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Authors	R. W. Hafer, and Scott E. Hein
Working Paper Number	1983-012B
Revision Date	January 1983
Citable Link	https://doi.org/10.20955/wp.1983.012
Suggested Citation	Hafer, R.W., Hein, S.E., 1983; Predicting the Money Multiplier: Forecasts from Component and Aggregate Models, Federal Reserve Bank of St. Louis Working Paper 1983-012. URL https://doi.org/10.20955/wp.1983.012

Predicting the Money Multiplier:
Forecasts from Component and Aggregate Models

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83-012
Revised

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We have received useful comments on this paper from Ted Balbach, Mike Belongia, Eduard Bomhoff, Al Burger, Clemens Kool, Anna Schwartz, Jack Tatom and Paul Veugelers. We would especially like to thank Jim Johannes and Bob Rasche for their assistance during early stages of this project and their comments on an earlier draft of this paper. The usual caveat, of course, applies. We also would like to thank Rob Hess for his research assistance. The views expressed are the authors' and may not represent those of their employers.

1. Introduction

A money stock control procedure that systematically adjusts the monetary base conditional on forecasts of the money multiplier has been suggested as an alternative to procedures used by the Federal Reserve System in its conduct of monetary policy. This approach has been demonstrated to reduce the volatility of quarterly money growth and to reduce the swings in economic activity that accompany such money stock behavior [see, for example, Hafer, Hein and Kool (1983)]. Since the monetary authorities possess a great deal of control over movements in the monetary base, a crucial element in this control procedure clearly is the ability to accurately predict short-term movements in the money multiplier.

Numerous papers that investigate the predictability of the money multiplier have appeared in the literature.[1/] Beginning with Bomhoff (1977), recent studies have dealt primarily with developing time series models of the multiplier process.[2/] Johannes and Rasche (1979, 1980, 1981a, b, c, 1982) have extended the work of Bomhoff in forecasting the multiplier by using a "component" approach. Instead of estimating and forecasting with a univariate model of the multiplier itself, their innovative approach is to model and forecast the separate ratios that comprise the multiplier. Combining the individual ratio forecasts gives one a prediction of the money multiplier.

Our purpose is to investigate the capabilities of component and aggregate time-series models in forecasting the money multiplier. This is done by directly comparing one-step-ahead monthly forecasts of the M1 and M2 multipliers derived from each procedure. The out-of-sample forecasts are generated for the period January 1980 through December 1982, a period in which a diverse set of events affected the multiplier and its components. For example, the period encompasses the credit control period in 1980 as well as the nationwide introduction of NOW accounts in 1981.

The question to be addressed is: Does the component approach to modeling and forecasting the multiplier yield superior forecasts relative to the aggregate model? Our findings indicate that, based on several forecasting criterion, little is gained from the component forecasting procedure, as presently employed. The advantage of the component approach must lie elsewhere, such as having a better understanding of the source of an aggregate forecast error or utilizing the correlation in component forecast errors to improve the aggregate forecast.[3/] Most importantly, however, is the finding both techniques do quite well in forecasting the money multiplier during the past few years.

The format of the paper is as follows: In Section 2 we describe the M1 and M2 multipliers to be estimated and forecast, and present component and aggregate models resulting from our estimations. Section 3 presents and discusses the forecasting results obtained using each model. Forecast summary statistics are evaluated for the entire period from January 1980 to December 1982, as well as the individual years. Finally, Section 4 closes the paper with some concluding remarks.

2. Multiplier Definitions

The relationship between movements in base money and the monetary aggregates is captured in the Brunner-Meltzer formulation:

(1) $M_t^i = m_t^i B_t$

where M_t^i is the ith monetary aggregate in period t, B represents the base measure used, and m_t^i is the appropriate multiplier for the aggregate being considered.[4/] The multiplier's value at any point in time (t) is, therefore, simply the ratio of money to base money (M_t^i/B_t).

The multiplier also may be defined by its component parts.[5/] Because the multiplier reflects actions on the part of the Federal Reserve, government, banks and the public, accounting for each action separately gives a clearer picture of why the multiplier has changed. Thus, the multiplier defined by its component ratios is given by:

$$(2) \quad m_1 = \frac{1 + k + tc}{(r + \ell)\,(1 + t_1 + t_2 + g + z) + k}$$

and

$$(3) \quad m_2 = \frac{1 + k + tc + t_1}{(r + \ell)\,(1 + t_1 + t_2 + g + z) + k}$$

where m_1 = M1 multiplier,

m_2 = M2 multiplier,

$k = C/D$,
$tc = TC/D$,
$t_1 = (M2 - M1)/D$,
$t_2 = (M3 - M2)/D$,
$g = G/D$,
$z = Z/D$, and
$(r + \ell) = (SB + RAM - C)/[M2 - C + (M3 - M2) + G + Z]$.

The mnemonics used in calculating the above ratios are:

C = currency in hands of the public,
D = total checkable deposits,
G = government demand deposits,
Z = demand, savings and time deposits at banks due to foreign commercial banks and official institutions,
TC = travelers checks,
SB = source base, and
RAM = reserve adjustment magnitude.

The M1 and M2 multipliers reveal one important aspect of the logic underlying the components approach; namely, each multiplier is merely a different combination of the same ratios. Thus, instead of estimating a different model for each multiplier separately, one can estimate each component and then combine the estimates into the desired multiplier.

To examine the relative multiplier forecast accuracy, time-series models were developed for each of the ratios comprising the multipliers, as well as the aggregate multipliers themselves. In all cases, the data are not seasonally adjusted and are expressed in terms of their logarithms.

2a. Component Model Estimates

The different component ratios of the multipliers are estimated using data from the sample period January 1959 to December 1979. In three instances, however, the sample period is shortened. The sample period for the t_2 ratio, which measures the ratio of the non-M2 components of M3 to total checkable deposits, begins in January 1961 because large negotiable certificates of deposit did not exist before this date. Moreover, the reserve ratio $(r + \ell)$ was estimated with data beginning in October 1968 to avoid any effects stemming from the switch from contemporaneous to lagged reserve accounting. Finally, the traveler's check component (tc) is modeled using data beginning in January 1969. As noted by Johannes and Rasche (1981c), the time series of tc indicates a break in the late 1960s, which they in part attribute to changes in the quality of data collected. Thus, we, too, model our tc component using data starting in January 1969, maintaining the comparability of results and data.

The time-series models estimated for the individual components are presented in table 1. As indicated by each specification, it was necessary to first-difference the seasonal difference $[(1-B)(1-B^{12})]$ of the data to estimate the models. The results in table 1 indicate that each model adequately captures the evolution of the series. The reported Q-statistics reveal that the residuals have been reduced to white noise at reasonable levels of significance.[6/] Moreover, the estimated coefficients are significant at the 5 percent level in nearly every instance.

Comparing the ratio estimates in table 1 to those of Johannes and Rasche (see Appendix A) indicates that the use of different data sets has not appreciably altered the estimating models. This is not true, however, for the traveler's check ratio. The reason for this is that Johannes and Rasche estimate the ratio of traveler's checks to currency, and we use the traveler's check to total checkable deposits ratio.[7/] The Q-statistic indicates that the residuals of our tc model are reduced to white noise, indicating that the model estimated is statistically appropriate.

2b. Aggregate Model Estimates

The autocorrelations of the M1 and M2 multipliers (in logarithms) indicated that first differencing and seasonal differencing were required to achieve stationarity. An examination of the autocorrelations and partial autocorrelations for the M1 multiplier suggested a relatively simple moving-average (MA) model. Thus, the model fit to the M1 multiplier for the period January 1959 to December 1979 is (standard errors appear in parentheses):

$$(4)\quad (1-B)(1-B^{12})\ \ln m1_t = (1 - \underset{(0.050)}{0.2843B} - \underset{(0.048)}{0.1513B^7} - \underset{(0.051)}{0.5140B^{12}})\, a_t$$

$$Q(12) = 12.69 \qquad SE = 0.4697 \times 10^{-2}$$

The estimated coefficients each are significant at the 5 percent level. The Q-statistic indicates that, at the 5 percent level, we cannot reject the hypothesis of white noise residuals. In the following section, therefore, equation (4) is used to generate forecasts of the aggregate M1 multiplier.

The autocorrelations for the M2 multiplier series suggested neither a simple autoregressive (AR) or MA model. After some experimentation, the best fitting M2 multiplier model was found to be a mixed process. Again using the January 1959 to December 1979 sample, the estimated model for the M2 multiplier is (standard errors appear in parentheses):

$$(5)\quad (1 - \underset{(0.082)}{0.1050\, B} - \underset{(0.064)}{0.2551\, B^3})(1-B)(1-B^{12})\ \ln m2_t =$$

$$(1 - \underset{(0.058)}{0.0879\, B} - \underset{(0.046)}{0.7349\, B^{12}})\, a_t$$

$$Q(12) = 19.25 \qquad SE = 0.4279 \times 10^{-2}$$

The Q-statistic reveals that, at the 5 percent significance level, this model adequately reduces the estimated residuals to white noise. Thus, equation (5) is the specification to be used to forecast the M2 multiplier.

3. Multiplier Forecasts

The reason for estimating time series models of the multipliers is to obtain reliable out-of-sample forecasts. In this section we compare the forecasting performance of the component and aggregate approaches to forecasting the money multiplier over the period January 1980 to December 1982.

The procedure by which we generate each multiplier forecast uses only the currently available multiplier or component data up to the time that the forecast is made. In other words, a June multiplier forecast is made with data through May. Fixing each model's parameter estimates to their values from the 1959-79 estimation period, the multipliers and their component ratios are forecast by incrementing the available multiplier information each month. Thus, the new information is not allowed to influence the models' estimates, but is utilized in forming the mutiplier forecast for the next month.[8/]

3a. Ratio Forecasts

Individual ratios that comprise the multipliers were forecast following the preceding guideline. Summary statistics for each component are presented in Appendix B. The various measures used to gauge forecasting performance suggest that the models in table 1 yield quite accurate out-of-sample forecasts. This finding holds for most ratio forecasts regardless of the year examined. To see this, the relative root-mean-square error (RMSE) for each component in its worst year is reported in table 2. There we see that in 1982 the RMSE for the g-ratio-- the ratio of government deposits to total checkable deposits-- was about 28 percent of the average level (0.01102/0.039429). Examining the individual forecast errors for the g-ratio (not reported) indicates that much of this error is from offsetting misses in February and June of 1982. With regard to the other ratios, however, the largest relative RMSE is less than 5 percent (4.7 percent for the z-ratio in 1981). Thus, the forecast results for the individual ratios indicate that the models have provided relatively accurate post-sample forecasts.

3b. M1 Multiplier Forecasts

The ratio forecasts expressed in equation (2) were used to form forecasts for the M1 multiplier. The aggregate multiplier model (equation (4)) also was used to generate monthly out-of-sample forecasts for the M1 multiplier. A comparison of these forecast results, reported in table 3, indicates that the two procedures produce nearly identical results.

Looking first at the full period, January 1980 to December 1982, the differences between forecasts are miniscule. For example, in terms of their RMSEs, the component approach improves upon the aggregate forecasts by at most 1 percent. The mean absolute error (MAE) statistics, however, reveal that the aggregate approach actually does better, albeit by a mere 0.5 percent. The Theil forecast decomposition statistics also indicate that each approach yields desirable forecasts. In each case little of the forecast error can be attributed to bias

(B). Instead, the evidence in table 3 indicates that the greatest proportion of the forecast errors is attributable to unequal covariation (CV) between the forecast and actual series: this factor accounts for about 95 percent of the forecast error for both the component and aggregate model.

The annual forecasting record for each multiplier forecasting technique again reveals little difference between the two. Indeed, the best performance of the component model relative to the aggregate is in 1982 when the component model's MAE is about 4 percent less than that for the aggregate. In terms of RMSE, however, the improvement is only 1 percent.

The subperiod results are important, because they permit us to assess the claim that the component approach is a superior forecasting model since more detailed information is used. This claim is not supported by the results of our forecasting experiment. Several important events have occurred during the forecast period that, *a priori*, should have favored the components approach. For example, the credit controls imposed during the second quarter of 1980 clearly affected the k-ratio more than the others. *A priori*, this type of event may have suggested that a components approach would be more successful in predicting multiplier developments. *Ex post*, it was not. Moreover, the nationwide introduction of NOW accounts in January 1981 also may have lead one to prefer the components approach. In this instance, the alternative forecasting models performed equally well. In fact, during 1981, the aggregate model yields a MAE that is 7 percent lower than the component forecasts.[9/] Thus, with regard to forecasting the M1 multiplier, there is no appreciable gain to employing the component multiplier model instead of the simple aggregate approach.

3c. M2 Multiplier Forecasts

The second forecasting experiment involves a comparison of the component model's M2 multiplier forecast, derived from the components of equation (3), to that from the aggregate model, equation (5). This comparison again is carried out for the full 1980-82 period and each individual year: the results are reported in table 4. The component model does not improve upon the simple aggregate model. Turning first to the full-period comparison, the aggregate model's forecasts improve upon those from the component model by 29 percent in terms of the RMSE. When the comparison is made using the MSE, however, the aggregate model's forecasts are lower by 100 percent. As with the M1 multiplier forecasts, a significant proportion of the forecast errors for each model is explained by unequal covariances between actual and forecasted values.

Comparing the M2 multiplier forecasts by individual years reveals a similar outcome. During 1980, the MAE, MSE and RMSE derived from the simple aggregate model are slightly less than those based on the components approach. For example, the aggregate model's RMSE is about 3 percent less than that derived from the component forecasts. The improvement in 1981 is striking: the aggregate model's forecasts reduce the MSE by over 100 percent and the RMSE by 34 percent. Moreover, much more of the aggregate model's forecast error is due to unequal covariance between the actual and predicted series. The dramatic improvement in forecasting using the aggregate model again appears in 1982. There we find that the aggregate model's RMSE is 33 percent lower than that derived from the component model. The forecast errors from the aggregate model also are less subject to bias (2 percent versus 45 percent), and again are due primarily to unequal covariation (91 percent).

The M2 multiplier forecast results again do not support the contention that capturing the changes in the individual components produces multiplier predictions superior to the aggregate model. To an even greater extent than was found for the M1 multiplier, the forecast comparison using the M2 multiplier suggests that the aggregate modeling/forecasting approach is preferable to the components method.

4. Conclusion

The usefulness of a components approach and an aggregate approach to forecasting the money multiplier has been examined. Based on one-step-ahead monthly forecasts for the period January 1980 to December 1982, the empirical evidence presented here indicates that both models do quite well in predicting movements in the M1 and M2 money multipliers. The accuracy of these forecasts is encouraging, because we have not updated the estimates of the models, we have not made use of judgmental adjustments as intra-monthly data becomes available, and we have not allowed for the introduction of intervening information to account for changes in the portfolio composition of the public. This means that the policy usefulness of forecasting the money multiplier combined with a proper adjustment of the monetary base could only be enhanced relative to the results reported here.

In terms of forecasting performance, it appears that the aggregate approach does equally well as the components method. For example, using the M1 multiplier, the best improvement over the aggregate model's forecast was less than a 5 percent reduction in the MAE in 1982. For the M2 multiplier, the aggregate approach yielded superior forecasts relative to the components model. This suggests that the advantage of the component approach is not in forecasting accuracy, per se, but more the ability to track down a forecast error.

FOOTNOTES

1/Some early attempts, among others, include Burger, Kalish and Babb (1971); Pierce and Thomson (1972); Levin (1973); and Frost (1977). The multiplier approach to controlling the money stock is based on the work of Brunner and Meltzer (1964).

2/Bomhoff's study presents evidence for the United States and the Netherlands. This technique also has been used to forecast the multiplier in Switzerland [Buttler, et. al. (1979)] and in seven EEC countries [Frantianni and Nabli (1979)].

3/An argument for the components approach is that certain events may influence one ratio more than any other. Consequently, the component approach would seem to make better use of pertinent information in modeling the multiplier relative to an aggregate approach. This present paper shows little gain from this avenue. Another important gain in forecasting accuracy is possible with the components approach if the movements in the affected components do not have negligible covariances, allowing one to ulitize the information contained in the cross-correlations of the estimated residuals to form more efficient forecasting models. Although Johannes and Rasche (1979) do present statistics on the cross-correlations among the different ratios' residuals, this avenue is not pursued in their forecasting experiments and is not investigated here.

4/In this paper, base money is defined as the St. Louis adjusted monetary base. For a discussion of this measure, see Gilbert (1980).

5/This discussion follows Johannes and Rasche (1981b). See also Burger (1971).

6/The Q-statistics reported in table 1 are distributed as χ^2 with 12 degrees of freedom. The critical 5 percent value is 21.0. Note that the Q-statistics for the g-ratio and the t_2-ratio exceed the critical value. If, however, we use the larger degrees of freedom reported by Johannes and Rasche (see Appendix A), then we cannot reject the hypothesis of white noise residuals. The Q-statistic for the g-ratio becomes 34.45 and, for the t_2-ratio, 37.09, both less than the 5 percent value.

7/The Johannes-Rasche formulation changes the numerator of equation (2) to 1+(1+tc')k. Because they define tc' to be TC/C, multiplying through by k(= C/D) yields our expression 1+k+tc where tc = TC/D. Thus, the two multiplier expressions are equivalent. We use the TC/D expression to maintain consistency.

8/It should be noted that the forecasting procedure followed in this study restricts the "new" information set to be only the evolution of the forecasted series. It is clear that the use of additional data that becomes available on an intra-monthly basis could improve the time series forecasts. Our purpose, however, is to compare "base line" ex ante forecasts of two approaches of forecasting the monetary multipliers. Thus, changes made after the fact are not incorporated into either model. In any case, such information could only improve upon the forecast record reported here.

9/The introduction of nationwide NOW accounts in January 1981 clearly affected the forecast record of each model. This is reflected in the noticeable increase in forecast error due to bias to over 15 percent for each approach. To account for this, Johannes and Rasche

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Table 1
Multiplier Component Models
In-Sample Estimates
(all-data not seasonally adjusted; standard errors in parentheses)

Ratio — **Model**

k

$$(1-B)(1-B^3)(1-B^{12})\ln k_t = (1-\underset{(0.045)}{0.7397}B^3)(1-\underset{(0.058)}{0.6239}B^{12})a_t$$

Q(12) = 15.60 SE = 0.567×10^{-2} Sample: 59.1-79.12

g

$$(1-B)(1-B^{12})\ln g_t = (1-\underset{(0.064)}{0.4143}B)(1-\underset{(0.073)}{0.1313}B^2)(1-\underset{(0.053)}{0.6318}B^{12})a_t$$

Q(12) = 23.14 SE = 0.1996 Sample: 59.1-79.12

z

$$(1-\underset{(0.062)}{0.3526}B)(1-B)(1-B^{12})\ln z_t = (1-\underset{(0.048)}{0.6947}B^{12})a_t$$

Q(12) = 15.76 SE = 0.270×10^{-1} Sample: 59.1-79.12

t_1

$$(1-B)(1-B^3)(1-B^{12})\ln t_{1t} = (1-\underset{(0.049)}{0.6536}B^3)(1-\underset{(0.060)}{0.5692}B^{12})a_t$$

Q(12) = 8.24 SE = 0.545×10^{-2} Sample: 59.1-79.12

t_2

$$(1-B^{12})[(1-B)\ln t_{2t} + \underset{(0.018)}{0.012}\, D1 + \underset{(0.012)}{0.041}\, D2 - \underset{(0.017)}{0.088}\, D3]$$

$$= (1-\underset{(0.062)}{0.4421}B)^{-1} \quad (1-\underset{(0.054)}{0.6522}B^{12})a_t$$

Q(12) = 21.98 SE = 0.320×10^{-2} Sample: 61.1-79.12

$r+\ell$

$$(1-B)(1-B^{12})\ln(r+\ell)_t = (1-\underset{(0.081)}{0.6966}B + \underset{(0.082)}{0.2568}B^2 - \underset{(0.068)}{0.3623}B^{12})a_t$$

Q(12) = 12.60 SE = 0.963×10^{-2} Sample: 68.10-79.12

tc

$$(1+\underset{(0.074)}{0.4306}B^{12})(1-B)(1-B^{12})\ln tc_t = (1-\underset{(0.074)}{0.6465}B)a_t$$

Q(12) = 13.73 SE = 0.6110×10^{-1} Sample: 69.1-79.12

Table 2
Relative RMSEs for Multiplier Ratios

Ratio	Relative RMSE[a]	Year
k	0.013	1980
g	0.279	1982
z	0.047	1981
t_1	0.013	1982
t_2	0.019	1981
$r+\ell$	0.015	1981
tc	0.038	1982

[a] The relative RMSE is calculated by dividing the RMSE by the ratio's mean value during the year listed.

Table 3
Summary Statistics for M1 Multiplier Forecasts
One-Step-Ahead Predictions: January 1980-December 1982
Component (COMP) Model vs. Aggregate (AGG) Model

Summary Statistics[a]	1980.1-1982.12		1980.1-1980.12		1981.1-1981.12		1982.1-1982.12	
	COMP	AGG	COMP	AGG	COMP	AGG	COMP	AGG
MAE	0.0186	0.0185	0.0195	0.0199	0.0209	0.0195	0.0154	0.0161
MSE	0.0005	0.0005	0.0005	0.0006	0.0006	0.0006	0.0004	0.0004
RMSE	0.0223	0.0225	0.0233	0.0234	0.0242	0.0245	0.0190	0.0192
U	0.0086	0.0087	0.0091	0.0091	0.0094	0.0095	0.0074	0.0074
B	0.0125	0.0339	0.0045	0.0042	0.1526	0.1551	0.0005	0.0496
V	0.0081	0.0177	0.1698	0.0356	0.0014	0.0275	0.0042	0.1290
CV	0.9795	0.9484	0.8257	0.9602	0.8460	0.8174	0.9953	0.8214

[a] MAE is the mean absolute error; MSE is the mean-squared error; RMSE is the root-mean-squared error; U is the Theil inequality coefficient; B, V and CV represent the proportion of forecast error due to bias, unequal variation and unequal covariation, respectively, between the actual and forecasted series. See Theil (1971).

Table 4
Summary Statistics for M2 Multiplier Forecasts
One-Step-Ahead Predictions: January 1980-December 1982
Component (COMP) Model vs. Aggregate (AGG) Model

Summary Statistics[a]	1980.1-1982.12		1980.1-1980.12		1981.1-1981.12		1982.1-1982.12	
	COMP	AGG	COMP	AGG	COMP	AGG	COMP	AGG
MAE	0.0470	0.0338	0.0319	0.0294	0.0659	0.0421	0.0432	0.0297
MSE	0.0036	0.0018	0.0014	0.0013	0.0057	0.0025	0.0036	0.0016
RMSE	0.0596	0.0425	0.0372	0.0362	0.0756	0.0501	0.0596	0.0399
U	0.0058	0.0041	0.0037	0.0036	0.0073	0.0049	0.0056	0.0038
B	0.0046	0.0218	0.0144	0.0018	0.3977	0.2821	0.4504	0.0243
V	0.1061	0.0047	0.0094	0.0689	0.0021	0.0051	0.0978	0.0649
CV	0.8893	0.9735	0.9762	0.9293	0.6002	0.7128	0.4517	0.9107

[a] See notes accompanying table 3.

Appendix A
Johannes-Rasche Component Model Estimates*

Ratio	Model
k	$(1-B)(1-B^3)(1-B^{12})\ln k_t = (1-0.7862B^3)(1-0.6633B^{12})a_t$
	$Q(28) = 39.91$ SE $= 0.629 \times 10^{-2}$ Sample: 59.1-80.12
g	$(1-B)(1-B^{12})\ln g_t = (1-0.4203B)(1-0.1533B^2)(1-0.6198B^{12})a_t$
	$Q(27) = 41.38$ SE $= 0.199$ Sample: 59.1-80.12
z	$(1-0.3513B)(1-B)(1-B^{12})\ln z_t = (1-0.7093B^{12})a_t$
	$Q(28) = 36.33$ SE $= 0.273 \times 10^{-1}$ Sample: 59.1-80.12
t_1	$(1-B)(1-B^3)(1-B^{12})\ \ln t_{1t} = (1-0.7352B^3)(1-0.6363B^{12})a_t$
	$Q(28) = 43.10$ SE $= 0.606 \times 10^{-2}$ Sample: 59.1-80.12
t_2	$(1-B^{12})[(1-B)\ln t_{2t} + 0.0092\ D1 + 0.0465D2 - 0.0848\ D3]$
	$= (1-0.4737B)^{-1}\ (1-0.6594B^{12})a_t$
	$Q(28) = 29.09$ SE $= 0.305 \times 10^{-1}$ Sample: 61.1-80.12
$r+\ell$	$(1-B)(1-B^{12})\ln(r+\ell)_t = (1-0.7186B + 0.2477B^2 - 0.3429B^{12})a_t$
	$Q(27) = 37.16$ SE $= 0.979 \times 10^{-2}$ Sample: 68.10-80.12
tc	$(1-B)(1-B^{12})\ln tc_t = (1-0.5966B - 0.0910B^3 + 0.1754B^9 - 0.6340B^{12})a_t$
	$Q(26) = 31.85$ SE $= 0.316 \times 10^{-1}$ Sample: 69.1-80.12

* Based on data revisions as of March 1982. These component estimates are reported in Johannes and Rasche (1982).

Appendix B
Table B1
Summary Forecast Statistics for Ratios

<u>k</u>

	80.1-82.12	80.1-80.12	81.1-81.12	82.1-82.12
ME	-0.00037	0.00016	-0.00073	-0.00054
MAE	0.00373	0.00456	0.00342	0.00323
MSE	0.00002	0.00003	0.00002	0.00001
RMSE	0.00433	0.00520	0.00403	0.00361
U	0.01102	0.01329	0.01027	0.00913
B	0.00728	0.00098	0.03310	0.02229
V	0.00220	0.14370	0.12210	0.04561
CV	0.99052	0.85532	0.84480	0.93211

<u>g</u>

	80.1-82.12	80.1-80.12	81.1-81.12	82.1-82.12
ME	-0.00012	-0.00040	0.00033	-0.00030
MAE	0.00652	0.00557	0.00633	0.00766
MSE	0.00007	0.00004	0.00005	0.00012
RMSE	0.00837	0.00602	0.00725	0.01102
U	0.22426	0.16902	0.20803	0.26754
B	0.00022	0.00431	0.00205	0.00076
V	0.06061	0.28978	0.00004	0.08213
CV	0.93917	0.70591	0.99790	0.91711

<u>z</u>

	80.1-82.12	80.1-80.12	81.1-81.12	82.1-82.12
ME	-0.00055	0.00020	-0.00114	-0.00071
MAE	0.00270	0.00247	0.00335	0.00228
MSE	0.00001	0.00001	0.00002	0.00001
RMSE	0.00328	0.00304	0.00392	0.00276
U	0.04057	0.03290	0.04670	0.04359
B	0.02832	0.00452	0.08530	0.06696
V	0.00033	0.12274	0.00282	0.01744
CV	0.97135	0.87273	0.91188	0.91559

t_1

	80.1-82.12	80.1-80.12	81.1-81.12	82.1-82.12
ME	-0.00480	0.00571	0.00348	-0.02357
MAE	0.04321	0.04590	0.04208	0.04166
MSE	0.00285	0.00287	0.00225	0.00342
RMSE	0.05366	0.05361	0.04739	0.05850
U	0.01264	0.01313	0.01126	0.01338
B	0.00808	0.01133	0.00538	0.16238
V	0.03690	0.16283	0.11472	0.01291
CV	0.95502	0.82585	0.87990	0.82471

Appendix B (cont.)

t_2

	80.1-82.12	80.1-80.12	81.1-81.12	82.1-82.12
ME	-0.00242	0.00118	-0.00202	-0.00642
MAE	0.01649	0.01332	0.01816	0.01799
MSE	0.00040	0.00027	0.00046	0.00046
RMSE	0.01996	0.01653	0.02153	0.02140
U	0.01784	0.01683	0.0191	0.01738
B	0.01466	0.00514	0.00880	0.08986
V	0.03671	0.00850	0.04283	0.00588
CV	0.94863	0.98637	0.94838	0.90426

$\underline{r+\ell}$

	80.1-82.12	80.1-80.12	81.1-81.12	82.1-82.12
ME	-0.00003	-0.00000	-0.00024	0.00015
MAE	0.00023	0.00021	0.00029	0.00019
MSE	0.00000	0.00000	0.00000	0.00000
RMSE	0.00030	0.00027	0.00035	0.00026
U	0.01256	0.01081	0.01493	0.01171
B	0.01053	0.00000	0.45798	0.30961
V	0.03685	0.13625	0.00046	0.04566
CV	0.95262	0.86375	0.54156	0.64474

<u>tc</u>

	80.1-82.12	80.1-80.12	81.1-81.12	82.1-82.12
ME	-0.00012	0.00003	-0.00002	-0.00039
MAE	0.00030	0.00029	0.00021	0.00041
MSE	0.00000	0.00000	0.00000	0.00000
RMSE	0.00042	0.00039	0.00033	0.00051
U	0.03021	0.02848	0.02370	0.03737
B	0.08782	0.00616	0.00243	0.57764
V	0.01895	0.00476	0.02944	0.04455
CV	0.89323	0.98908	0.96814	0.37780