Stability of Velocity in the G-8 Countries: A Kalman Filter Approach

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Abstract: This paper estimates forecasting models using annual data for the income velocity of money in the G-7 countries. The predictions are conditional upon the realized value of the long-term domestic government bond rate. Such conditional forecasts did not deteriorate over the period 1980-1988 as compared with the earlier post-war period. Velocity of M1 is found to be very interest-elastic in almost all countries; velocity of M2 less so. The specifications (based on Kalman filters and smoothers) point to a non-constant (stochastic) trend in velocity, hence questioning the assumptions required for the co-integration techniques used in other research on the demand for money.

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1. Introduction[1]

In the early 1980s many economists became convinced that the demand for money schedule was too unstable to be used for policy purposes. One reason was the influential article by Cooley and LeRoy (1981) which cast serious doubts on the identification of a demand for money function. Another cause was the apparent failure of monetary models to explain movements in floating exchange rates, in particular changes in the external value of the U.S. dollar. Also, many demand for money relations for U.S. M1 or M2 appeared to break down when used for post-sample forecasting, particularly those models that incorporated a small or zero interest rate elasticity. Finally, domestic financial deregulation or international currency substitution were claimed to have shifted the demand for money in an unpredictable manner.

Prescriptions for monetary policy that are formulated in terms of a path for some monetary aggregate must be based on a demand for money function. Doubts about the stability of that function generate doubts about such recipes for policy. This is one reason for the interest in policy prescriptions that are based on targets for interest rates or exchange rates, because such policy rules can (under sometimes unattractive assumptions) be derived from macroeconomic models that do not require identification of a demand for money schedule, or precise knowledge about the interest rate or income elasticities of the demand for money.

Statements about the stability or otherwise of the relationship between money and nominal income are conditional upon the selection of countries in the data set and on the type of statistical analysis performed. Here I have applied identical specifications to annual post-war data for all G-7 countries, using both M1 and M2. The statistical methodology in the paper reflects an important difference of opinion regarding the demand for money

[1]Work on this paper began during my stay as visiting scholar at the Fund's Research Department. Michael Cox and Gerald O'Driscoll of the Dallas Fed provided useful comments. Camiel de Koning and Johan Koenes very ably did much of the programming work and performed the calculations. Peter Gerbrands, Linda van Tuyl and Tom de Vries provided efficient research assistance. Part of the methodological discussion is summarized from my (1990) paper.

function.

Some researchers do not reject the hypothesis that the levels (of the natural logarithms) of money, income and possibly a relevant interest rate are co-integrated, meaning that a regression of the level of real balances on the level of income (and the opportunity cost variable) is permissible (see Boughton,1990, who uses data from five of the G-7 countries; see also Hendry and Ericsson, 1991, for the U.K. only, and Hoffman and Rasche, 1989, for the U.S.).[2] Others prefer to work in terms of first differences of money, income and interest rates without reliance on a long-term relationship in terms of the levels (see, for example, Rasche, 1987, and Hetzel and Mehra, 1989 for the U.S.). Finally, the monograph by Bordo and Jonung (1987) on the long-run behavior of velocity in many countries shows that velocity has a stochastic trend. Unless explanatory variables can explain all changes in the rate of growth of velocity - and the work by Bordo and Jonung suggests that neither income nor institutional variables that represent monetization or economic development can provide more than a partial explanation - it follows that regressions in first differences are misspecified: one would have to difference at least twice.

The simple fact that there are three co-existing schools of thought on this particular issue proves how hard it is to resolve the dispute with least squares regression techniques. Recall that the natural context for any least squares model is that of stationary variables, because least squares regressions for nonstationary variables have to work with a system matrix X'X that is a function of the number of data points. Such regressions do not satisfy ergodicity, meaning that it is not plausible that a single collection of historical data can be used for the estimation of coefficients with distributions that relate to repeated sampling.[3]

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[2]When no danger of confusion exists, the words "natural logarithm of" will be omitted in the sequel.

[3]Durlauf and Phillips (1988) provide an excellent theoretical analysis of the difficulties that arise when ordinary least squares are applied to nonstationary time series with the possibility that the errors are also nonstationary and nonergodic. See also Plosser and Schwert (1979) and Nelson and Plosser (1982). This line of research originated with Paul Newbold, see Granger and Newbold (1974).

Of course each differencing operation increases the probability that the transformed series are stationary. But, if the relationship when specified in terms of levels is subject to both temporary and permanent disturbances, differencing results in a deterioration of the signal-to-noise ratio and less well-determined coefficients.

By contrast to linear regression techniques, Kalman filters and smoothers are designed to work with non-stationary data, because the filters and smoothers produce distributions of the so-called state variables that are conditional on the previous realization of the states. For that reason, non-stationarity in itself presents no problem, and ergodicity can be satisfied, implying that the distributions of the coefficients have a meaningful interpretation. The only reason why Kalman filtering has not yet become the natural way to model multivariate time series has been the technical difficulty to combine estimation of the states with estimation of other parameters required to run the filter successfully.

In this paper I present a method for estimating states and parameters jointly, using smoothing algorithms developed by Maybeck (1979, 1982) together with an estimation technique developed by Dempster, Laird and Rubin (1977) and adapted to the Kalman filter case by Shumway and Stoffer (1982).

The Kalman filter model will be estimated in terms of levels, with allowance for three types of shocks to velocity (V):

(1) temporary shocks to the level of V;
(2) permanent shocks to the level of V;
(3) permanent changes in the trend of V.

Note that type (2), permanent shocks to the level, can be described also as representing temporary disturbances to the rate of growth.

The variances of the different types of shocks and hence their relative importance will be estimated on the basis of the data. In this way the methodological difficulties associated with indirect tests for non-stationarity or co-integration are avoided: the data will tell us whether it is useful or not to account for stochastic changes in the trend.[4]

However useful for dealing with nonstationarity and mixtures of different types of shocks, the Kalman filter cannot deal with the issues raised by Cooley and LeRoy. These authors emphasized two complications that hamper empirical investigations of the demand for money schedule:

1. disentangling demand and supply of money may be impossible;[5]
2. measurement errors in the explanatory variables effect the estimated coefficients in the demand for money relation.

Perhaps the best response is to give up the ambition to <u>estimate</u> a demand for money function and try only to <u>forecast</u> the income velocity of money. In this paper I take the position that forecasts of velocity remain useful, even though it may not be possible to classify the forecast formula as an inversion of the demand for money schedule. Thus, the forecasts may be based on some mixture of demand and supply schedules, and the coefficients will indeed be sensitive to measurement errors in the right-hand-side variables and possibly to the so-called Lucas critique[6]. Hence, the principal connections between the forecasting formulas and economic theory are the choice of explanatory variables - legitimized by their association with the demand or perhaps the supply of money - , the maximum length of any lags in the formulas, and perhaps prior distributions on some of the coefficients.

The remainder of the paper is organized as follows. Section 2 introduces a multivariate Kalman filter technique that can be used to estimate a relationship between the level of V, and the level of the interest rate. In section 3 I present the results of implementing this multivariate Kalman filter for the velocity of M1 and M2 in all G-7 countries using annual data. Section 4 tests a number of simple hypotheses regarding the stability of velocity and the size of the forecast errors in velocity during the

[4]See Swamy, Von zur Muehlen and Mehta (1989) for a very critical methodological discussion of co-integration tests.

[5]see for example Hamilton (1989) for a brief analysis why standard money demand equations are a mixture of supply and demand effects.

[6]Neither issue can be circumvented with the use of instrumental variables (see Cooley and LeRoy).

1980s. Section 5 draws some statistical and economic conclusions.

2. A Kalman filter model for velocity

Consider the simplest possible relationship between real balances, real income and an interest rate:

(1) $p_t + y_t - M_t = V_t = c + \alpha tr_t + \theta i_t + u_t$

In equation (1), p_t represents the natural logarithm of the price level in an economy, y_t the log of a measure of income appropriate to the demand for money, M_t the log of the money supply and hence V_t the log of the income velocity of money. c Represents a shift term in the regression, tr_t a linear trend for the log of V, i_t the log of some relevant interest rate and u_t the residual in the regression. α and θ are coefficients to be estimated.

If we model in terms of levels, we shall have to accept that the residual part of the equation will be non-stationary. Time-varying stochastics offer the best chance to cope with the dynamic aspects of the demand for money listed above. One way to embed the linear least squares equation (1) in a richer dynamic model is to change to the state-space formulation. The state vector is composed of all regression coefficients. The state transition matrix would be the unit matrix in the case of recursive least squares without correction for serial correlation, but can be different in order to represent dynamic features that are hard or impossible to model in the least squares context.

The general state-space notation is as follows:

$$(2) \quad V_t = (1 \quad 0 \quad i_t) \begin{pmatrix} c_t \\ tr_t \\ \vartheta_t \end{pmatrix} = u_t$$

$$var\,(u) = R$$

$$(3) \quad \begin{pmatrix} c \\ tr \\ \vartheta \end{pmatrix}_{t+1} = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} c \\ tr \\ \vartheta \end{pmatrix}_t + \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix}_t$$

$$var \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} = \begin{pmatrix} Q_1 & 0 & 0 \\ 0 & Q_2 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Equation (2) is the observation equation. It states that the level of the log of velocity, V, equals the sum of a shift parameter, the product of the interest rate elasticity, θ, and the long-term interest rate, i_t, and a residual term u_t. This observation equation is identical to an ordinary regression equation.

The Kalman filter methodology adds equation (3), the so-called state update equation. It shows how three state variables change from period to period. The equation has a predetermined part and a stochastic part. In the predetermined part, the shift parameter is adjusted upwards in each period by the amount, tr_t, which represents a trend. In the stochastic part of equation (3), the trend term, tr_t, is subject to a stochastic shock, w_2, and the shift parameter is subject to permanent stochastic shocks, w_1. The interest rate elasticity is not subject to stochastic shocks over time.

The user of a Kalman filter is asked to provide estimates of the variances Q_1, Q_2, and R. The Kalman filter then processes the data "on line" and produces estimates of the state variables - here: the shift parameter, the trend and the interest elasticity - and their variance-covariance matrix, P_t.

The variances, Q_1, Q_2, and R may be chosen in such a way that the specification becomes equivalent to either equation (1) in terms of the levels or the same specification in terms of first or second differences. The Kalman filter specification of equations (2) and (3) thus includes both the levels and the first-difference specification. Other statistical techniques for comparing levels and first difference specifications suffer from the disadvantage that the two competing hypotheses are non-nested.

The Kalman filter model may be re-written as follows:

(4) $$\Delta V_t = \theta \Delta i_t - 1.0 (V_{t-1} - m_{t-1} - \theta i_{t-1}) + e_t$$

In eq. (4), m_t represents a stochastic trend subject to the three types of shocks discussed before: temporary to the level, permanent to the level and permanent to the rate of growth. The equation shows that the state-space formulation is equivalent to an error correction model for money demand. In this particular simple case the adjustment parameter happens to be unity (and the coefficient on i_{t-1} equals the coefficient on Δi_t) because with annual data and a stochastic trend there is no serial correlation in the residuals and hence no need for lagged terms. An important difference with standard error-correction models is the behavior of the intercept m_t which is constrained to be constant over time in such models. Hence the Kalman filter formulation incorporates all error-correction models - one could allow for lagged values of velocity and opportunity cost variables - but it is richer in one crucial respect because it allows for permanent shocks to the level and rate of growth of velocity.

3. Velocity in the G-7 countries

All data are taken from the International Financial Statistics tape produced by the Fund. Starting points for the analysis were dictated by data availability on the tape as indicated in table 1; the terminal year is 1988. There are discontinuities in some of the monetary series; I have inserted a dummy variable for each of the non-trivial breaks in a series for M1 or M2.[7] Since estimation is in terms of levels, the dummies are of the type {0,0,..0,1,1,..1,1}. Dummies have been inserted because of the following discontinuities in the money series, as indicated by the I.M.F.:

	M1	M2
US	–	1959
UK	1981	1975 1981
France	1958 1969 1977	1958 1969 1977
Canada	1968	1967 1968

The economic model is the simplest possible one. The income elasticity of money demand is fixed at unity and a single interest rate is used to represent the opportunity cost of money, using the simplifying assumption that the own rate of return on money in each country is constant over time at the margin. With such simple assumptions the resulting models will not be the optimal forecasting tools for velocity. However, the results from these minimal specifications may contribute more convincingly to the debate about the predictability of velocity, because uniform and simple models for seven different countries are less subject to the suspicion of being based

[7] Note that the dummies relate only to breaks in one of the variables in the definition of velocity, not to observed outliers in the estimated statistical models.

on data mining than multi-parameter models with extensive lag structures and many free parameters that are tuned to the actual data in each country.

The only free parameters in the models are the interest elasticity which is assumed to be constant over time, and two variance terms: the variance of the permanent shocks to the level of the series and the variance of the permanent shocks to the trend in velocity.[8]

The income elasticity of money is not a free parameter in this Kalman filter model. I hypothesize that financial innovations lead to changes in velocity trends that are spuriously picked up by non-unitary income elasticities in the traditional money demand specifications. The principal attraction of this hypothesis is that it is not troubled by the substantial differences between the income elasticities in different countries over identical time periods in traditional models that do not allow for stochastic trends but include the income elasticity as a free parameter.

The exogenous explanatory variable is the domestic yield on long-term government bonds. No experiments were undertaken with other rates of return or with lag structures, and the same specification was imposed for all countries. I have tested for stability of this interest rate elasticity by allowing for a different value before and after 1980. The hypothesis that the interest rate elasticity did not differ between these two sub-periods was not rejected for any of the G-7 countries.

The analysis is limited to a single opportunity cost variable and I have made no attempts to incorporate measures for the own return on money. In recent years, many G-7 countries have witnessed an increase in the explicit payment of interest on large fractions of M1 and M2 and therefore it would certainly make sense to collect data for the own rate of interest and test for its significance.

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[8]The variance of the temporary shocks to the level of velocity could be seen as a third variance parameter, but the models are homogeneous of the first degree in all the variance and covariance terms. Hence, this variance is best viewed as computed ex-post from the results of the Kalman filter.

The filtering and estimation algorithm consists of five different blocks. First, there is a normal ("forward") Kalman filter that produces an estimate of the state variables at time T+1 (in our case: the shift parameter, the trend and the interest rate elasticity) based on all the data from time t=1 up to and including time t=T. Second, a backward filter is used which generates a backward "forecast" for time T using all the data from period T+1 through to the final period.

A smoothed estimate of the state at time t=T can be formed by combining the forward and backward filters. In order to generate a meaningful covariance matrix for the smoothed estimates of the states, one has to start both filters with an uninformative prior distribution for the covariance matrix of the states. With this initialization, the smoothing algorithm will reproduce the o.l.s. variance matrix of the parameters (and the o.l.s. residuals) in the special case that all the states are constant and correspond to o.l.s. parameters.[9]

The fourth block of the algorithm uses the results of the Kalman smoother to compute adjustments to the three unknown variance terms. I use the Expectation Maximization algorithm, described by Dempster et al. (1977) and adapted to our case by Shumway and Stoffer (1982)[10]. Then the separate forward and backward Kalman filters (blocks 1 and 2) are run again in order to prepare inputs for the Kalman smoother in the next iteration. This process stops when the estimated values of the unknown parameters have converged to their optimal values.[11]

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[9]In this important respect my program differs from the "Stamp" program, developed by Harvey and described in Harvey (1989). His program uses up the first two values of the observed series in order to initialize the two unknown variance terms for the shocks to the level and growth rate of the series. By contrast, I apply a smoother in each iteration of the program which is computationally more costly but avoids this loss of degrees of freedom in estimation.

[10]See Nelson (1988) for evidence from his univariate research of U.S. gnp that optimization with respect to the unknown variances of the different shocks to the level and the shocks to the trend of a nonstationary time series may be a delicate matter. This is a topic for additional research.

[11]See Bomhoff (1990) for further details on the statistical procedure used.

Finally the fifth block of the algorithm is applied just once. It starts with the optimal values for the interest rate elasticity and all variance terms and uses these inputs for a single run through the data. The forecast errors of this filter are analyzed in the tables. Such a forward filter does use a few inputs that are based on an analysis of the complete sample period: the interest rate elasticity and the relative importance of permanent shocks to the level of velocity versus permanent shocks to its growth rate. However, the final forward filter does not use knowledge about the specific realization of the shocks in the sample. Hence it should be classified as a recursive method rather than an ex-post method such as ordinary least squares or least squares with an error-correction specification.

Table 1 summarizes the results for the G-7 countries. For each country the interest rate elasticity is shown for M1-velocity and M2-velocity, together with the estimated standard error of the coefficient. All t-values are significant at the 0.05 level on a two-sided test, except in France, where the interest rate elasticity for M2 is insignificant and the coefficient for M1 has a t-value of 2. In all countries the interest rate elasticity of M2 is smaller than that of M1, except in the U.S. where the elasticities are estimated to be about equal. In five out of the seven G-7 countries the interest rate elasticities for M1 are quite close together (U.S, Japan, Germany, U.K., Italy). The elasticities are higher but still of the same order of magnitude as found in earlier work by Den Butter and Fase (1980).

Table 1 also shows the size of the forecast errors. These are conditional on the realized value of the long-term domestic bond yield and the estimated interest rate elasticity and on the optimal estimates of the relative importance of the three different types of shocks that effect velocity as well as on the covariance between the permanent shocks to the level and the permanent shocks to the growth rate. As far as the intercept and the trend in velocity are concerned, the forecasts are purely ex ante and computed recursively without any smoothing. The stochastic trend does change over time, but the filter does not utilize future observations to fit a trend to the complete period; instead it moves through the data and learns from the data how to adjust the trend as time proceeds.

The stochastic trend gives the Kalman filter its competitive edge over standard regression techniques, including the co-integration method with an error-correction step. Proponents of co-integration have to assume that all changes in the dependent variable that are not explained by a linear combination of the levels of the explanatory variables are stationary and can be taken care of in the error-correction step. This assumption, however, is implausible in cases, such as the demand for money, in which all the explanatory variables that are included do exhibit non-stationarity. Is it attractive to accept that the influences which we can measure (opportunity cost, possibly inflation or income) are non-stationary, but to assume that other factors for which we do not have proper empirical measurements (innovations in payments techniques, development of new substitutes for money) are stationary as required by the co-integration technique? The Kalman filter, by contrast, is designed to deal with non-stationarity of the unobserved components in the model.

The reasons for computing the forecasts conditional on the interest rate for the current year are twofold. First, the outcomes are directly comparable to results from studies of the demand for money, the principal differences being that the Kalman filter is an one-line technique in stead of an ex post method and allows for a stochastic trend in velocity. Second-ly, because interest rates are observed without lag and without measurement error, policymakers can always adjust any targets for a monetary aggregate if interest rates during the planning period deviate from their predicted values when the targets were set. Hence, one could argue that forecasts conditional on interest rate realizations produce more useful evidence about the forecastability of velocity than forecasts that are conditional only on past values of velocity, income and interest rates.

Table 1 gives two estimates of the accuracy of the forward Kalman filter. The first number for each country and each monetary aggregate indicates the root mean square error of the forecasts for the period as indicated. The second number is a robust estimate of that same root mean square error, computed using the median absolute deviation divided by the correction factor 0.6745. For normally distributed values this robust estimate has the same expectation as the standard error. Outliers in the series cause the robust estimate to be smaller than the "official" standard error.

The table confirms that outliers are important in several countries. Here is a list of all outliers, defined as forecast errors (in percent) in excess of three times the robust estimate of the standard error of the forecasts for the country and aggregate concerned:

	M1-velocity	M2-velocity
Japan	1971: -16.2	1971: -11.2
Germany	-	1960: 93.0
UK	1963: -16.3	1972: -14.5
France	-	1987: -10.9
Italy	1960: 12.7 1970: -13.5 1974: 14.2	1960: 13.5
Canada	-	1954: -11.1 1983: 14.9

Note that two out of the twelve outliers relate to years in the period 1980-1988, which does not support the hypothesis that outliers became more frequent in the recent period.

4. Has velocity become more unpredictable?

This section discusses a number of additional hypotheses regarding the unpredictability of velocity. In table 2 I present results of a formal test whether the forecasts of velocity have become more imprecise in the 1980s. For each country the two numbers in each cell in the table refer to the variance of the forecast errors over the period through 1979 and the variance of the forecast errors over the period 1980–89. Forecasts errors are taken from the final forward filter as discussed in section 2.2 and use the current realization of the interest rate. The sum of squared forecast errors has been divided by n–1, with n the number of errors in the sample.

The results in table 2 reject the notion that the income velocity of money has become more unpredictable worldwide in the 1980s. The errors become larger in the U.S. and in Canada, as well as for M2 in France, in each case by a factor of approximately 2. On a formal F–test this is insufficient in all five instances to reject the null–hypothesis that the variance of velocity has remained unchanged. Velocity of M2 in Italy is as predictable before 1980 as after that year. In all eight other cases, the forecast errors decline, sometimes by a very large margin.

If we arrange the variances for both M's and both periods in order of magnitude across the countries, we see that for M1 velocity the median value of the variance falls from 26.7 to 10.3 and for M2 from 17.5 to 16.4. It is also interesting to note that before 1980 M2 velocity was less variable than M1 velocity in all seven countries, but during the 1980s in four of the seven countries. Particularly small are the forecast errors in the 1980s for M2 velocity in Japan and Germany.

Table 3 shows how the Kalman filter forecasts compare to an alternative method of generating forecasts of velocity. The Kalman filters have been re–estimated for periods through 1979 and extrapolated through 1988.[12] As an alternative, regressions have been performed for both monetary aggregates according to the following specification:

[12] Japan had to be omitted because of the limited length of the data series.

$$(5) \quad V_t = c + \alpha tr_t + \beta y_t + \theta i_t + u_t$$

$$u_t - \phi u_{t-1} = a_t$$

In eq. 5, velocity is regressed on a linear trend, on real income and on the long-term interest rate. A first-order autoregressive parameter is estimated for the residuals in all cases. The equation is estimated using data through 1979 and the regression coefficients are used for dynamic forecasts conditional on the realized values of real income and the interest rate, and again incorporating the serial correlation correction. The numbers in the table show the mean errors (the bias) and the standard deviations of the conditional forecasts for 1980-1988. The Kalman-filter gives less biased forecasts with far lower forecast errors.

Finally, table 4 investigates whether the differences in predictability of velocity across countries is related to the unpredictability of the money supplies. I have applied uniform Box-Jenkins time-series models to the money supply data, assuming a first-order moving average model applied to the second differences of money stock data. The table shows the estimated standard errors of the fourteen Box-Jenkins models, together with the robust estimates of the standard errors of the forecasts in velocity. I have computed Spearman's rank correlation coefficients between these errors and the forecast errors for velocity. For both M1 and M2 the rank correlation coefficient equals 0.71 which is at the 0.05 significance level.

Table 4 investigates the rankings of the forecast errors in money and in velocity on a cross-sectional basis. One can also rank the forecast errors for money and velocity in each country in order to see whether years in which realized money growth deviated much from predicted money growth tended to be years in which velocity also deviated a lot from its conditional forecast.

Significant rank correlations at the 0.05 level, using Spearman's method, are obtained in the following cases: United Kingdom M1 (coefficient=0.60) and M2 (0.65), Japan M1 (0.61), Italy M1 (0.52) and M2 (0.37) and Canada M1 (0.49) and M2 (0.55). There were no significant negative correlations. Hence, in the countries in which M1 or M2 velocity was most variable, years with large forecast errors in money tended to be years with large forecast errors in velocity.

5. Conclusions

The Kalman filter results indicate a substantial interest rate elasticity of the demand for money for M1. Niskanen (1988) and Poole (1988) were the first economists to point out that earlier estimates of the demand for real balances in the U.S. might have gone astray by assuming that the secular increase in velocity during the 1970s should be represented by a linear trend. They pointed to the alternative hypothesis that the demand for money fell during that period because of higher trending interest rates. Poole's paper describes why a substantial interest rate elasticity makes the conduct of a disinflationary monetary policy more difficult: the rate of growth of the money supply has to decline in order to lower inflationary expectations, but as the lower inflationary expectations lead to lower long-term interest rates, the demand for real balances goes up.

The results lend no support to the hypothesis that the income velocity of money has become significantly more unpredictable in the 1980s. Forecast errors did increase in the U.S. but became smaller in most other countries. The frequency of outliers, defined as particularly large forecast errors, did also not increase during the years 1980-88. There is a significant correlation between the size of the forecast errors in velocity and the size of the forecast errors in money: predictable monetary policies are associated with predictable behavior of velocity.

Finally, regarding methodological issues, the Kalman filter allows us to specify the model in terms of levels, even though the dependent variable, the explanatory variables and the error terms are nonstationary. The levels specification has important advantages: smaller measurement errors in the dependent (and independent) variables; superior estimates of the coefficients, if the independent variable(s) effect velocity with a variable lag. Also, the Kalman filter has the advantage over the co-integration technique that no assumption needs to be made (and tested using weak power tests) about the degree of co-integration of the dependent and independent variables. If the hard-to-model effects on velocity of changes in payments techniques or the introduction of new money substitutes have persistent effects, the co-integration technique breaks down, but the Kalman filter can cope with such permanent shifts in the demand for money through its incoporation of a stochastic trend.

Biographical note

Eduard J. Bomhoff has been professor of economics at Erasmus University Rotterdam (The Netherlands) since 1981. He has been an adviser to the Bank of Japan and the Commission of the European Communitities as well as to the Fund's Research Department. He serves on the Editorial Board of the Journal of Monetary Economics and on the Advisory Board to the Carnegie-Rochester Conferences.

Table 1 Forecast errors of velocity

	M1		M2	
	int. el.	stand. error	int. el	stand. error
U.S. 1956–1988	0.23 (0.034)	2.4 1.9	0.24 (0.036)	2.2 2.5
Japan 1968–1988	0.24 (0.075)	5.5 4.6	0.15 (0.062)	4.4 3.8
Germany 1958–1988	0.22 (0.034)	3.3 3.1	0.16 (0.036)	3.0 2.4
U.K. 1953–88	0.25 (0.077)	5.2 4.1	0.12 (0.055)	4.6 3.6
France 1952–88	0.084 (0.042)	3.9 4.4	0.012 (0.061)	3.4 2.7
Italy 1953–88 (M1) 1955–88 (M2)	0.19 (0.072)	5.1 3.6	0.14 (0.063)	4.5 3.7
Canada 1950–88	0.56 (0.12)	5.8 5.1	0.15 (0.069)	4.7 4.3

Standard errors are printed behind each interest rate elasticity. All "official" and robust estimates of the standard error of the forecasts are in percent.

Table 2 Forecast errors in velocity

	M1	M2
U.S.	5.1/8.4	4.2/ 8.5
Japan	49.5/10.3	34.4/ 4.4
Germany	12.8/ 8.9	12.4/ 2.5
U.K.	27.5/30.9	24.8/16.4
France	18.4/ 7.1	10.0/19.5
Italy	30.5/18.1	22.4/19.3
Canada	26.7/69.0	17.5/45.7

All numbers must be multiplied by 10^{-4}. The first number in each pair refers to the variance of the forecast errors before 1980; the second number to the variance over 1980-88. Forecast errors are based on an on-line Kalman Filter that uses the current value of the long-term government bond rate.

Table 3 Forecast errors for 1980-88

		Kalman filter		regressions	
		bias	stand. error	bias	stand. error
U.S.	M1	-1.46	2.09	2.48	2.15
	M2	0.24	2.89	0.55	4.71
U.K.	M1	-5.50	6.14	5.47	6.97[13]
	M2	-1.98	4.20	6.06	4.52
Fr.	M1	0.25	2.69	-2.80	3.51
	M2	-0.71	4.14	8.65	3.07
It.	M1	3.79	2.58	18.26	6.14
	M2	4.16	2.94	15.26	4.03
W.G.	M1	-0.25	2.96	5.92	3.17
	M2	0.05	1.81	3.74	1.07
Ca.	M1	-2.83	7.38	3.40	9.99
	M2	1.39	6.61	-3.64	5.70

[13]The dummy variable for 1981 haas not been inserted in the calculations for the U.K.

Table 4 Forecast Errors in Money and Velocity

		M1	(rank)	M2	(rank)
U.S.	velocity	1.90	(1)	2.50	(2)
	money	2.75	(1)	3.10	(4)
U.K	velocity	4.10	(4)	3.60	(4)
	money	5.32	(5)	5.20	(7)
Fr.	velocity	4.40	(5)	2.70	(3)
	money	3.48	(2)	2.83	(2)
W.G.	velocity	3.10	(2)	2.40	(1)
	money	4.02	(3)	2.17	(1)
It.	velocity	3.60	(3)	3.70	(5)
	money	4.42	(4)	3.13	(5)
Ca.	velocity	5.10	(7)	4.30	(7)
	money	6.55	(7)	4.36	(6)
Jp.	velocity	4.60	(6)	3.80	(6)
	money	5.37	(6)	2.96	(3)

All errors are percentages.

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