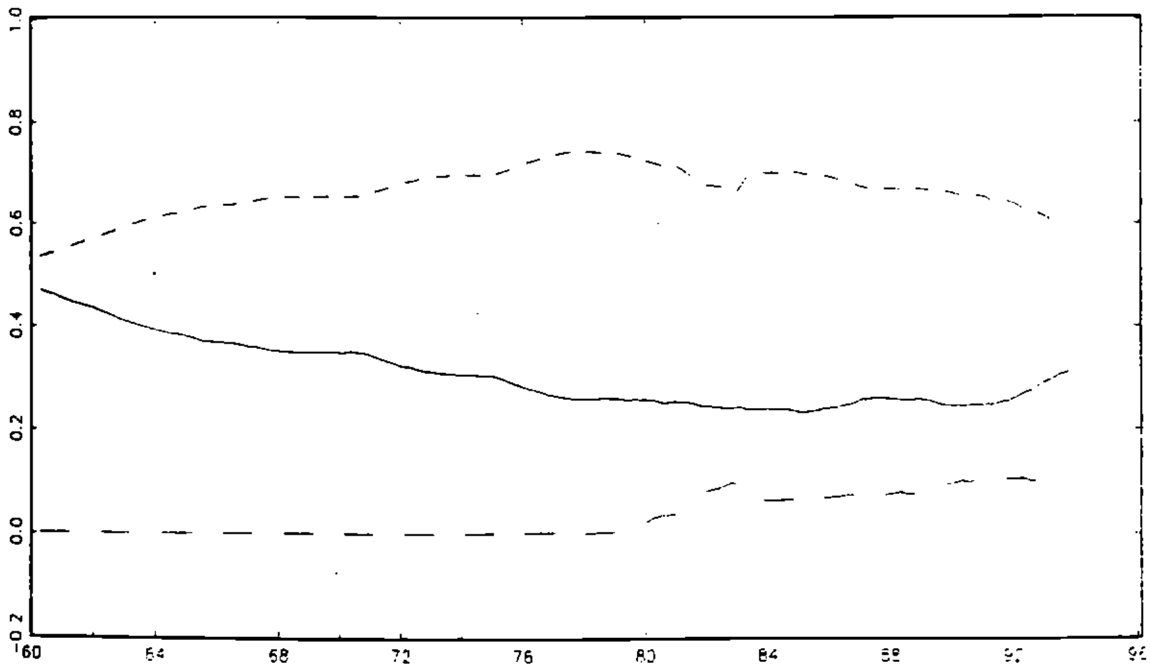
Subaggregates: (i) M1, (ii) M2 ex M1, MMMF (iii) MMMF (80:1 start); $\sigma_\eta = .05$; 3 lags

Key: (i) solid line; (ii) short-dashed line; (iii) long-dashed line

(a) Time-varying weights, alternative monetary aggregate



(b) Implicit weights on growth rate, M2 (current definition)



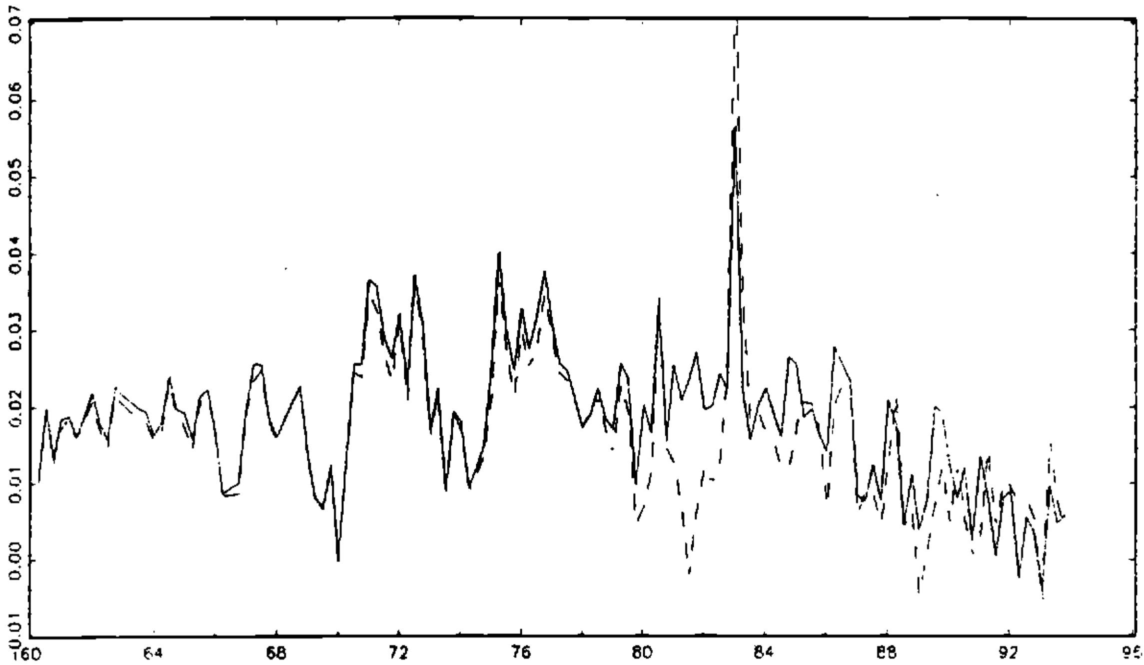


Figure 8
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Historical series produced by TVP model.

Full-sample estimates, 1960:2 - 1993:4

Subaggregates: M1, M2 ex M1 and MMMF, MMMF; σ_η = .05, 3 lags

Consider first the results for $\sigma_\eta = .025$ in figures 5 and 6. Overall, the pattern of weights placed on the subaggregates by the TVP model is broadly similar to the pattern of implicit weights they receive in M2. In both aggregates M2R receives the greatest weight, followed by M1 and MMMF's. However, there are some important differences in the weights in specific episodes. Although MMMF's receive similar weights in the two aggregates in the late 1980's, during most of the sample the weight placed on MMMF's is less than the weight with which it implicitly enters the M2 growth rate. In fact, for several years, including 1991 and 1992, the weight placed on MMMF growth is actually negative, so that a decline in MMMF's *increases* the growth of this monetary aggregate, and during this period the weight given M1 slightly increases. However, this result should not be overinterpreted, since the weights on the individual components are rather poorly estimated; for example, the smoothed TVP weight on MMMF's in 1991:1 is -.04 with a standard error of .09. More importantly, the estimated new aggregate and M2 are similar over most of the period, as can be seen from figure 6. The greatest discrepency between the two is during the 1981-1982 recession, when the new aggregate grew approximately six percentage points (annual rate) more slowly than M2, and during the final two years of the sample, when its grows somewhat more rapidly than M2.

When the smoothing parameter is increased to $\sigma_\eta = .05$, the weights in the TVP model are more variable, but the results remain similar to those for $\sigma_\eta = .025$. Importantly, even though the weights differ in the two cases, comparing figures 6 and 8 shows that the estimated monetary aggregates are robust to this change in σ_η. With some important episodic differences, the main conclusion is that the new aggregate is quite similar to M2.

Our TVP model presumes that the relation between the monetary aggregate and output is stable. This is an overidentifying restriction in the model and therefore can be tested. To check for instability in the presumed time-invariant parameters α_0, $\alpha(L)$, $\gamma(L)$, and σ_ϵ^2, we reestimated the model by maximum likelihood (imposing $\sigma_\eta = .025$) on the first and second halves of the data set (through 1992:4), that is, over 1960:2 - 1976:3 and over 1976:4 - 1992:4. The resulting likelihood ratio statistic, which has a χ_8^2 distribution, is 6.89 which has a p-value of .55. This provides no evidence against the overidentifying restriction that the time variation enters only through the weights β_t.

We next consider how this procedure would have worked in a simulated real-time setting, in which the parameters as well as the weights are reestimated in each period. For this exercise, $\alpha(L)$ and $\gamma(L)$ were estimated by NGLS for the various subsamples. The results are summarized in figure 9, for the case $\sigma_\eta = .05$. In general the monetary aggregates are close to M2 and close to each other. The greatest differences between the aggregates and M2 are for the early samples, where there is the least data and presumably the greatest sampling error in the estimation of the parameters. All subsamples which include the early 1980's yield TVP aggregates which have slower growth than M2 during the 1980-82 period.

B. Introduction of Stock and Bond Mutual Funds

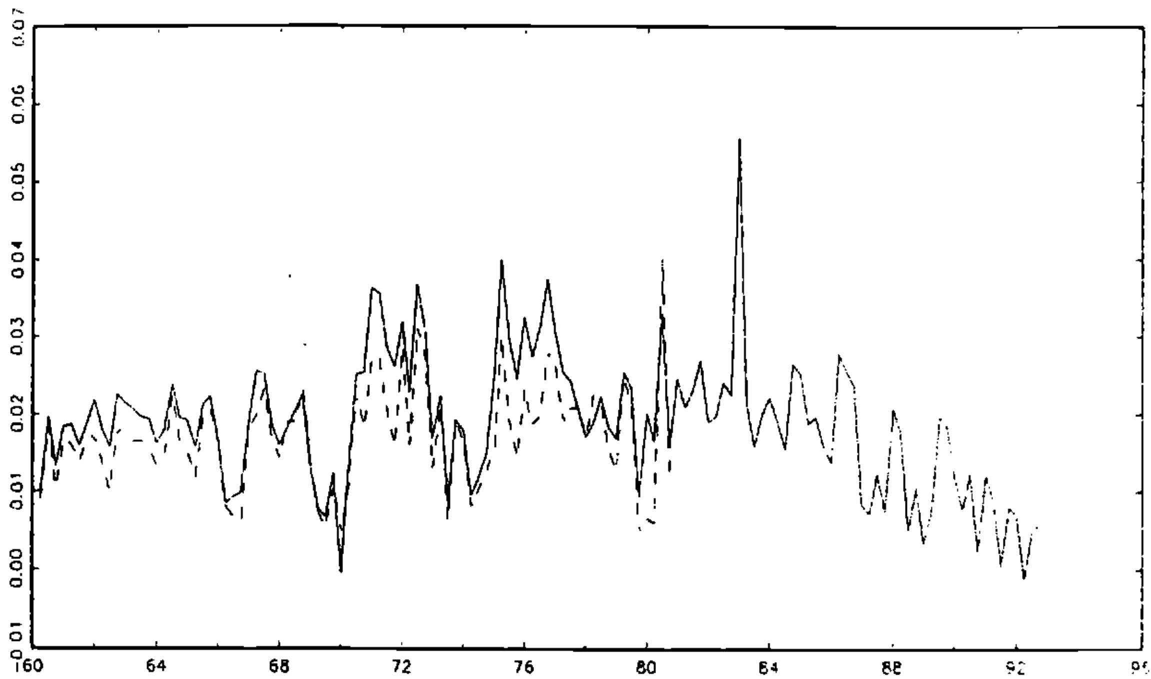
The three mutually exclusive subaggregates considered here are M2, bond mutual funds (MFB), and stock mutual funds (MFS). Estimates of the parameters of the model are given in table 4, with σ_η fixed to .025 in the first column, σ_η fixed to .05 in the second column, and σ_η estimated in the third column. Like MMMF's, stock and bond mutual funds had relatively small dollar values in the 1970's and consequently had highly variable growth rates. We therefore use 81:1 as the quarter in which MFB and MFS are first considered for inclusion in the new aggregate, that is, the weights on MFB and MFS are set to zero through 80:4.

Figures 10 and 11 respectively show the weights and the resulting aggregate computed with σ_η set to .025, and figures 12 and 13 present results for $\sigma_\eta = .05$. In figures 10(b) and 12(b), the "equal-weighting implicit weights" are the implicit weights on growth rates of the subaggregates for the total, M2+MFB+MFS, that is, the shares. Values of the weights for $\sigma_\eta = .025$, along with their standard errors, are tabulated in table A-2.

The results for the two values of σ_η show qualitatively similar patterns, although of course the weights vary more smoothly for the smaller value of σ_η. A noteworthy feature of the results is the different weights placed on MFB and MFS. With the exception of a single quarter

Figure 9
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Simulated real-time series produced by TVP model.
Subaggregates: M1, M2 ex M1 and MMMF, MMMF; σ_{η} = .05, 3 lags
Recursive estimates for samples from 1960:2 - 1980:4 through 1960:2 - 1992:4

(a) Sample: 1960:2 - 1980:4



(b) Sample: 1960:2 - 1982:4

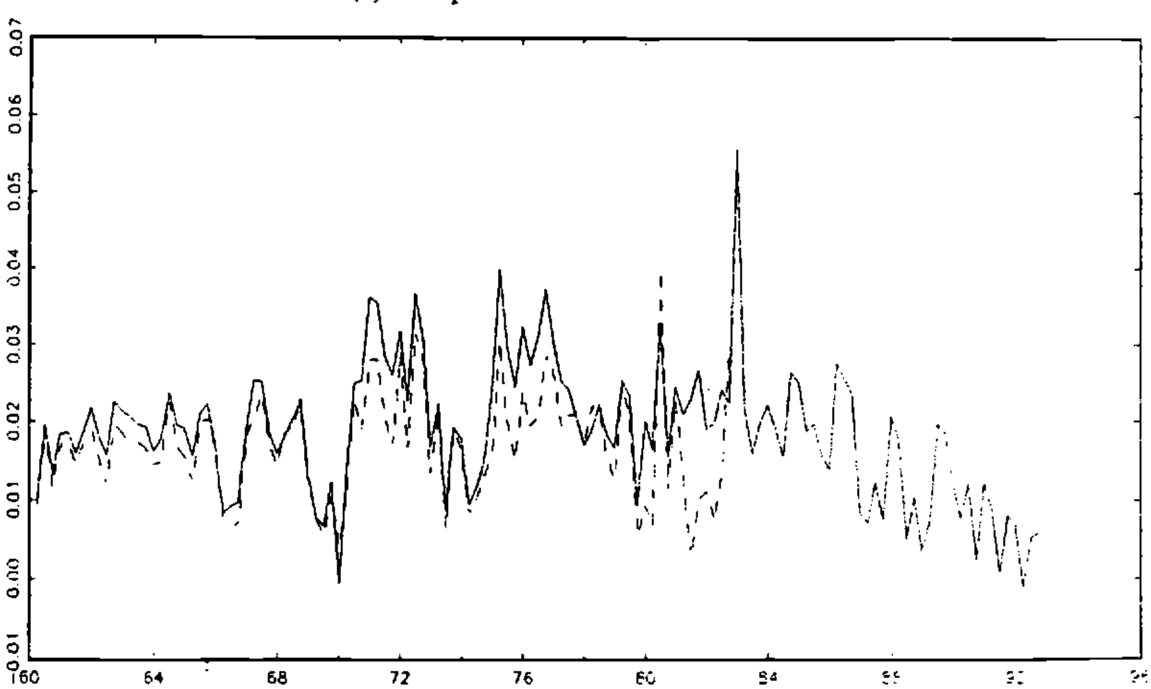
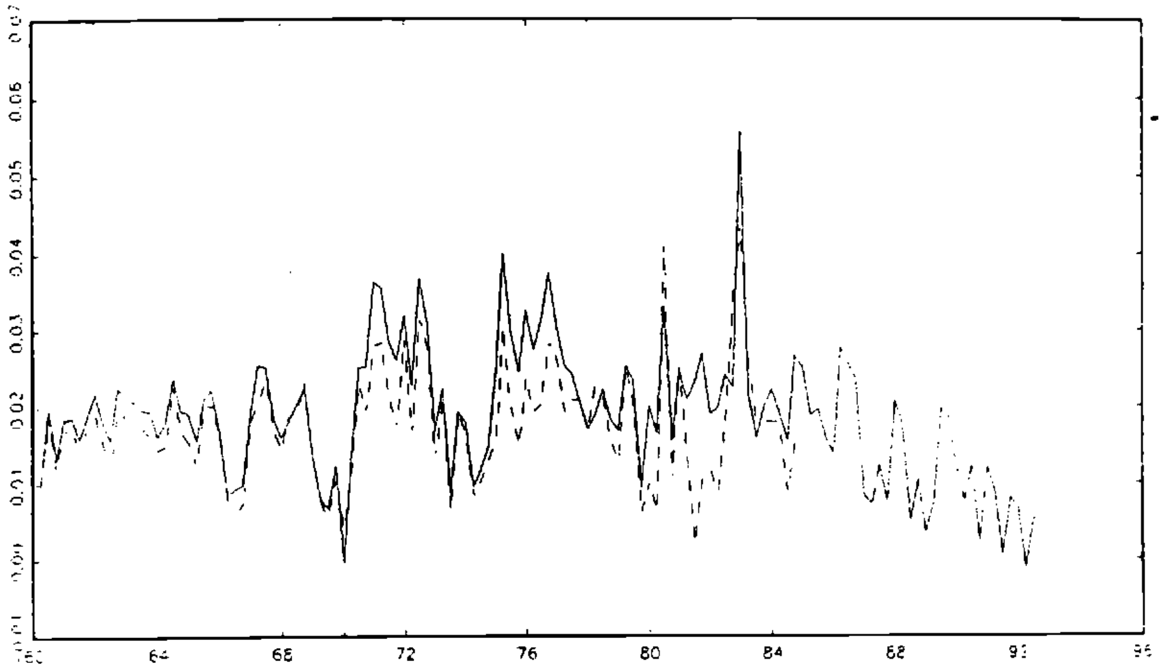


Figure 9, continued
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Recursively estimated simulated real-time series produced by TVP model.

(c) Sample: 1960:2 - 1984:4



(d) Sample: 1960:2 - 1986:4

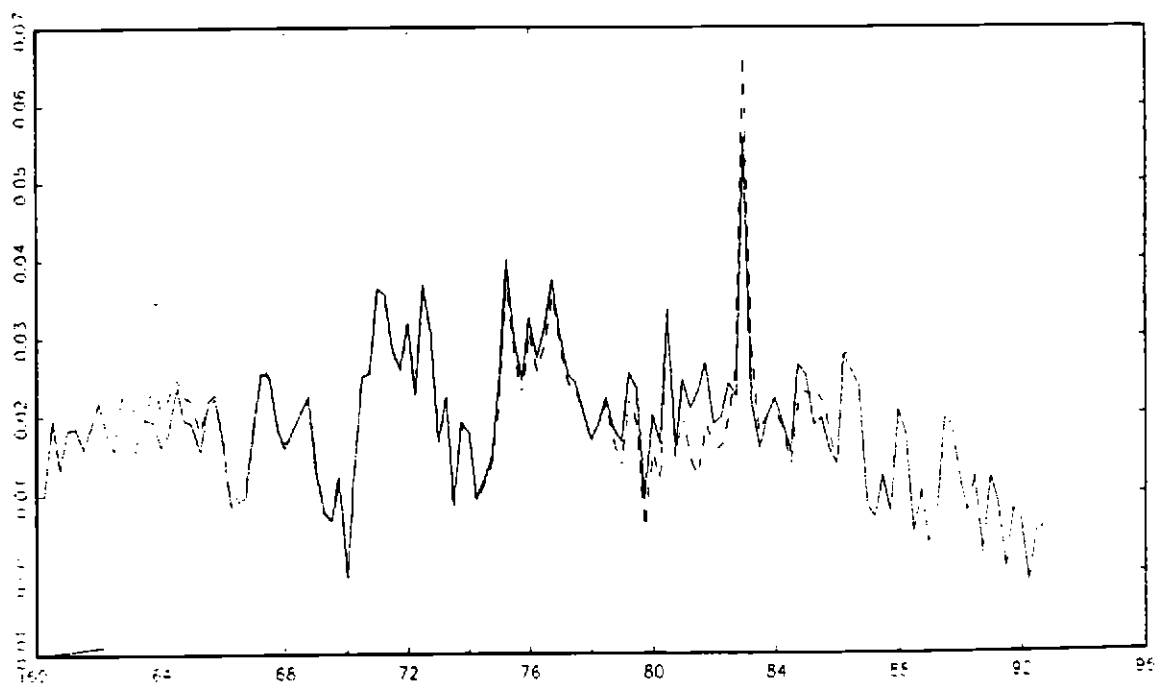
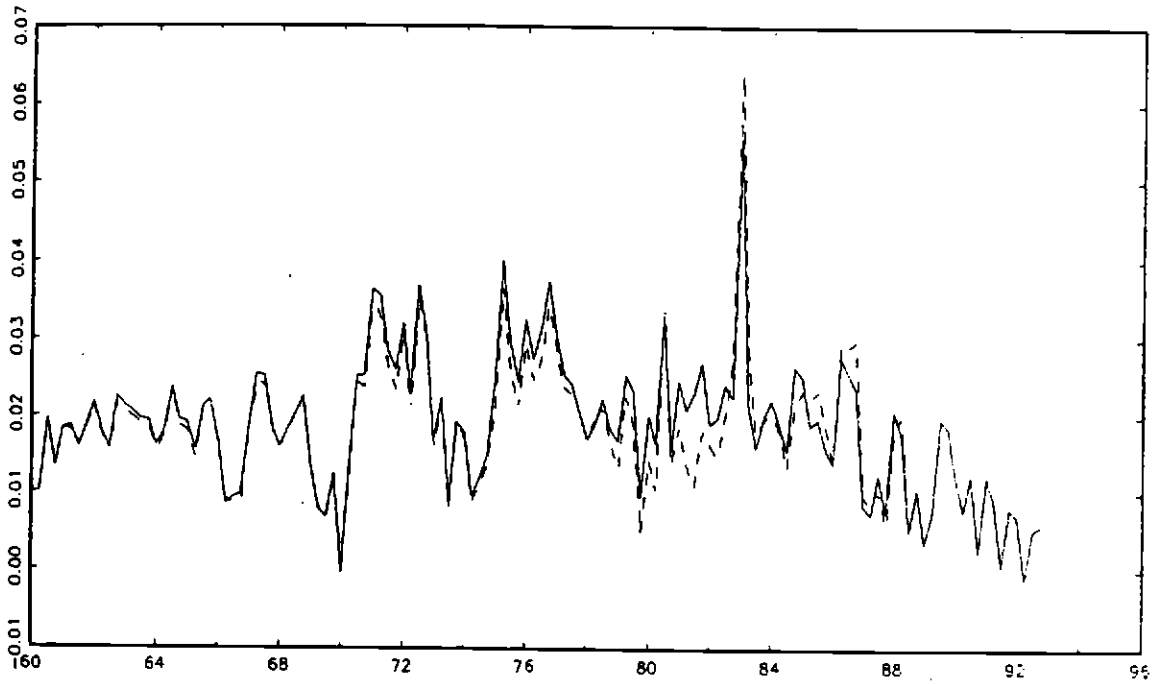


Figure 9, continued
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Recursively estimated simulated real-time series produced by TVP model.

(e) Sample: 1960:2 - 1988:4



(f) Sample: 1960:2 - 1990:4

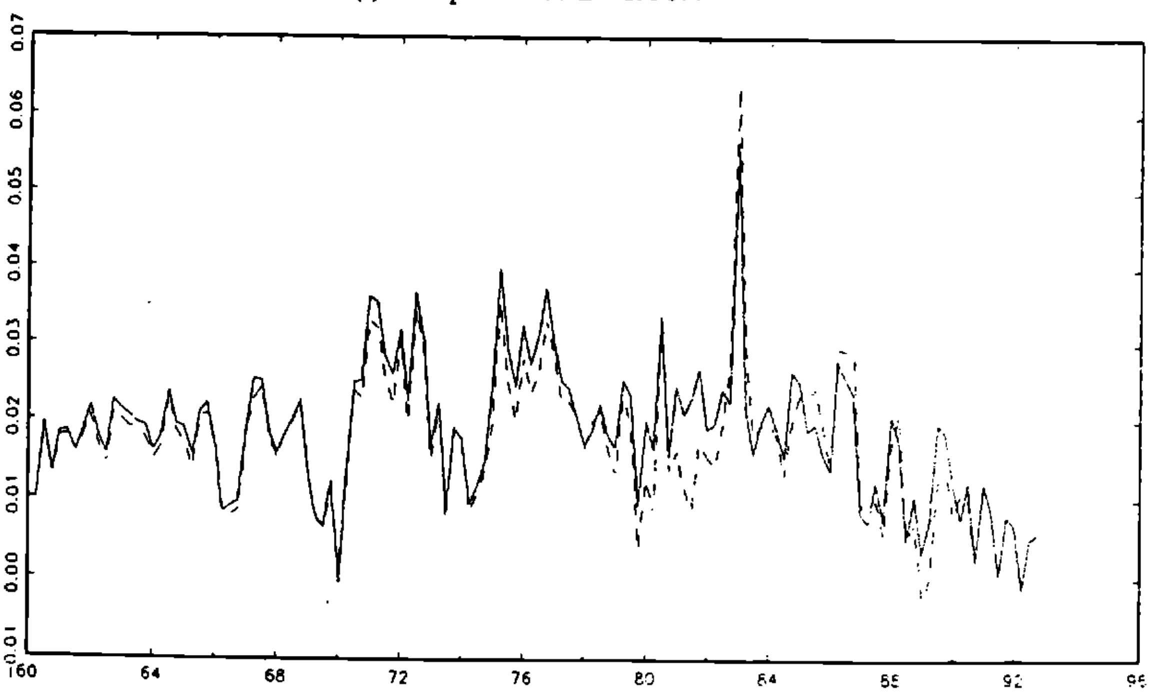


Figure 9, continued
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Recursively estimated simulated real-time series produced by TVP model.

(g) Sample: 1960:2 - 1992:4

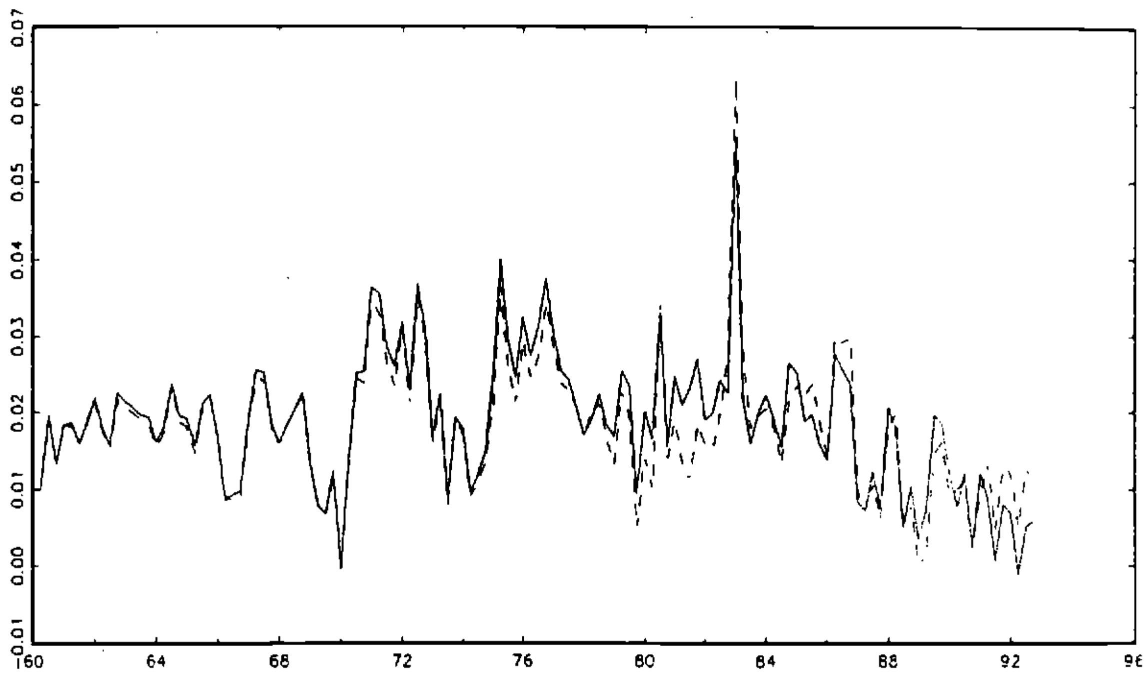


Table 4

Parameter estimates: TVP model

Three subaggregates: M2, MFB, MFS

Estimation period: Quarterly, 60:2 - 93:4

Notation: $\alpha(L) = \sum_{i=1}^{k}\alpha_i L^i$, $\gamma(L) = \sum_{i=1}^{k}\gamma_i L^i$

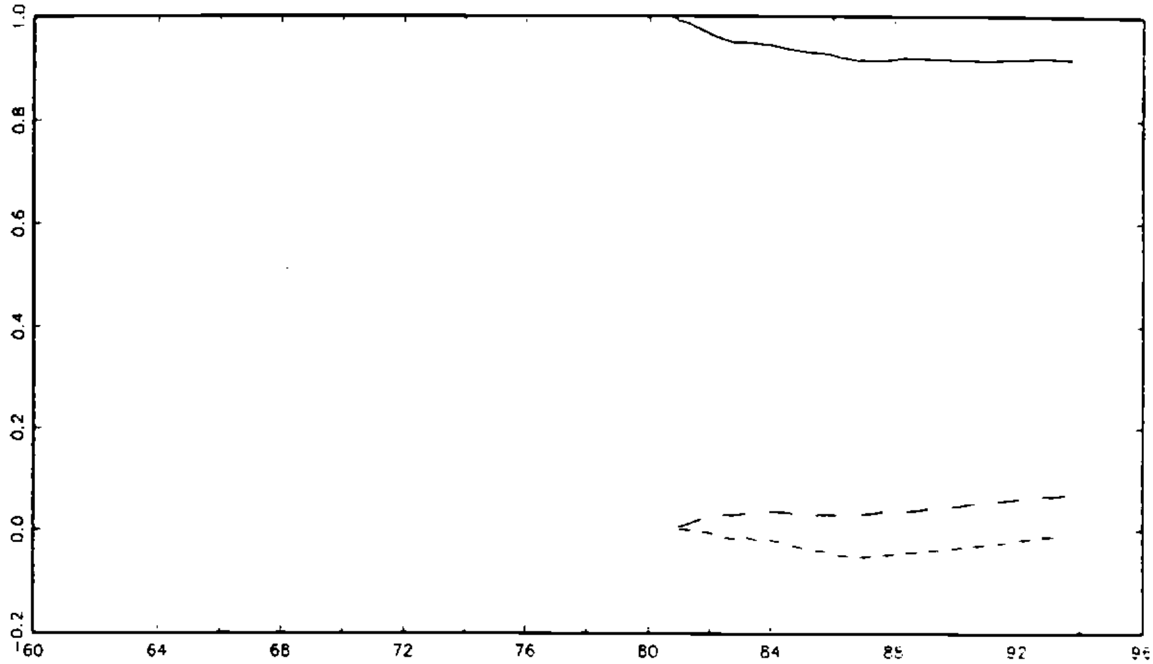
Parameter	(1)	(2)	(3)
α_0	0.0068 (0.0028)	0.0080 (0.0027)	0.0055 (0.0025)
α_1	0.095 (0.088)	0.099 (0.090)	0.058 (0.086)
α_2	0.046 (0.085)	0.048 (0.085)	0.057 (0.086)
α_3	0.021 (0.081)	0.022 (0.081)	0.038 (0.080)
γ_1	0.130 (0.091)	0.099 (0.072)	0.138 (0.108)
γ_2	0.245 (0.107)	0.181 (0.093)	0.290 (0.119)
γ_3	0.071 (0.093)	0.031 (0.075)	0.143 (0.116)
σ_ϵ	0.00871 (0.00054)	0.00871 (0.00055)	0.00885 (0.00055)
σ_η	0.025[a]	0.05[a]	0.00076 (0.00766)
2xlog likelihood	1137.773	1133.573	1141.802

Notes: See the notes to table 3.
[a]value imposed.

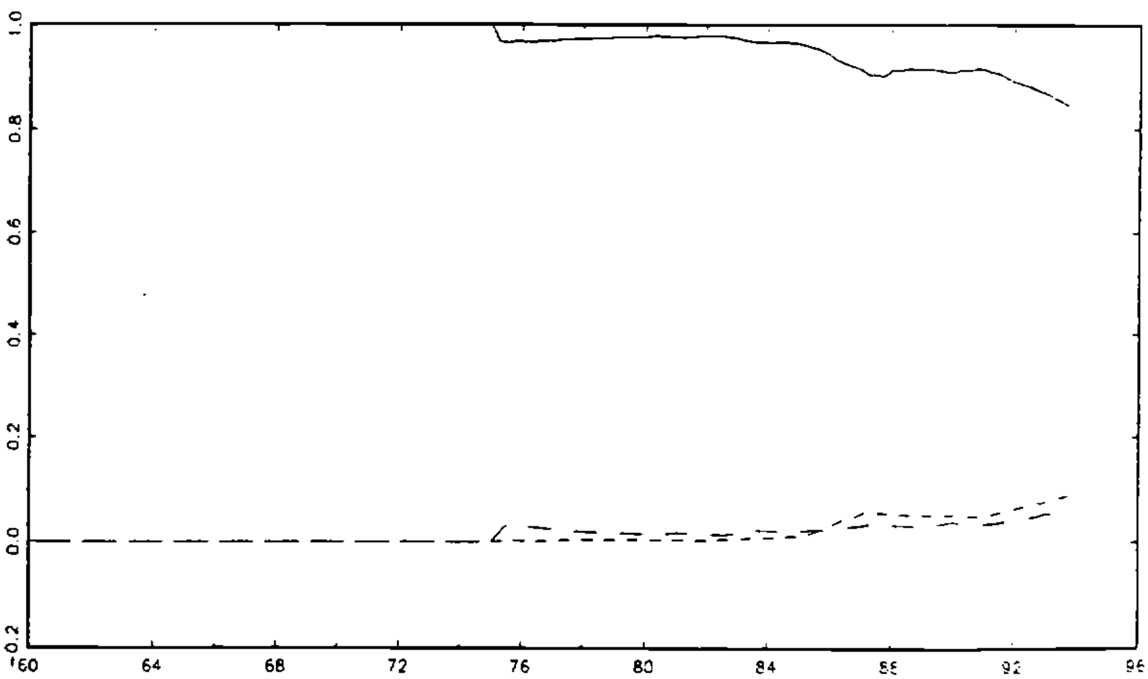
Figure 10
Weights on Alternative Monetary Aggregate and M2
Subaggregates: (i) M2, (ii) MFB (81:1 start) (iii) MFS (81:1 start); σ_η = .025; 3 lags

Key: (i) solid line; (ii) short-dashed line; (iii) long-dashed line

(a) Time-varying weights, alternative monetary aggregate



(b) Implicit weights on growth rate, M2+MFB+MFS aggregate



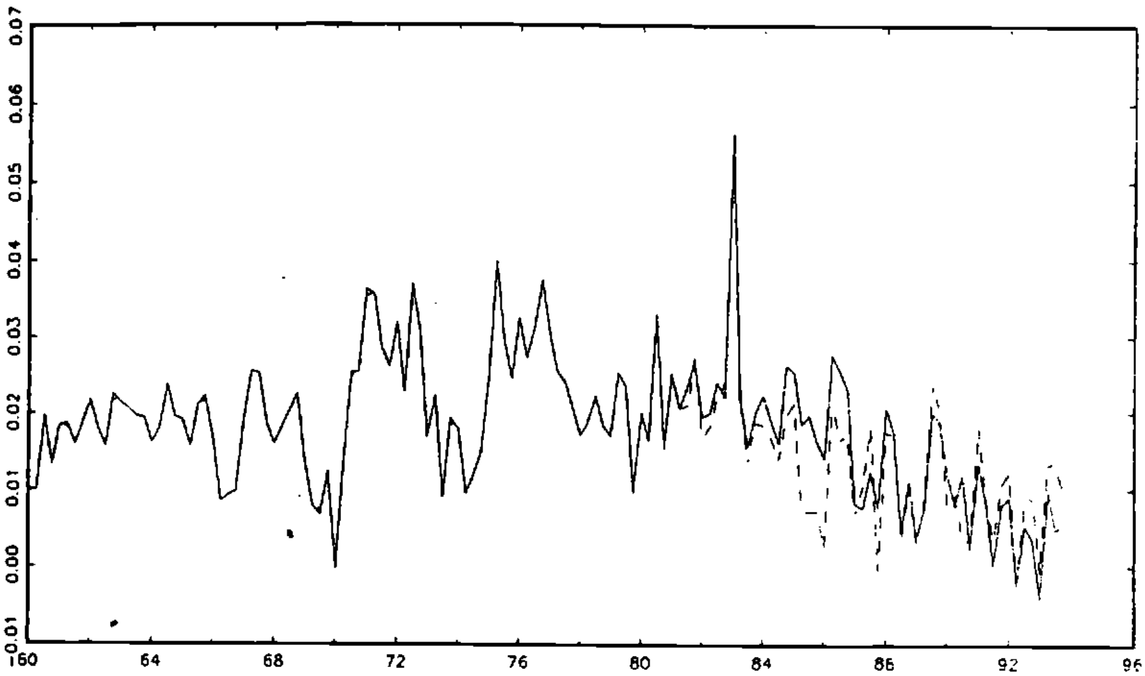


Figure 11
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Historical series produced by TVP model.

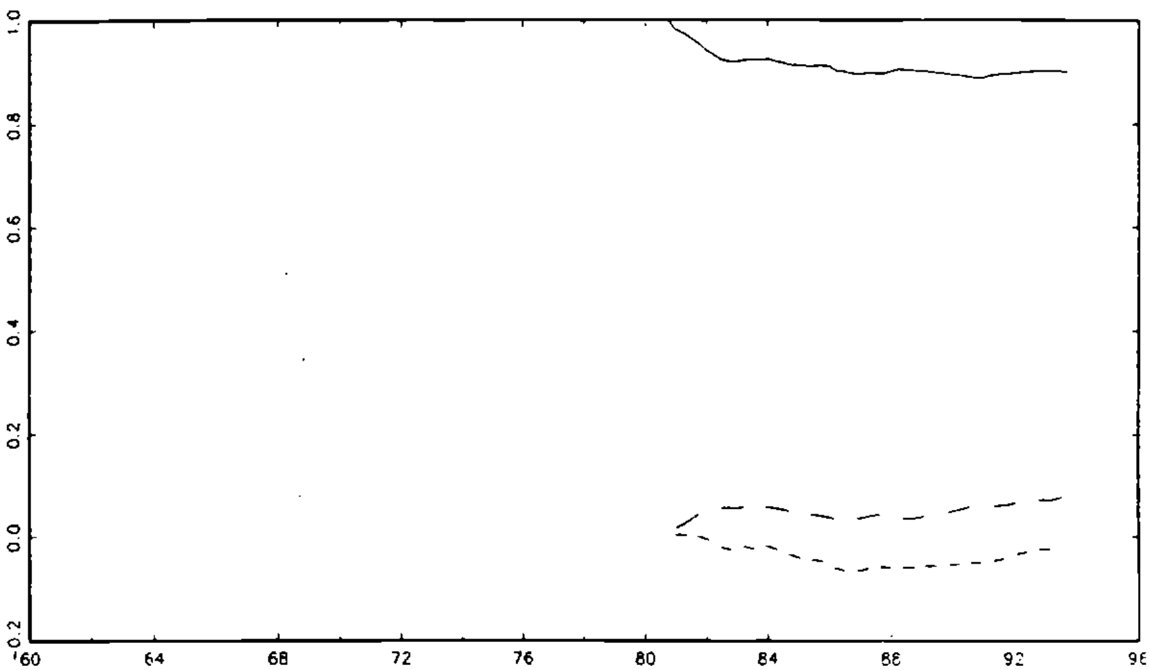
Full-sample estimates, 1960:2 - 1993:4

Subaggregates: M2, MFB, MFS; σ_η = .025, 3 lags

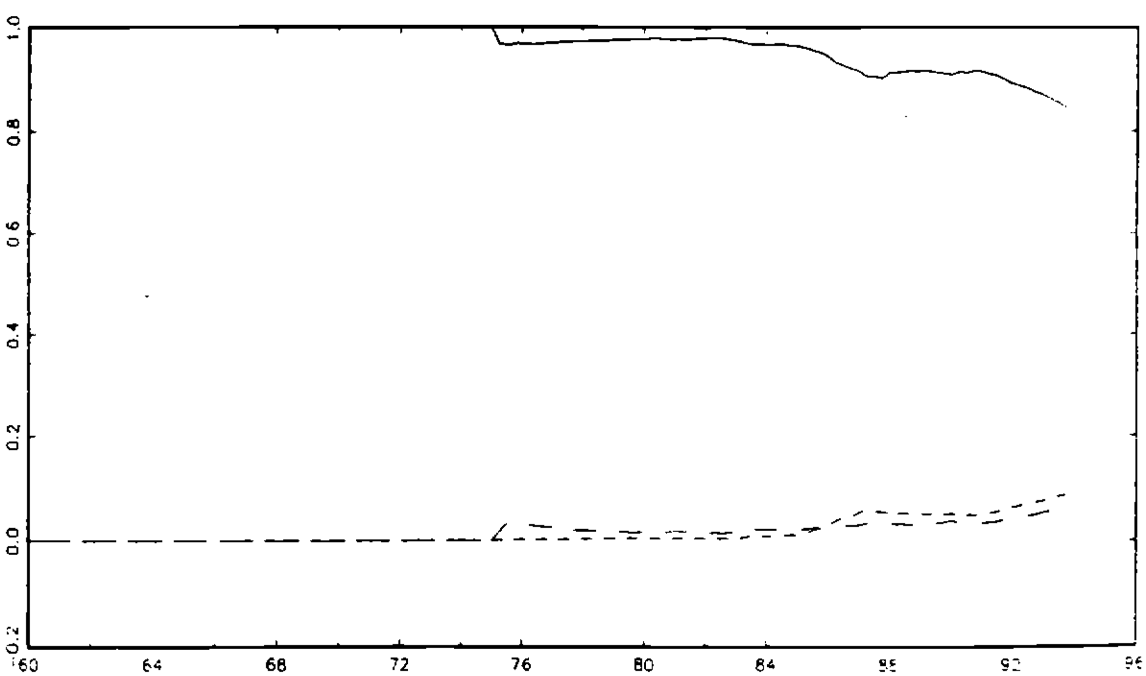
Figure 12
Weights on Alternative Monetary Aggregate and M2
Subaggregates: (i) M2, (ii) MFB (81:1 start) (iii) MFS (81:1 start); $\sigma_\eta = .05$; 3 lags

Key: (i) solid line; (ii) short-dashed line; (iii) long-dashed line

(a) Time-varying weights, alternative monetary aggregate



(b) Implicit weights on growth rate, M2+MFB+MFS aggregate



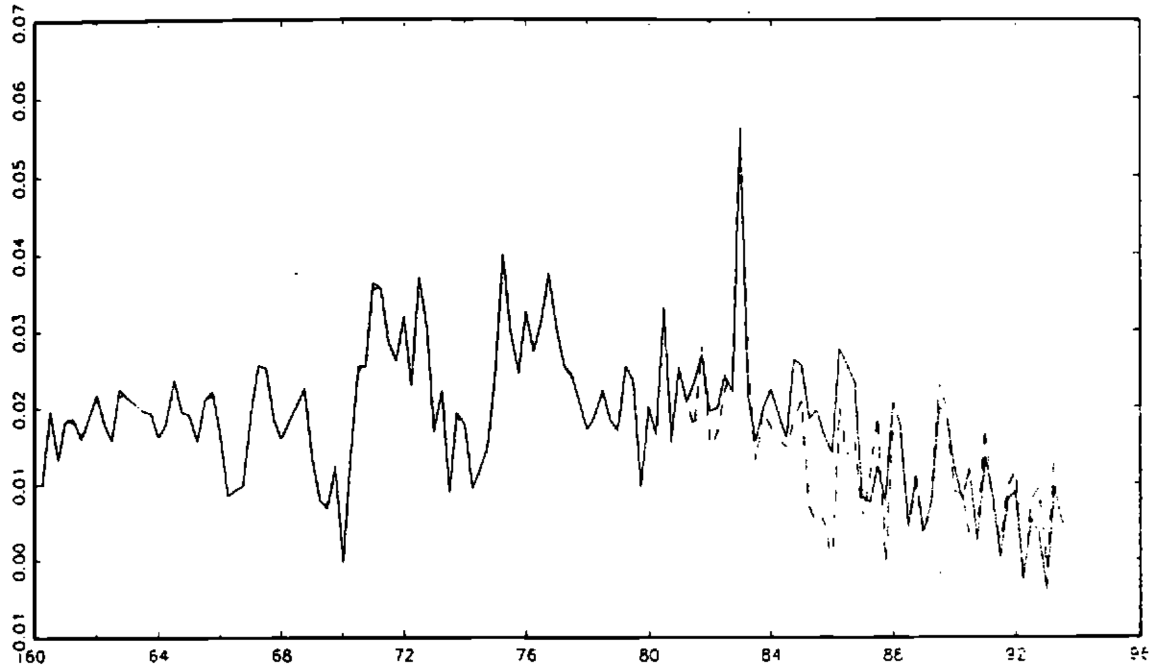


Figure 13
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line): Historical series produced by TVP model.

Full-sample estimates, 1960:2 - 1993:4

Subaggregates: M2, MFB, MFS; σ_η = .05, 3 lags

(1981:1), throughout the sample bond funds receive zero or negative weight in the new aggregate. In contrast, stock funds receive positive weight, with the magnitude of the weight approximately what it would be in an equal-weighted levels index (figures 10(b) and 12(b)). Because the growth rate of the stock funds reflects both changes in stock prices and net flows into the funds, without further analysis we cannot say whether it is the flow of funds or changes in stock prices which are driving this positive weight on stock funds. It is not surprising however that including a subaggregate which is determined in part by stock prices improves the predictive content of M2.

The estimated new monetary aggregate including stock funds has a growth rate similar to M2, although their growth rates differ in some episodes. For example, the aggregate including stock funds decreased sharply with the stock market crash of 1987. Over 1992 and 1993, the new aggregate exhibited a slightly higher average growth rate than M2.

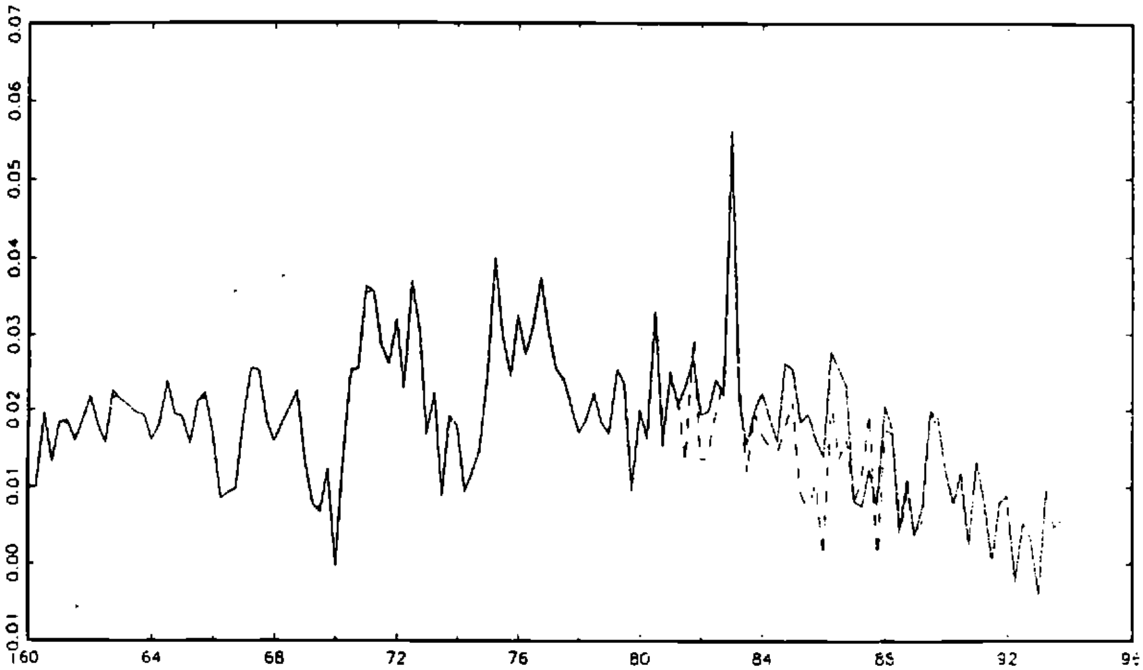
The simulated real time aggregates are presented in figure 14 for $\sigma_\eta = .05$. Based on the full sample and in the subsamples, the TVP aggregate is very similar to M2 from 1988 through 1990; the two aggregates begin to diverge substantially only in late 1991 and 1992. As seen in figure 14(d), by the end of 1992 this aggregate had diverged sufficiently to suggest that it might be appropriate to switch or to consider tracking this broader TVP aggregate as a monetary indicator. While the long-term differences between M2 and the new aggregate are slight, these initial results suggest that a new aggregate which includes bond and stock funds with a time-varying weight could provide an improved monetary indicator of future nominal GDP.

6. Discussion and Conclusions

The past few years have seen an historically unprecedented deterioration of the relationship between M2 and nominal GDP, most notably an increase in M2 velocity in the face of low and declining interest rates. One way to judge the importance of using these alternative aggregates

Figure 14
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Simulated real-time series produced by TVP model.
Subaggregates: M2, MFB, MFS; σ_η = .05, 3 lags
Recursive estimates for samples from 1960:2 - 1989:4 through 1960:2 - 1993:4

(a) Sample: 1960:2 - 1989:4



(b) Sample: 1960:2 - 1990:4

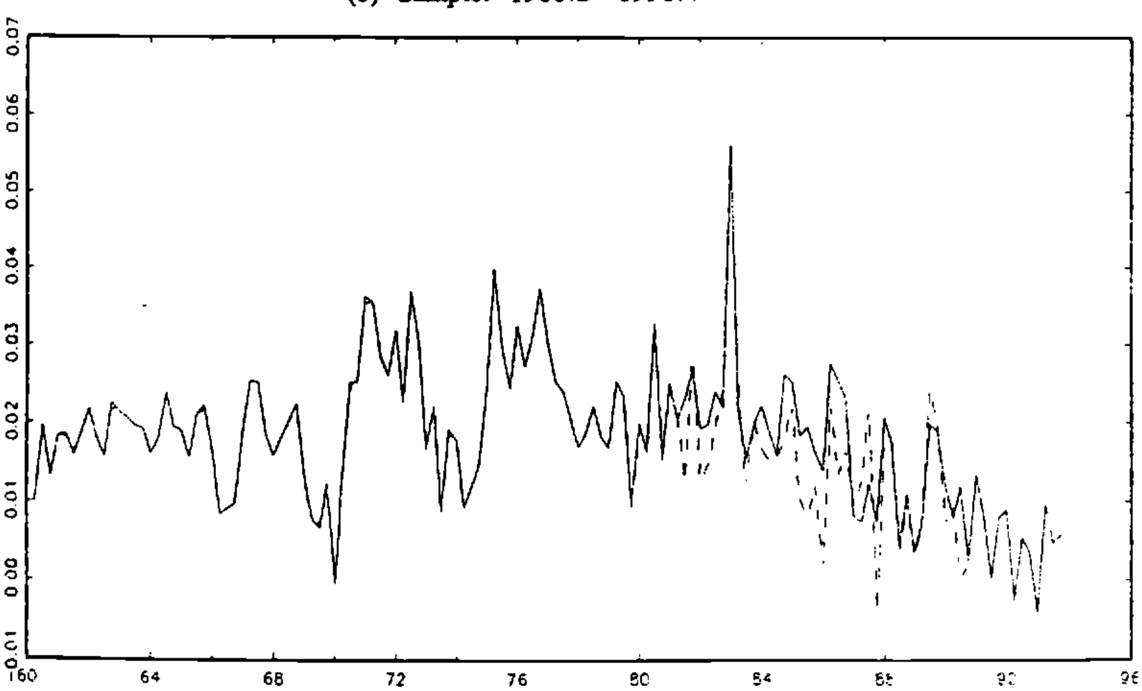
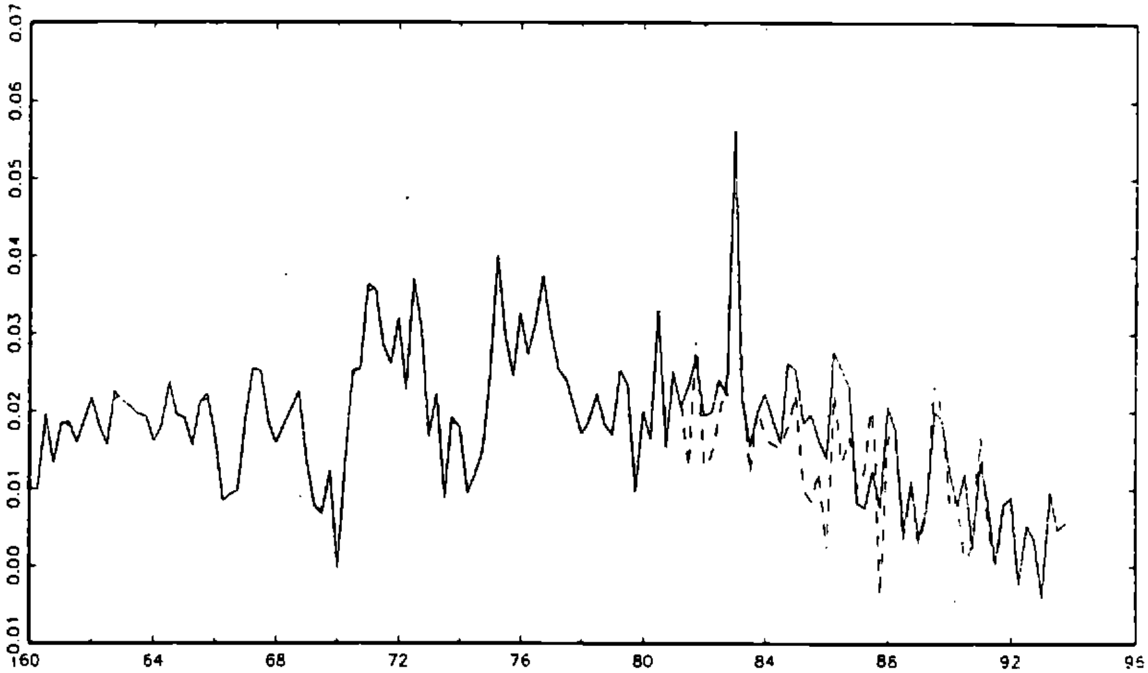


Figure 14, continued
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Recursively estimated simulated real-time series produced by TVP model.

(c) Sample: 1960:2 - 1991:4



(d) Sample: 1960:2 - 1992:4

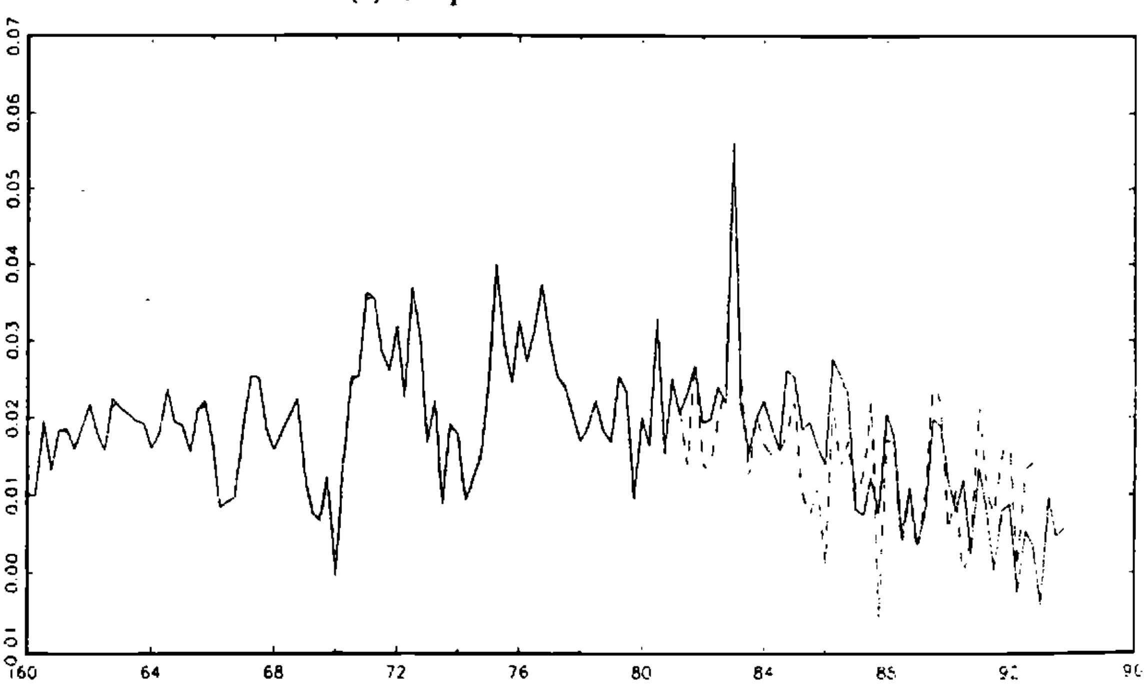
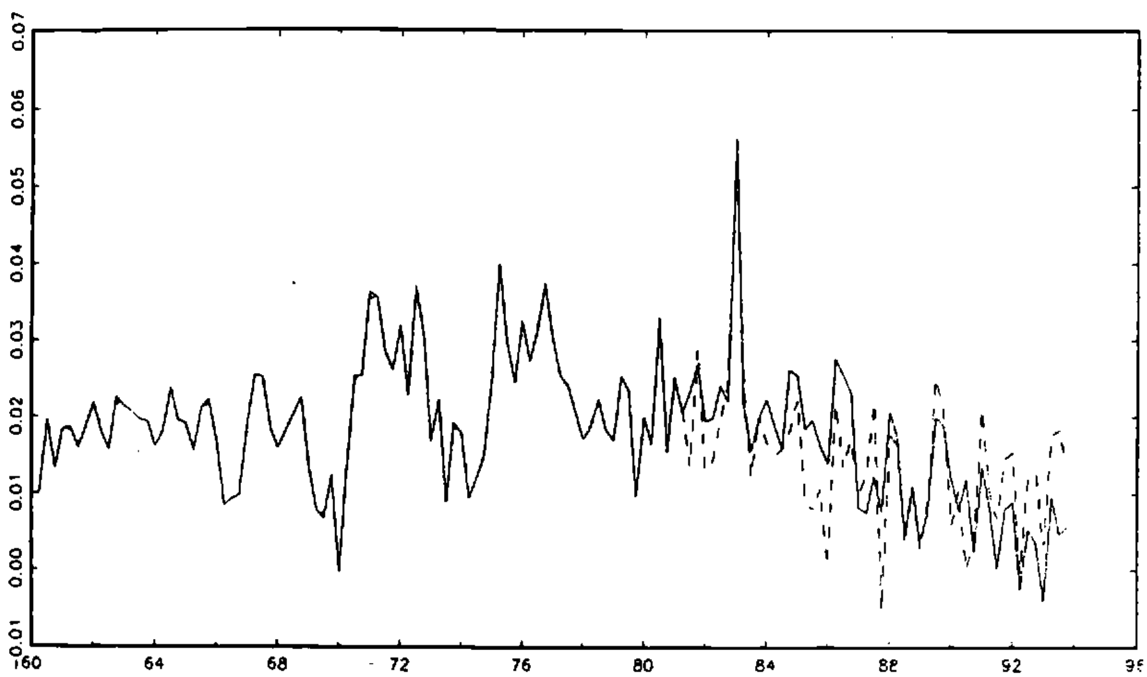


Figure 14, continued
Growth rate of alternative monetary aggregate (dashed line) and M2 (solid line):
Recursively estimated simulated real-time series produced by TVP model.

(e) Sample: 1960:2 - 1993:4



is therefore to compare the forecasts of GDP growth based on the switching and TVP aggregates which consider stock and bond mutual funds, with forecasts based on M2. One-quarter ahead forecasts using the various monetary aggregates over the period 1988:1 - 1993:4 are given in table 5 and are plotted in figure 15. These forecasts are computed recursively to simulate real-time implementation of the alternative aggregates. For example, the forecast of GDP growth in 1991:4 based on M2 is computed using the regression of GDP growth on its lags and on lagged values of M2 growth over the period 1960:2 - 1991:3 (earlier values are used as initial conditions). The switching forecasts are based on the simulated real-time switching aggregate plotted in figure 4, that is, the switching aggregate and its GDP forecasting equation are computed using data through the quarter prior to the quarter being forecasted. The TVP aggregate is based on the weights for σ_η=.025 (parameter values in table 4, column 1). As discussed previously, it is computationally infeasible to compute MLE's of the time-invariant parameters of the TVP model recursively, so the TVP forecast is based on the full-sample parameter estimates in column 1 of table 4, but the weights used are the Kalman filter estimates $\beta_{t|t-1}$, where t denotes the quarter being forecasted.

The different forecasts in table 5 and figure 15 show that using an alternative monetary aggregate matters over this period. For the entire period 1988-1993, conventional M2 forecasted better than the switching regression aggregate but not as well as the TVP aggregate. But although none of the monetary aggregates forecasted the 1990 recession, especially the nearly zero growth in the fourth quarter of 1990, both the switching and TVP aggregates forecasted growth over the final two years more accurately than M2. Because these regressions are computed using recursive forecasts, this is not an artifact of the aggregate being defined ex-post as that which forecasts GDP well over this period. Rather, this can be taken as reflecting a deterioration in the forecasting performance of M2 relative to the broader aggregates.

While these results are promising, they are limited in several regards. The analysis has focused entirely on the bivariate M2-output relation. A natural extension is to higher dimensional models, in particular models with interest rates. Of particular interest are models

Table 5

Recursive forecasts of quarterly GDP growth using various monetary aggregates
(percent growth over the previous quarter at an annual rate)

Subaggregates: M2, MFB, MFS

Quarter	Actual	- - - Recursive forecast based on: - - - M2	Switching M2*	TVP M2*
88:1	5.9	5.7	8.9	6.1
88:2	8.7	5.9	3.2	5.2
88:3	7.4	7.4	10.5	6.6
88:4	7.8	6.4	7.3	6.3
89:1	8.3	5.1	7.7	5.3
89:2	6.1	5.3	8.1	5.3
89:3	3.8	4.6	7.3	4.8
89:4	5.0	5.2	7.7	5.7
90:1	8.7	6.7	6.8	7.1
90:2	5.7	7.1	6.9	6.9
90:3	3.1	5.8	6.1	5.6
90:4	1.0	4.8	7.1	4.8
91:1	2.4	3.9	4.0	3.8
91:2	4.7	3.5	6.7	4.4
91:3	4.3	4.7	6.8	5.6
91:4	3.1	3.8	6.0	4.9
92:1	7.2	3.1	6.4	4.4
92:2	5.6	4.6	7.0	5.4
92:3	4.5	4.1	6.7	5.0
92:4	8.8	3.2	6.2	4.1
93:1	4.3	4.4	8.0	5.1
93:2	4.2	3.5	6.5	4.8
93:3	4.3	3.4	5.1	4.4
93:4	8.4	4.3	5.8	5.4
		Summary: Forecast RMSE's		
88:1 - 89:4	-	1.64	3.03	1.81
90:1 - 91:4	-	2.00	3.02	1.98
92:1 - 93:4	-	2.92	2.26	2.24
88:1 - 93:4	-	2.25	2.79	2.02

Notes: Entries are one-quarter ahead forecasts computed recursively, that is, using data from 1959:1 through the quarter preceding the forecast date, with the exception that the TVP model uses recursive weights but full-sample estimates for the time-invariant parameters. For the TVP model, σ_η was set to .025. All regressions included a constant, three lags of gdp growth, and three lags of the relevant monetary aggregate as discussed in the text.

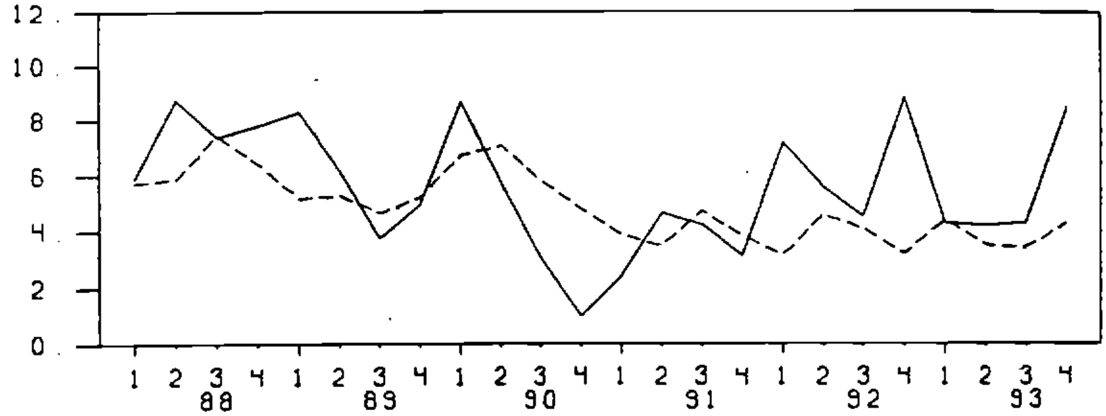
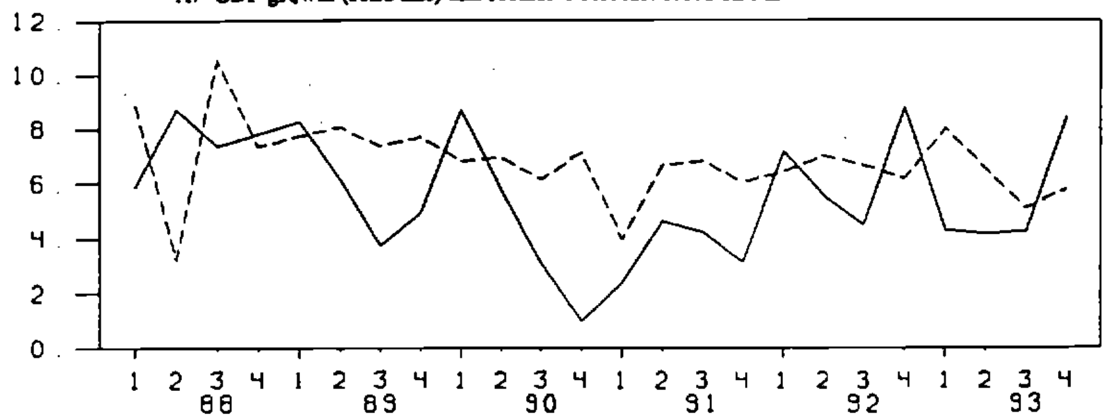
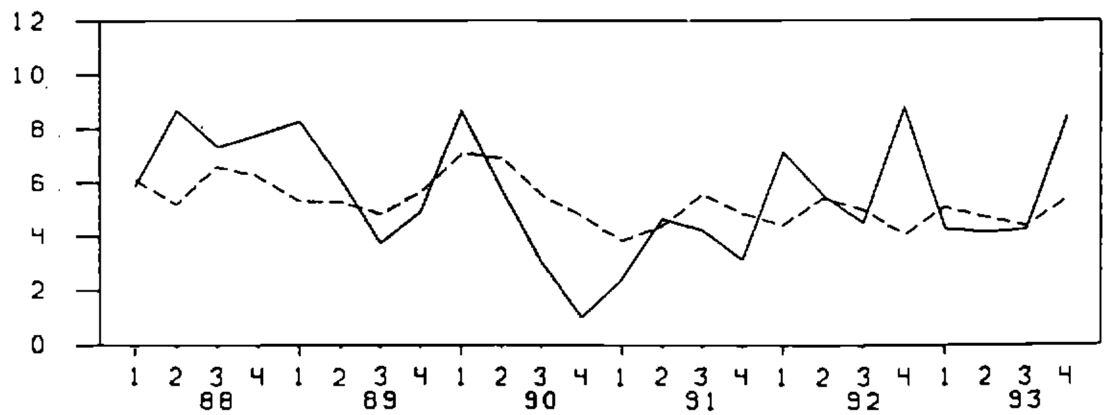


Figure 15. Actual quarterly GDP growth and forecasts based on monetary aggregates

A. GDP growth (solid line) and recursive forecast based on M2



B. GDP growth (solid line) and recursive forecast based on switching model



C. GDP growth (solid line) and recursive forecast based on TVP model (σ_η = .025) in which the weights are determined in part so that the long-run velocity-interest rate relationship remains stable. This would entail extending the foregoing bivariate regressions to single-equation error correction specifications. This involves technical complications, particularly for the TVP model, and work on this extension is under way.

Footnotes

1. It would be appropriate to examine longer term relations as an alternative to the quarterly forecast.

2. The level of the aggregate would be given by S_{it} when the growth rate is given by s_{it}. At τ_{i-1}, the date of switching to the i-th aggregate, there would be a jump in the level of the aggregate from $S_{i-1,\tau_{i-1}-1}$ to $S_{i,\tau_{i-1}}$. This jump does not imply a spike in the growth rate as defined in (2.1), however, because at date τ_{i-1}, the growth rate of $S_{i\tau_{i-1}}$ is used.

3. We thank John Duca for providing the stock and bond fund data. These data are market values and exclude IRA and Keogh accounts and institutional holdings, which are also excluded from M2. By using market values, the data also include capital gains. These two features make these data less like M2. An alternative approach is to use total inflows excluding capital gains, as is used by Orphanides, Reid and Small (1993). Different results could of course obtain using other data, and in this sense our results should be taken as illustrative.

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Table A-1

Time-varying weights and their standard errors for the alternative monetary aggregate

Three subaggregates: M1, M2R (M2 excluding M1 and MMMF's), and MMMF's

Note: Weights are rescaled to add to one in each period. Weights are based on MLE's reported in Table 3, column (2), with $\sigma_\eta = .025$

	Weights on growth rate of:					
	- - M1 - -		- - M2R - -		- - MMMF - -	
Quarter	weight	SE	weight	SE	weight	SE
60:2	0.471	0.025	0.529	0.025	0.000	0.000
60:3	0.471	0.035	0.529	0.034	0.000	0.000
60:4	0.471	0.042	0.529	0.041	0.000	0.000
61:1	0.471	0.049	0.529	0.047	0.000	0.000
61:2	0.470	0.054	0.530	0.051	0.000	0.000
61:3	0.470	0.058	0.530	0.055	0.000	0.000
61:4	0.470	0.063	0.530	0.059	0.000	0.000
62:1	0.469	0.066	0.531	0.062	0.000	0.000
62:2	0.469	0.070	0.531	0.064	0.000	0.000
62:3	0.469	0.073	0.531	0.067	0.000	0.000
62:4	0.469	0.076	0.531	0.069	0.000	0.000
63:1	0.468	0.079	0.532	0.071	0.000	0.000
63:2	0.467	0.081	0.533	0.073	0.000	0.000
63:3	0.465	0.083	0.535	0.074	0.000	0.000
63:4	0.464	0.085	0.536	0.076	0.000	0.000
64:1	0.463	0.087	0.537	0.077	0.000	0.000
64:2	0.462	0.089	0.538	0.078	0.000	0.000
64:3	0.461	0.090	0.539	0.080	0.000	0.000
64:4	0.460	0.092	0.540	0.081	0.000	0.000
65:1	0.459	0.093	0.541	0.081	0.000	0.000
65:2	0.458	0.094	0.542	0.082	0.000	0.000
65:3	0.456	0.095	0.544	0.083	0.000	0.000
65:4	0.455	0.097	0.545	0.084	0.000	0.000
66:1	0.455	0.098	0.545	0.085	0.000	0.000
66:2	0.454	0.099	0.546	0.086	0.000	0.000
66:3	0.453	0.100	0.547	0.087	0.000	0.000
66:4	0.453	0.101	0.547	0.087	0.000	0.000
67:1	0.452	0.102	0.548	0.088	0.000	0.000
67:2	0.451	0.103	0.549	0.088	0.000	0.000
67:3	0.451	0.104	0.549	0.089	0.000	0.000
67:4	0.450	0.104	0.550	0.089	0.000	0.000
68:1	0.449	0.105	0.551	0.089	0.000	0.000
68:2	0.448	0.106	0.552	0.090	0.000	0.000
68:3	0.448	0.107	0.552	0.090	0.000	0.000
68:4	0.447	0.107	0.553	0.091	0.000	0.000
69:1	0.446	0.108	0.554	0.091	0.000	0.000
69:2	0.446	0.109	0.554	0.091	0.000	0.000
69:3	0.445	0.109	0.555	0.091	0.000	0.000
69:4	0.444	0.110	0.556	0.091	0.000	0.000
70:1	0.444	0.110	0.556	0.091	0.000	0.000
70:2	0.443	0.111	0.557	0.091	0.000	0.000
70:3	0.442	0.111	0.558	0.091	0.000	0.000
70:4	0.442	0.112	0.558	0.091	0.000	0.000

Table A-1, continued

71:1	0.441	0.112	0.559	0.091	0.000	0.000
71:2	0.441	0.113	0.559	0.091	0.000	0.000
71:3	0.440	0.113	0.560	0.090	0.000	0.000
71:4	0.439	0.113	0.561	0.090	0.000	0.000
72:1	0.438	0.113	0.562	0.090	0.000	0.000
72:2	0.437	0.113	0.563	0.090	0.000	0.000
72:3	0.436	0.113	0.564	0.090	0.000	0.000
72:4	0.436	0.113	0.564	0.090	0.000	0.000
73:1	0.435	0.113	0.565	0.090	0.000	0.000
73:2	0.434	0.113	0.566	0.090	0.000	0.000
73:3	0.433	0.113	0.567	0.090	0.000	0.000
73:4	0.433	0.113	0.567	0.091	0.000	0.000
74:1	0.432	0.113	0.568	0.091	0.000	0.000
74:2	0.431	0.113	0.569	0.091	0.000	0.000
74:3	0.431	0.113	0.569	0.091	0.000	0.000
74:4	0.430	0.113	0.570	0.091	0.000	0.000
75:1	0.429	0.113	0.571	0.091	0.000	0.000
75:2	0.429	0.113	0.571	0.091	0.000	0.000
75:3	0.428	0.113	0.572	0.091	0.000	0.000
75:4	0.428	0.113	0.572	0.091	0.000	0.000
76:1	0.427	0.113	0.573	0.091	0.000	0.000
76:2	0.427	0.113	0.573	0.091	0.000	0.000
76:3	0.427	0.113	0.573	0.092	0.000	0.000
76:4	0.427	0.113	0.573	0.092	0.000	0.000
77:1	0.426	0.113	0.574	0.093	0.000	0.000
77:2	0.426	0.113	0.574	0.093	0.000	0.000
77:3	0.425	0.113	0.575	0.094	0.000	0.000
77:4	0.425	0.113	0.575	0.095	0.000	0.000
78:1	0.425	0.112	0.575	0.096	0.000	0.000
78:2	0.424	0.112	0.576	0.097	0.000	0.000
78:3	0.423	0.112	0.577	0.098	0.000	0.000
78:4	0.423	0.113	0.577	0.099	0.000	0.000
79:1	0.422	0.113	0.578	0.101	0.000	0.000
79:2	0.421	0.113	0.579	0.102	0.000	0.000
79:3	0.420	0.114	0.580	0.103	0.000	0.000
79:4	0.419	0.114	0.581	0.104	0.000	0.000
80:1	0.418	0.115	0.581	0.105	0.001	0.016
80:2	0.415	0.115	0.579	0.106	-0.006	0.021
80:3	0.415	0.115	0.580	0.107	0.005	0.024
80:4	0.412	0.115	0.578	0.108	0.010	0.027
81:1	0.414	0.117	0.584	0.110	0.002	0.030
81:2	0.410	0.117	0.581	0.111	-0.009	0.031
81:3	0.406	0.117	0.578	0.112	-0.016	0.031
81:4	0.399	0.116	0.571	0.112	-0.029	0.031
82:1	0.395	0.116	0.568	0.112	-0.037	0.033
82:2	0.394	0.117	0.569	0.114	-0.038	0.036
82:3	0.392	0.117	0.568	0.115	-0.040	0.039
82:4	0.391	0.118	0.570	0.116	-0.040	0.042
83:1	0.390	0.119	0.571	0.118	-0.039	0.045
83:2	0.390	0.119	0.573	0.119	-0.037	0.047
83:3	0.389	0.120	0.575	0.121	-0.036	0.049
83:4	0.387	0.120	0.575	0.122	-0.038	0.051
84:1	0.385	0.120	0.574	0.124	-0.041	0.054
84:2	0.383	0.120	0.574	0.125	-0.043	0.056
84:3	0.380	0.121	0.574	0.127	-0.045	0.058
84:4	0.378	0.121	0.575	0.129	-0.047	0.060
85:1	0.377	0.121	0.575	0.131	-0.048	0.061
85:2	0.375	0.121	0.575	0.132	-0.050	0.063

Table A-1, continued

85:3	0.373	0.121	0.576	0.134	-0.051	0.065
85:4	0.372	0.121	0.577	0.136	-0.052	0.067
86:1	0.370	0.121	0.578	0.138	-0.052	0.069
86:2	0.369	0.121	0.578	0.140	-0.053	0.070
86:3	0.369	0.121	0.579	0.141	-0.052	0.071
86:4	0.369	0.121	0.580	0.143	-0.051	0.072
87:1	0.370	0.122	0.581	0.145	-0.049	0.074
87:2	0.371	0.122	0.583	0.146	-0.046	0.075
87:3	0.373	0.123	0.584	0.148	-0.043	0.076
87:4	0.374	0.124	0.585	0.149	-0.041	0.077
88:1	0.375	0.124	0.586	0.151	-0.038	0.077
88:2	0.377	0.125	0.587	0.152	-0.036	0.078
88:3	0.377	0.126	0.588	0.154	-0.035	0.079
88:4	0.378	0.126	0.589	0.155	-0.033	0.079
89:1	0.379	0.127	0.589	0.157	-0.032	0.080
89:2	0.380	0.127	0.590	0.158	-0.031	0.080
89:3	0.380	0.128	0.590	0.160	-0.030	0.081
89:4	0.380	0.128	0.590	0.161	-0.030	0.082
90:1	0.381	0.129	0.589	0.162	-0.030	0.083
90:2	0.380	0.129	0.588	0.164	-0.032	0.084
90:3	0.380	0.129	0.587	0.165	-0.034	0.087
90:4	0.379	0.129	0.585	0.166	-0.035	0.089
91:1	0.379	0.129	0.585	0.167	-0.036	0.091
91:2	0.380	0.130	0.584	0.168	-0.036	0.093
91:3	0.380	0.130	0.583	0.169	-0.037	0.095
91:4	0.380	0.130	0.582	0.170	-0.038	0.097
92:1	0.381	0.130	0.581	0.171	-0.038	0.099
92:2	0.381	0.131	0.580	0.172	-0.039	0.102
92:3	0.381	0.131	0.580	0.173	-0.039	0.104
92:4	0.381	0.132	0.579	0.174	-0.040	0.106
93:1	0.381	0.133	0.578	0.176	-0.040	0.108
93:2	0.382	0.134	0.578	0.177	-0.040	0.110
93:3	0.382	0.135	0.577	0.178	-0.041	0.112
93:4	0.382	0.137	0.577	0.179	-0.041	0.114

Table A-2

Time-varying weights and their standard errors for the alternative monetary aggregate

Three subaggregates: M2, MFB, MFS

Note: Weights are rescaled to add to one in each period. Weights are based on MLE's reported in Table 4, column (2), with σ_η = .025

	Weights on growth rate of:					
	- - M1 - -		- - MFB - -		- - MFS - -	
Quarter	weight	SE	weight	SE	weight	SE
≤80:4	1.000	0.000	0.000	0.000	0.000	0.000
81:1	0.991	0.106	0.001	0.021	0.008	0.021
81:2	0.988	0.107	-0.000	0.028	0.012	0.029
81:3	0.981	0.108	-0.002	0.033	0.018	0.034
81:4	0.974	0.109	-0.003	0.036	0.023	0.039
82:1	0.966	0.109	-0.006	0.039	0.027	0.042
82:2	0.960	0.110	-0.011	0.040	0.029	0.044
82:3	0.954	0.111	-0.015	0.040	0.031	0.046
82:4	0.951	0.112	-0.017	0.040	0.032	0.048
83:1	0.950	0.113	-0.017	0.040	0.033	0.049
83:2	0.949	0.114	-0.016	0.041	0.035	0.050
83:3	0.947	0.115	-0.019	0.042	0.033	0.051
83:4	0.946	0.117	-0.019	0.043	0.035	0.053
84:1	0.945	0.118	-0.019	0.044	0.036	0.055
84:2	0.942	0.119	-0.023	0.044	0.035	0.057
84:3	0.938	0.120	-0.028	0.044	0.034	0.058
84:4	0.935	0.121	-0.032	0.043	0.033	0.059
85:1	0.933	0.122	-0.035	0.041	0.032	0.060
85:2	0.930	0.123	-0.038	0.039	0.031	0.061
85:3	0.930	0.124	-0.039	0.037	0.031	0.061
85:4	0.928	0.126	-0.041	0.035	0.030	0.062
86:1	0.926	0.127	-0.044	0.035	0.030	0.062
86:2	0.921	0.127	-0.051	0.036	0.028	0.061
86:3	0.919	0.128	-0.052	0.039	0.029	0.061
86:4	0.917	0.129	-0.053	0.042	0.030	0.060
87:1	0.917	0.130	-0.051	0.045	0.032	0.060
87:2	0.917	0.132	-0.048	0.049	0.035	0.059
87:3	0.917	0.133	-0.047	0.052	0.037	0.058
87:4	0.917	0.134	-0.046	0.055	0.038	0.058
88:1	0.919	0.136	-0.045	0.059	0.037	0.059
88:2	0.921	0.137	-0.044	0.062	0.036	0.059
88:3	0.920	0.138	-0.043	0.064	0.037	0.060
88:4	0.920	0.140	-0.041	0.066	0.039	0.061
89:1	0.919	0.141	-0.040	0.069	0.041	0.062
89:2	0.919	0.142	-0.039	0.071	0.042	0.063
89:3	0.919	0.144	-0.037	0.073	0.044	0.064
89:4	0.918	0.145	-0.036	0.074	0.046	0.064
90:1	0.917	0.146	-0.034	0.076	0.049	0.064
90:2	0.917	0.148	-0.033	0.077	0.051	0.066
90:3	0.916	0.149	-0.031	0.078	0.053	0.067
90:4	0.915	0.150	-0.030	0.080	0.055	0.068
91:1	0.916	0.152	-0.028	0.081	0.056	0.069
91:2	0.917	0.154	-0.027	0.082	0.057	0.070

Table A-2, continued

91:3	0.918	0.155	-0.025	0.083	0.057	0.071
91:4	0.918	0.157	-0.023	0.084	0.059	0.072
92:1	0.919	0.158	-0.019	0.085	0.062	0.074
92:2	0.919	0.160	-0.017	0.086	0.063	0.075
92:3	0.920	0.161	-0.015	0.088	0.065	0.077
92:4	0.920	0.162	-0.013	0.089	0.067	0.078
93:1	0.920	0.164	-0.012	0.091	0.068	0.080
93:2	0.920	0.165	-0.012	0.093	0.069	0.081
93:3	0.919	0.166	-0.011	0.095	0.070	0.083
93:4	0.918	0.167	-0.009	0.097	0.072	0.085