THE INFORMATION CONTENT OF FINANCIAL AGGREGATES IN AUSTRALIA

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Abstract

This paper examines the information provided by financial aggregates as predictors of real output and inflation. We employ vector autoregression (VAR) techniques to summarise the information in the data, providing evidence on the incremental forecasting value of financial aggregates in a range of forecasting systems for these variables. The in-sample results suggest significant predictive power in only a small number of cases. We then test the forecast performance of the VAR systems for two years out-of-sample in order to mimic more closely the real-time forecasting problem faced by policymakers. Overall, both in-sample and out-of-sample results suggest no robust finding of exploitable information for forecasting purposes in any of the financial aggregates under examination. There is some evidence that the aggregates yield improved forecasts late in the sample period, but there is insufficient subsequent data to draw robust conclusions from this.

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1. Introduction

Policymakers base decisions on the expected behaviour of inflation and real output, using information from a wide range of macroeconomic indicators. Measures of financial aggregates often figure in discussions of monetary policy, but the usefulness of these variables as macroeconomic indicators, in Australia as in many other industrialised countries, is considered debatable. In the mid 1980s, changes in the regulation of financial intermediaries and various innovations of financial products altered the perceived relationship of financial aggregates with real output and inflation. Proponents of the importance of these aggregates argue that monetary authorities should nonetheless monitor the financial aggregates closely as they may still provide valuable forward-looking information.

This paper addresses the question of the usefulness of financial aggregate measures in policymaking by proposing a minimal standard on the information value of financial aggregates. The usefulness of monetary and financial aggregate measures can be judged by how the information contained in these data helps forecast the subsequent behaviour of output and inflation. This view is also expressed by Friedman (1996) '... the whole concept [using monetary aggregate information as an information variable] is senseless unless observed fluctuations in money do anticipate movements of prices, or output, or whatever constitutes the ultimate objective of monetary policy: What would it mean to exploit an information variable that contains no relevant information?'

To investigate the forecasting value of financial aggregates on output growth or inflation, we employ the vector autoregression methodology. This empirical strategy is useful in summarising the dynamics of a small economic model. In this way, we can examine the interrelationships between the financial aggregates and policy goals, as well as take into account other important variables, such as interest rates and exchange rates. The methodology allows investigation of correlations among the data without imposing strong exclusion restrictions on lags of the chosen variables.

The motivation for this approach is to uncover correlations in the least restrictive setting; that is, one that does not rely on the imposition of a single theoretical structure. This has the advantage that any correlations uncovered are not dependent upon the chosen structural restrictions.

We employ four different financial aggregates to conduct this investigation: currency (CU), M3, broad money (BM), and credit of all financial intermediaries (CR). Prices and output are measured by the underlying CPI and real GDP(A). Initially, the financial aggregates are investigated in bivariate systems: that is, using a financial aggregate and either real output growth or inflation in a system. The systems are then expanded to three variables containing the growth of the financial aggregate, inflation, and the growth of real output. Subsequently, the system is expanded further to include the differenced interest rate (90 day bank bill rate) and the rate of change in the exchange rate (trade-weighted index).

The initial in-sample VAR results suggest that financial aggregates are not particularly useful for predicting either real output or inflation. Tests of exclusion restrictions (F-tests and block exogeneity tests[1]) of lags of the financial aggregates indicate that in a reduced-form setting there are few instances where any of the financial aggregates appears useful. Evidence from variance decompositions is used to investigate further the explanatory power of financial aggregates for forecasting real output and inflation. Three different specifications are used to generate the variance decomposition evidence, varying the sample period and the identification ordering. We fail to find any results in support of an informational role for financial aggregates that are robust across all three settings.

The above in-sample results indicate the correlations in the data, and document the usefulness of financial aggregates in an artificial setting. Policymakers, however, are more interested in whether the information in financial aggregates can help forecast output and inflation in real-time settings: that is, when we forecast today values that

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[1] Block exogeneity tests assess whether the addition of lagged values of a variable are important for explaining the dynamics of the other variables in the system of equations in addition to the explanatory power of the lags of those other variables.

will only be known at some time in the future. To mimic this problem faced by policymakers, we generate tests of the accuracy of out-of-sample forecasts of VAR systems that include a financial aggregate relative to the corresponding VAR system that excludes the financial aggregate.[2]

For output growth forecasts, the results suggest that adding the financial aggregate rarely improves forecast accuracy relative to the VAR that excludes that aggregate. In some cases, the addition of the financial aggregate improves out-of-sample forecast accuracy for inflation relative to the corresponding VAR without a financial aggregate. But on closer inspection, the improvement in forecast accuracy occurs almost entirely in the latter part of the forecast sample, and appears uncharacteristic of the previous empirical relationship, suggesting that the result has not been stable over time.

2. Literature Survey

Not surprisingly, there have been a sizeable number of research papers on the explanatory power that financial aggregates have for real output and the price level. These studies employ a variety of research methodologies and there is some variation in the data sets with respect to both the component data series and the sample period. The description below draws some overall conclusions from this set of research studies and emphasises how the current research relates to the existing literature.

There has been considerable interest in Australia about the relationship between financial aggregates and price and output variables. Orden and Fisher (1993) examine the relationship between money, prices and output for New Zealand and Australia using a VAR methodology. Of the existing literature, it is among the most

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[2] In no sense are we pursuing the optimal forecasting model for output growth and inflation. The forecasting tools employed in this paper were selected for their usefulness as criteria for comparing the respective models, as well as for inferring the marginal forecast contribution of the respective aggregates.

similar to the present study. Variance decomposition results for the period 1965:Q2 to 1982:Q4 suggest that in Australia money shocks contributed significantly to subsequent variations in prices (5 to 30 per cent of forecast-error variances), but have contributed little to subsequent variations in output. This result is notable because the implied causal ordering chosen to generate the variance decompositions and impulse response functions places prices and output before money, and therefore restricts the contemporaneous influence of financial aggregate innovations on output growth and inflation to zero. These results are in direct contrast with the variance decomposition results reported below. We note, however, that there are some important differences between their study and ours. For example, their sample period ends before the major financial deregulation, their data set employs the GDP deflator as the price level measure and uses only M3 as the financial aggregate, and the estimation is conducted in an error correction framework rather than a VAR in levels or differences.[3]

Several studies from the Reserve Bank of Australia investigate the correlations among financial aggregates, inflation and real output growth. Bullock, Morris and Stevens (1989) employ correlation analysis on a data set of financial aggregates and output and inflation over the period 1968 to 1987. The results in their study lead them to conclude that M1 and short-term interest rates are the most useful financial indicators because they have a consistent, leading relationship to real private demand.[4] In a follow up to that study, Stevens and Thorp (1989) employ VAR methods to detect the leading and lagging relationships among the data over the sample period 1969 to 1988. They find that GDP tends to lead broader financial aggregates such as credit of all financial intermediaries (credit) and M3, consistent with the idea that the broader financial aggregates are endogenous to the movements in real output. In addition, the study refines the results in Bullock, Morris, and

3 The vector error correction (VECM) framework differs from the VAR in that the VECM implies cointegration of the data series.

4 The sample period in the study ends in 1987 and the sample therefore provides only a partial reflection of the major changes that took place following deregulation of the financial system.

Stevens by showing that M1 does not have a strong leading relationship with real output.[5]

Blundell-Wignall and Gizycki (1992) estimate a VAR with credit data from 1976 to 1991; they find that in the post-deregulation period total credit and nominal GDP have been useful for forecasting each other, while business credit (a sub-component of total credit) has been a strong leading indicator for nominal investment. A difficulty in assessing the results of Blundell-Wignall and Gizycki relative to the ones cited above is that they fail to disentangle real output from the price level, so that we cannot infer whether the credit measure can predict real output and inflation separately, as policymakers would like.

Rather than examining the relationship between financial aggregates, real output and the price level in an unrestricted reduced form, recent research by de Brouwer, Ng and Subbaraman (1993) focused on a more narrow question, namely whether the standard money demand specification is stable. A stable money demand would imply cointegration among the variables, provided the data series are integrated of the same order. Thus, the researchers test for cointegration among candidate measures of prices, output, financial aggregates and interest rates. The study examines a wide assortment of alternative data measures to investigate the sensitivity of the inferences to modest alterations in the specification. The results suggest that the empirical estimates of the function are not in general cointegrated over the sample, suggesting that money demand was unstable over the period. De Brouwer *et al*. argue that this finding supports the view that monetary aggregates may have limited indicator properties in the long run.

In addition, Fahrer and Myatt (1991), Coelli and Fahrer (1992) and de Brouwer and Ericsson (1995) investigate models to forecast inflation, and find weak to

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5 Weber (1994) finds evidence that innovations associated with M1 had a significant impact on real output in an historical decomposition of the 1990-1992 recession in Australia. One criticism of the paper is that the VAR does not include the cash rate, which is the operational instrument of monetary policy. The innovations in M1 may only be proxying for interest rate innovations.

nonexistent support for financial aggregate measures as predictors of inflation. The results of the empirical studies on the financial aggregates in Australia suggest that evidence in support of their usefulness for predicting (as well as inferring monetary policy effects on) real output growth and inflation is weak, and has weakened as the data sample has grown.

In other related literature, several studies employ US data and the VAR methodology as the main method of inquiry, highlighting the diversity of results obtained using the general VAR techniques, and noting the sensitivity of the results to changes in the chosen variables, sample period, and identification method.

Friedman (1996), in one of the most recent examples of the US literature, notes that regardless of whether money growth acts as an intermediate target or simply as an information variable, it needs to anticipate movements in prices and/or output to fulfil either of these roles. Friedman uses US data on the log-level of output, the price level, and a monetary aggregate in a three-variable VAR as well as a four-variable VAR that includes the interest rate. He imposes a recursive causal ordering that places money last in order to generate variance decompositions to investigate money growth's contribution in explaining subsequent output and price fluctuations. The results indicate that the predictive role of US monetary aggregates (M1 and M2) declined in the 1990s to the point where it is virtually nonexistent.[6]

There have also been several studies in the US literature that focus entirely on the predictive power of monetary aggregates for real output, searching for a non-neutrality of money. Stock and Watson (1989) provided evidence from three and four-variable VARs, in differences as well as in levels, that a narrow monetary aggregate (M1) was a statistically significant predictor of real output (as proxied by industrial production). Friedman and Kuttner (1993) examine the robustness of this finding by extending Stock and Watson's sample period and using a different interest rate measure. In-sample causality tests show that the Stock and Watson results are not robust to these changes. In addition, Friedman and Kuttner show that

[6] We note, however, that these results may be sensitive to the choice of causal ordering.

in the United States the spread between commercial paper interest rates and the Treasury bill rate was superior to monetary aggregates at forecasting real activity in a VAR.

Thoma and Gray (1994) point out that Friedman and Kuttner fail to confirm the forecasting power of the spread variable by performing out-of-sample forecasting tests. Thoma and Gray find that there is little difference in the forecasting power of the paper-bill spread and M2 in an out-of-sample setting. This argument is relevant because real-time forecasting is an essential element to policymaking. For Australian data, Trevor and Thorp (1988) investigate out-of-sample properties of simple VAR models for forecasting the Australian economy. Their concern is to emphasise the difficulty of the real-time forecasting problem for policymakers, an issue dealt with more extensively below.

This paper extends the literature by presenting a comprehensive analysis of the information value of financial aggregates by examining both in-sample and out-of-sample tests of a set of financial aggregates for predicting prices and output. The data and methodology adopted are discussed below.

3. Data

The data sample consists of quarterly data on four financial aggregates (specifically, currency, M3, broad money, and credit of all financial intermediaries).[7] The sample period for estimation begins at 1976:Q4, and ends in 1995:Q3. Some of the aggregates have much earlier start dates but the sample is restricted so that all measures are evaluated on the same basis.

The other measures in the study are real GDP (output), underlying CPI (price level), the 90-day bank bill rate (interest rate), and the trade-weighted index of the exchange rate. We transform all measures by taking logarithms, except for the

7 See the Data Appendix for a description of the series.

interest rate. The short sample of the data limits the size of the VAR that can be studied in an unrestricted form. As discussed earlier, the addition of the interest rate and the exchange rate provide a more comprehensive system in which to analyse the information content of financial aggregates.[8] The data are presented in graphical form for first differences in Appendix A.

For descriptive purposes, the data in quarterly growth rates (first differences) are quite noisy, and it is useful to transform them into four-quarter-ended growth rates to emphasise the longer term trends.[9] Figures 1 and 2 compare the movements in the growth rate of the financial aggregates with the movements of inflation and real output growth. For the majority of the sample, the movements in the four-quarter-ended growth in the financial aggregates do not appear to be tracking those of the CPI. In the period around the 1990-91 recession, however, the growth in each of the aggregates as well as the inflation rate trended sharply downwards. The overall correlations between the aggregates and the CPI may be strongly influenced by this period, which may not be representative of the long-term relationship between the variables.

All the aggregates appear to display a noticeable correlation with real output growth, but there does not appear to be an obvious leading relationship between any of the aggregates and real GDP. This examination of the figures provides a reference point for interpreting the relationships among the data that are uncovered in the statistical work below.

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[8] The introduction of additional variables into the VAR system could be important if an additional variable alters the observed predictive power of money.

[9] The trends most noticeable in this transformation were also evident in the quarterly growth rate transformation used in the estimations.

Figure 1: Comparison of Four-Quarter-Ended Changes in Aggregates with CPI

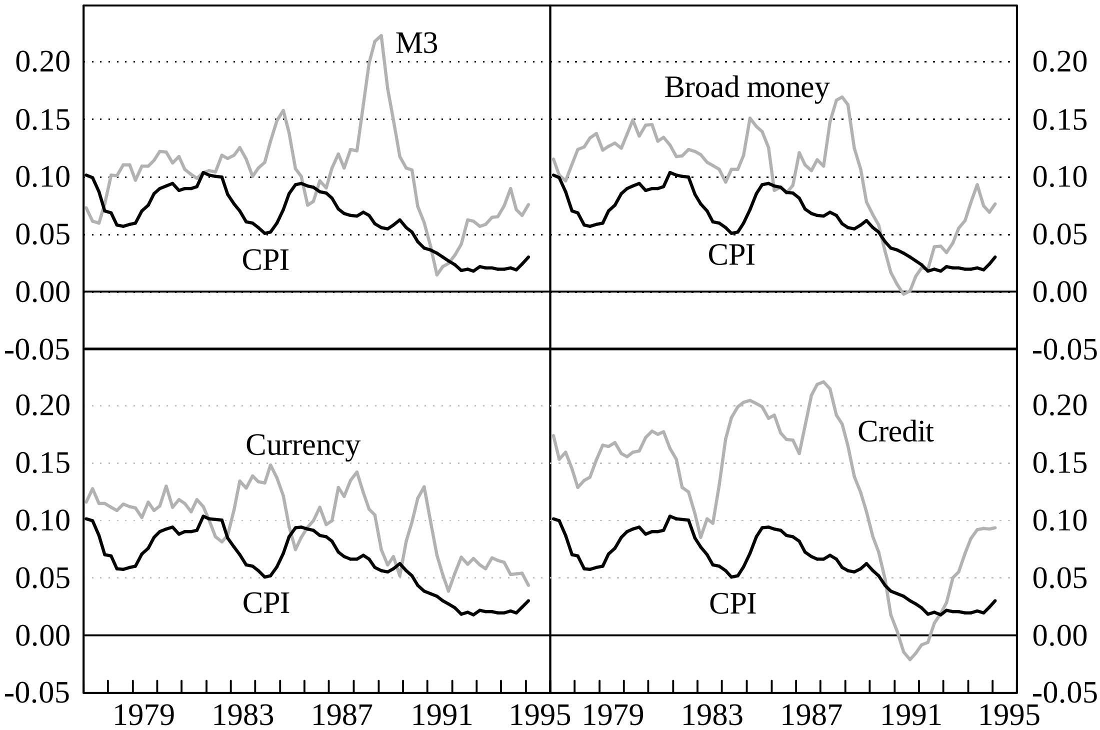
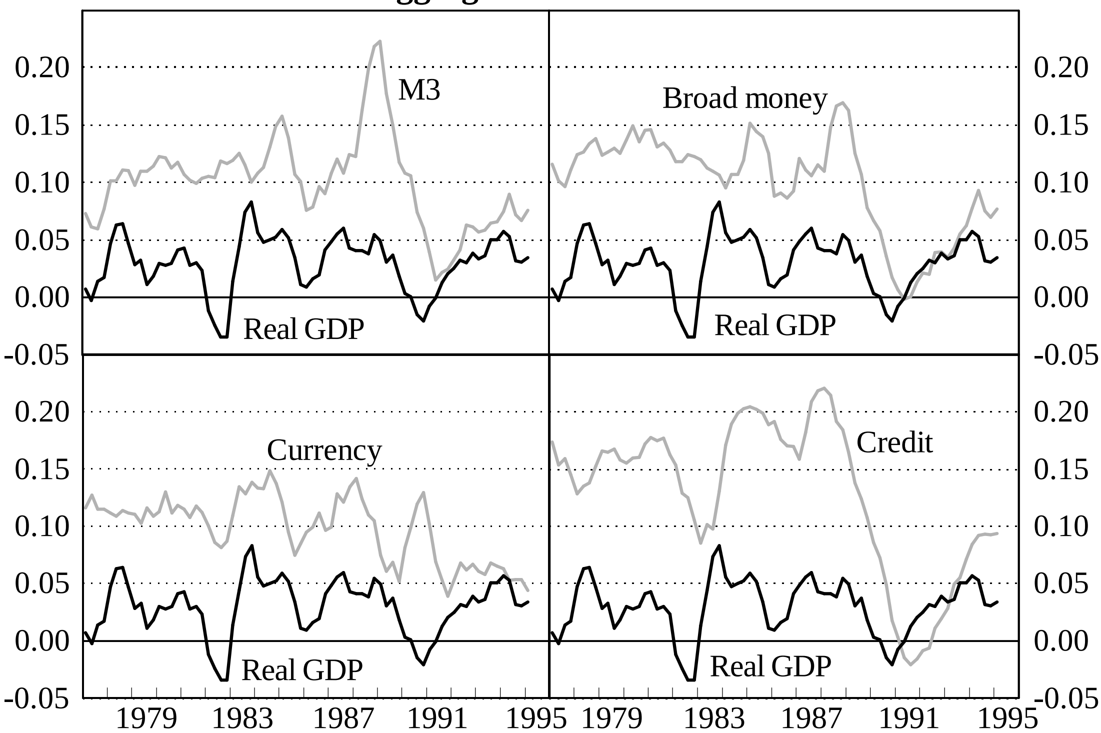


Figure 2: Comparison of Four-Quarter-Ended Changes in Aggregates with Real GDP



4. Empirical Methods

4.1 In-Sample Tests – Overview

The information content of the financial aggregates is initially assessed by examining their forecasting power for subsequent observations of output growth and inflation on an in-sample basis. The ordering of tests is from the simplest models to the most complex, so as to ascertain whether money correlations are robust by examining systems with an increased number of variables. The models are specified in first difference form due to test statistics that suggest nonstationarity of the data in log-level form. We note, however, that the tests have low power, and as a result, we also estimate systems in log-levels (except for the interest rate).[10] Each VAR is estimated with 4 lags of each variable in the system. The structure is outlined below:

$$x_t = A(L)\, x_{t-1} + \varepsilon_t$$

where x_t is the vector of endogenous variables.

ε_t is the vector of error terms.

A is a series of square matrices representing correlations among endogenous variables, and L is the lag operator.

The methodology involves examining F-tests, block exogeneity tests, and variance decompositions for each of the systems under consideration.[11] The F-tests measure whether money is significant for predicting real GDP and the CPI in the single reduced form equation for the respective variables. F-tests are examined for the two, three, four and five-variable systems containing the respective financial aggregates. The basic two-variable system contains the growth rate of the financial aggregate

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[10] Results are available on request from the authors. Use of levels rather than differences affects some of the in-sample inferences but has little effect on the out-of sample results.

[11] Both F-test and block exogeneity tests employ the reduced form of the VAR. In contrast, the variance decomposition results require orthogonalization of the reduced-form errors.

and inflation or the growth rate of output. The three-variable system contains the growth rate in money, real output growth, and inflation. The four-variable system adds the differenced interest rate while the five-variable system adds also the differenced exchange rate.

In bi-variate VARs, the F-test is equivalent to a Granger causality test. In the larger VAR systems, the F-tests are insufficient for determining Granger causality because the restrictions test only the direct effect of money in single equations of inflation and output growth. For the VAR systems of three or more variables, we therefore test whether the system is block exogenous to the movements in the financial aggregates. These tests are interpreted as detecting whether the relevant financial aggregate is important to the system as a whole. We follow up on these results by employing a standard tool of VAR analysis, the variance decomposition, to uncover their quantitative importance in predicting output and inflation.[12]

The variance decompositions measure the percentage of forecast error variance in real output growth and inflation that can be attributed to innovations in the particular financial aggregate under examination. The extraction of variance decompositions from a VAR typically requires orthogonalisation of the errors from the reduced-form equations. We orthogonalise the shocks to the four-variable VAR system using a Choleski decomposition, which implies a recursive structural ordering for the variables.[13]

[12] Variance decompositions reveal the proportion of forecast variance explained by innovations associated with it or another variable. See Hamilton (1994).

[13] We adopt an agnostic view of the ordering as ‘structure’, choosing this method because it provides directly interpretable results for examining whether a monetary aggregate contributes forecasting power for real output and inflation.

Using the Choleski decomposition from the reduced form errors, orthogonal innovations can be obtained in the following way, which is equivalent to running OLS on the reduced form errors:

$$\varepsilon_{t1} = \upsilon_{t1}$$

$$\varepsilon_{t2} = R_1\, \varepsilon_{t1} + \upsilon_{t2}$$

$$\varepsilon_{t3} = R_2\, \varepsilon_{t2} + R_1\, \varepsilon_{t1} + \upsilon_{t3}$$

$$\varepsilon_{t4} = R_3\, \varepsilon_{t3} + R_2\, \varepsilon_{t2} + R_1\, \varepsilon_{t1} + \upsilon_{t4}$$

where:

the R_i's are OLS regression coefficients

ε_{ti} are the reduced-form error terms and

υ_{ti} are the orthogonal errors.

Orthogonal errors, υ_t, are required in order to generate variance decomposition evidence.

Evidence from variance decompositions investigates the explanatory power of financial aggregates for forecasting real output and inflation. The Choleski factorisation orthogonalises the variance-covariance matrix so that the Choleski factor is lower triangular with positive elements on the diagonal (positive variance). This is what imposes the recursive ordering on the variance decomposition results.

Variance decomposition results can be sensitive to both the ordering imposed on the system as well as the data sample. For our variance decomposition results, we experimented with three estimated VAR models. The base specification estimates a VAR over the full sample period with the following ordering (recursive structure):

change in the interest rate, monetary aggregate growth, inflation, and real output growth.[14]

Placing the financial aggregate second in the ordering allows innovations in the equation for financial aggregates to affect contemporaneously inflation and real output growth. The motivation for this ordering is to test the contribution of the financial aggregate measure to forecasting output and inflation in a favourable specification. By placing the growth rate in the aggregate ahead of output growth and inflation in the ordering, we increase the chances of finding results that show orthogonalized innovations in financial aggregates influencing the subsequent behaviour of output growth and inflation. In such an ordering, the innovation associated with the financial aggregate appears in the equations for output growth and inflation in the system, whereas innovations to output and inflation do not appear in the equation for the financial aggregate. This is a strong identification restriction. The second specification generates variance decomposition results from an abbreviated sample that ends in 1988:Q4 using the ordering from the base specification. The third specification places the financial aggregate last in the ordering and estimates the VAR over the full-sample. By placing the financial aggregate last in this case, we restrict the contemporaneous impact of innovations to the financial aggregates on inflation and output growth to be zero. The results from the final ordering highlight the importance of the contemporaneous correlations on the subsequent results.

[14] We justify this formulation as the base specification by suggesting that monthly numbers for the aggregates are available before the release of inflation and output measures. The interest rate variable is observable more frequently than financial aggregates and is placed before the aggregate in the ordering using the same temporal justification as above.

Attention in the discussion below is focused on the four-variable VAR results, although initial results using a five-variable VAR are generally consistent with these.[15]

4.2 In-Sample Results

We begin by generating F-test p-values from a sequence of data samples starting from the shortest sample 1976:Q4 to 1984:Q1. The procedure then adds one more observation and generates the F-test and the associated p-value, continuing this process until the end of the sample [1995:Q3]. A similar procedure is followed for block exogeneity restrictions in the larger systems.

The F-test results for systems containing the respective aggregates are shown in Figures 3 and 4. The figures summarise the results from the tests of the joint significance of four lags of money in the output growth and inflation equations respectively. The F-tests have been done for each of the output growth and inflation equations in the two, three, four and five-variable systems. For each aggregate, there is a line that reflects the p-value from the F-test of the exclusion restriction, one line for each of the four estimated systems. The solid black horizontal line in each panel indicates the 10 per cent significance level while the solid grey horizontal line indicates the 5 per cent significance level. When the line reflecting the p-value of the restrictions crosses the solid horizontal lines, it implies a rejection of the restriction at the specified significance level.

The F-test results for the output growth equations indicate that M3, currency and broad money are not significant for predicting real GDP. In contrast, credit appears significant in some instances in the three and five-variable systems for predicting real output growth.

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[15] In addition, the four-variable VAR does not involve the difficulty of forecasting the change in the exchange rate. Out-of-sample results suggest that the inclusion of the exchange rate worsens out-of-sample forecast performance of the VAR as well.

Figure 3: F-Tests of Aggregates in Predicting Output Growth

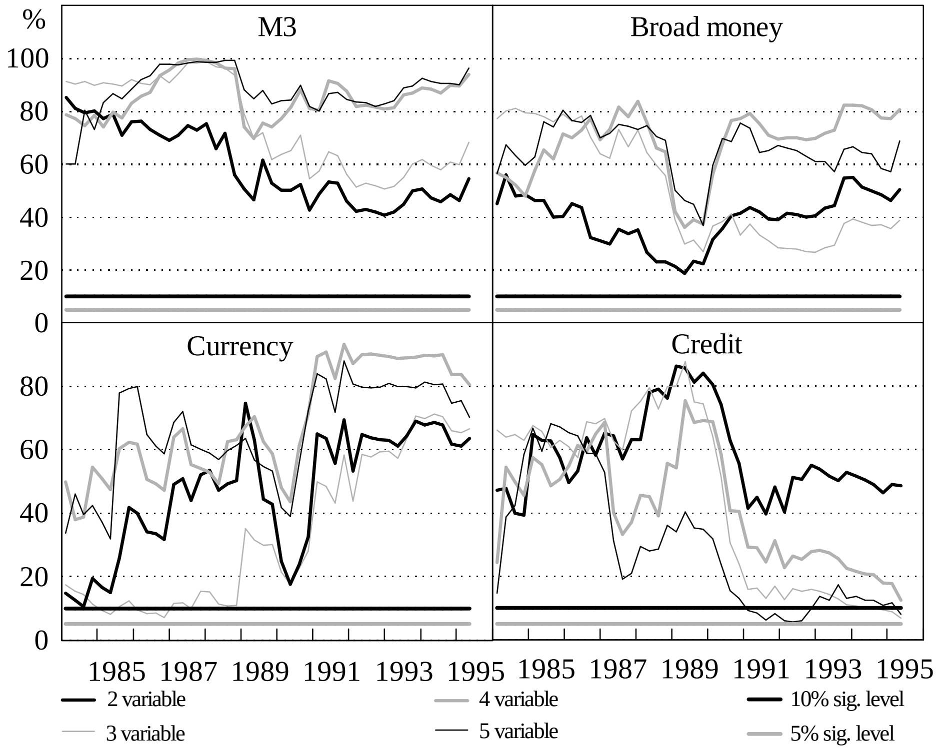
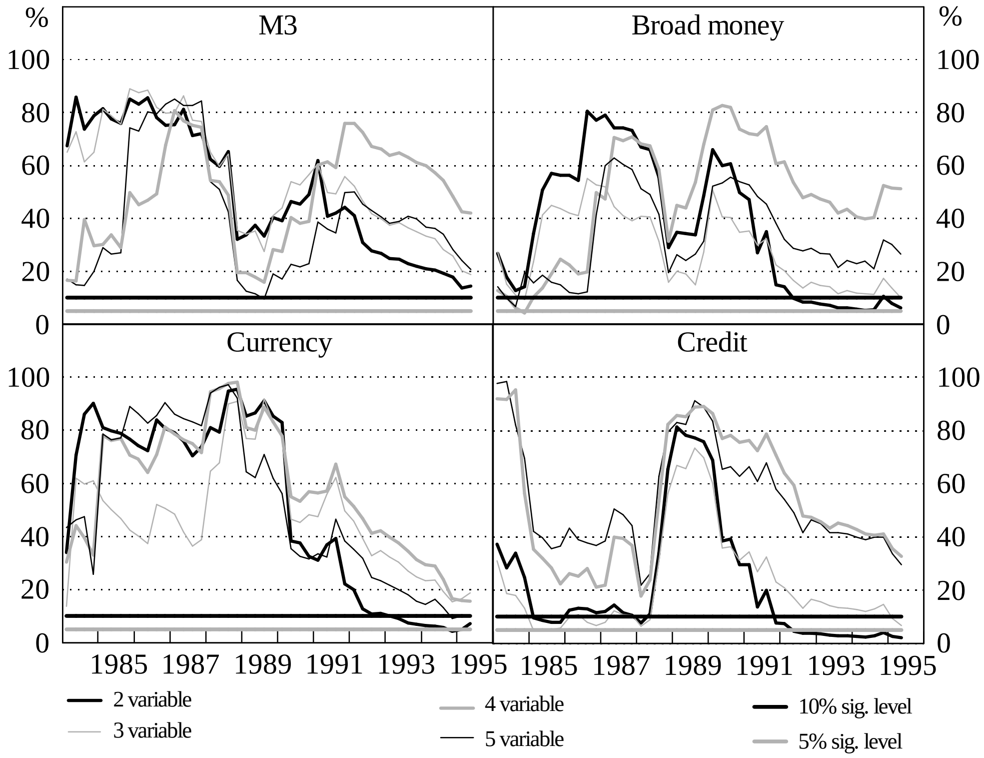


Figure 4: F-Tests of Aggregates in Predicting CPI



For inflation equations, the F-tests indicate that M3 is not significant for predicting inflation in any of the VAR systems. Results for the other aggregates are mixed, with significant predictive power in a subset of cases. Currency appears significant for predicting inflation in the two and five-variable systems for samples ending after 1993:Q2. Broad money and credit appear important after 1992 in the two and possibly three-variable cases. However, these results are not robust to the addition of interest rate and exchange rate variables, so we do not give them much credence.[16]

On a similar basis, we present p-value charts for block exogeneity tests for the financial aggregates for the three, four, and five-variable VAR systems in Figure 5. The results suggest that M3 is important in the four and five-variable systems towards the end of the sample. In contrast to the M3 results, the test results for currency indicate that it is not statistically significant for any of the systems over any portion of the sample period. Broad money appears significant only in the five-variable system after 1991. The most consistently significant variable is credit, which appears statistically significant in the three, four and five-variable systems after 1992. It is notable, however, that for the credit aggregate the p-value rises dramatically for the three and four-variable systems between 1988 and 1990, perhaps reflecting instability in the relationship between credit and policy variables during the asset price volatility at that time.

These block exogeneity tests are not conclusive evidence that financial aggregates are unimportant for output growth and inflation, because they ignore the possibility that there are important contemporaneous correlations among the data. We generate variance decompositions to explore this issue further.

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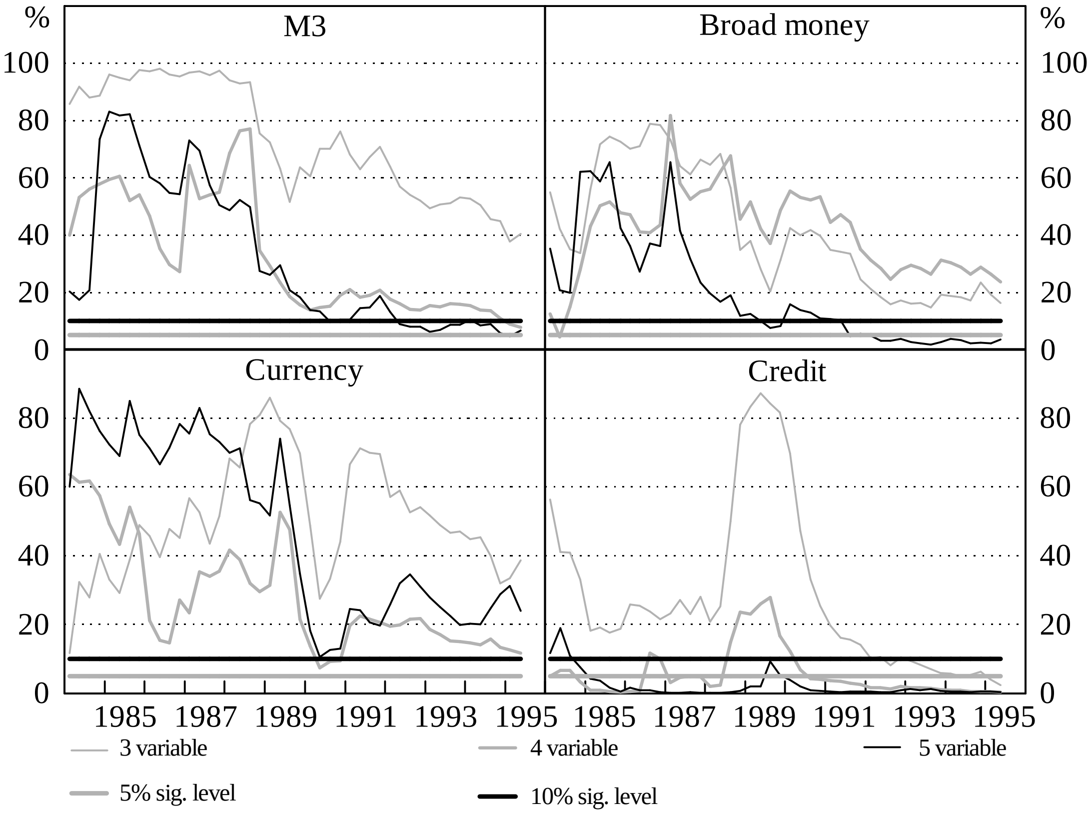
[16] The sum of the coefficients on the four lags of the financial aggregate variables in the output equations estimated over the full sample were as follows: -.0384 for M3, .0504 for BM, .2937 for credit, and .0552 for currency. Similarly for the inflation equations, the sums were: -3.507E-3 for M3, .0750 for BM, .1181 for credit and .1532 for currency. None of the coefficient sums were statistically different from zero at the 10 per cent level in the four-variable specification over the full sample.

Figure 5: Block Exogeneity Tests for the Aggregates



The results for the three specifications of the variance decompositions are listed in Tables 1 and 2, which also present 90 per cent confidence bounds on these variance decompositions to help infer the statistical importance of the results.[17] The bounds provide one method to infer the statistical importance of innovations associated with a financial aggregate in a variance decomposition.

Table 1: Variance Decompositions from Difference Specification

Aggregate in system	Variance of:	Forecast horizon	Per cent of forecast innovations explained by innovations in the financial aggregate[(a)]

[17] The 90 per cent probability bands are calculated for each specification of the variance decompositions using Monte Carlo integration techniques similar to those described in the RATS 4.0 manual. We generate 1000 draws of the variance-covariance matrix, generate associated variance decompositions, and choose the 5th and 95th percentile observations. These extreme observations provide the error bands. Details of the procedures are available from the authors upon request.

Aggregate in system	Variance of:	Forecast horizon	Per cent of forecast innovations explained by innovations in the financial aggregate[(a)]		
			Initial ordering 1977:Q4-1995:Q3	Initial ordering 1977:Q4-1988:Q4	Ordering with M after P,Y 1977:Q4-1995:Q3
M3	Inflation	6	3.7 (1.7, 16.1)	7.1 (4.2, 35.7)	3.3 (1.3, 13.3)
		12	5.4 (2.0, 25.9)	7.4 (5.5, 45.0)	3.0 (1.5, 19.1)
	Output growth	6	14.1 (6.2, 30.4)	8.8 (5.2, 35.2)	3.4 (1.6, 14.6)
		12	15.4 (6.9, 32.4)	8.6 (7.3, 40.7)	4.6 (2.3, 17.7)
CU	Inflation	6	13.2 (3.7, 29.0)	4.7 (2.4, 20.8)	13.4 (3.5, 26.4)
		12	18.2 (5.3, 35.5)	5.4 (2.9, 23.9)	15.7 (4.1, 29.0)
	Output growth	6	6.2 (2.4, 19.0)	6.0 (3.1, 21.7)	1.6 (0.9, 10.5)
		12	7.1 (3.2, 20.7)	5.9 (4.2, 23.7)	2.2 (1.4, 12.2)

Note: (a) Each variance decomposition represents the per cent of forecast error variance explained by the innovation associated with the variable at the top of the column. The percentile bounds are in parentheses.

Runkle (1987) argues that variance decomposition results should be considered important if the lower bound is above 10 per cent. We use this general suggestion as a guide to the importance of the variance decomposition. Employing this criterion, there is no aggregate that explains an important proportion of the forecast error variance of either output growth or inflation in all of the three specifications of the VAR. For example, over the 12-quarter horizon, credit explains about 40 per cent of subsequent fluctuations of inflation (with a lower bound of approximately 17 per cent) using the initial ordering over the full

Table 2: Variance Decomposition from Difference Specification

Aggregate in system	Variance of:	Forecast horizon	Per cent of forecast innovations explained by innovations in the financial aggregate[(a)]

Aggregate in system	Variance of:	Forecast horizon	Per cent of forecast innovations explained by innovations in the financial aggregate[(a)]		
			Initial ordering 1977:Q4-1995:Q3	Initial ordering 1977:Q4-1988:Q4	Ordering with M after P,Y 1977:Q4-1995:Q3
BM	Inflation	6	15.0 (3.6, 33.4)	12.1 (4.2, 34.1)	6.6 (2.0, 19.6)
		12	30.3 (8.4, 51.1)	15.4 (5.6, 38.0)	14.9 (2.8, 33.5)
	Output growth	6	17.4 (7.5, 32.7)	6.8 (4.1, 26.9)	6.0 (2.3, 17.3)
		12	19.0 (9.9, 35.3)	8.1 (6.2, 34.4)	7.9 (3.3, 21.6)
CR	Inflation	6	16.3 (4.9, 33.5)	5.7 (2.2, 20.7)	8.2 (2.2, 19.1)
		12	40.0 (17.4, 55.1)	8.8 (3.2, 25.6)	16.9 (6.2, 28.8)
	Output growth	6	24.0 (11.4, 38.6)	7.3 (3.4, 22.0)	8.7 (3.0, 19.2)
		12	23.6 (11.6, 37.8)	8.6 (4.5, 24.0)	9.0 (3.6, 19.5)

Note: (a) Each variance decomposition represents the per cent of forecast error variance explained by the innovation associated with the variable at the top of the column. The percentile bounds are in parentheses.

sample. In the other two specifications, the explanatory power of the credit innovation at the 12-quarter horizon greatly diminishes, to the extent that it appears no longer important, that is, the lower bounds fell below 10 per cent. There is a similar lack of robustness whenever a significant result is found. In contrast to previous studies, there appears to be no explanatory power for M3 as an inflation predictor in any specification.[18]

[18] We note that these negative results contrast with results in Orden and Fisher (1993) in which M3 had significant impact on the price level. This may be due to the difference in the data sample as well as their use of an error-correction specification.

5. Out-Of-Sample Forecasting

5.1 Out-Of-Sample Overview

The in-sample tests of the previous section suggest that certain financial aggregates may have limited usefulness in forecasting output and inflation in real life situations. But Cecchetti (1995, p. 199) argues: 'Whether a model fits well in-sample tells us virtually nothing about its out-of-sample forecasting ability.' If money is useful for explaining subsequent variations in prices and/or output within the sample, that fact does not indicate that the variable will be useful for forecasting in real time (when all future values are unknown). In this section, we use out-of-sample forecasts to compare the relative accuracy of real GDP and CPI forecasts from VAR models that contain monetary aggregates with those that do not.

There are several inadequacies of in-sample evaluation techniques for the purpose of determining the relevant information content of financial aggregates. The test statistics from the VAR (F-tests) indicate whether the lags of the financial aggregates aid in the forecast of output growth and inflation one period into the future. Although these tests are often informative about the explanatory power of the data series, policymakers have a longer time horizon than one quarter. The variance decomposition evidence indicates the information content of financial variables for longer forecast horizons, and thus overcomes this short-horizon issue. The results of the variance decomposition exercises, however, are heavily dependent on the causal ordering that is imposed on the data, and the parameter estimates are generated using data unavailable at the time of the forecast. To mimic more closely the real-time forecasting problem faced by policymakers, we employ a series of out-of-sample forecasting exercises.[19] The forecasts are evaluated using an eight-quarter forecast horizon, likely to be more representative of the horizon taken into account in policy formulation. The forecasts begin in 1984, giving 38 overlapping observations of an eight period out-of-sample forecast.

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[19] The data series we employ have been revised thus reflecting information unavailable at the time of the forecast, so the tests are not purely 'real time' forecasting experiments.

Forecasts of a VAR out-of-sample are dynamic forecasts that only use information available at the time of the forecast to predict movements in the data series in the VAR for the desired number of periods in the future (eight in our case). They are dynamic in the sense that all variables in the system must be forecast jointly in order to produce a sequence of forecasts for the variables of interest. For example, forecasting two periods into the future in an approximately real-time setting implies that in order to generate a forecast for the second period out, the VAR must use the forecasts one period out as right-hand side variables. Given that the VAR model employs four lags of the data, forecasts of five periods or more rely only on forecasts of the dependent variables as the right-hand side variables.[20]

Under the assumption that all variables in the model are available at approximately the same time, the forecasting model cannot exploit contemporaneous relationships among financial aggregates and the variables of interest. Unlike structural simultaneous equations models, there are no exogenous variables to ‘choose’. Simultaneous equation models generate forecasts conditional on the path of the exogenous variables, values that may be chosen or may be taken from other forecasting models. In contrast, a VAR model generates unconditional forecasts (forecasting all variables in the system) unless we impose a set of conditions upon it. All forecasting exercises that follow employ unconditional forecasts.

To perform the out-of-sample forecast evaluations, VAR models with and without a financial aggregate are estimated over the sample period up until the first forecasting period. Forecasts one to eight periods into the future are generated for each model. The estimation sample is then extended to include the first forecasting period and the forecast process is repeated. This procedure is conducted for each of the two, three, four, and five-variable systems that include M3, broad money (BM), credit, and currency. We then evaluate the forecast performance of the models using two measures of forecasting accuracy.

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[20] It is notable that errors in the forecasts become compounded in the dynamic setting, but it remains the most realistic setting to evaluate forecasts.

The first measure of forecast accuracy is the ratio of the root mean squared errors of the out-of-sample forecasts. For each forecast horizon from 1 to 8 periods into the future, the root mean squared error (RMSE) is generated for each model. We compare forecasting accuracy for real GDP and CPI by examining the root mean square error in the model with the financial aggregate relative to the root mean square error in the corresponding model without the financial aggregate. Ratios greater than one suggest that adding the financial aggregate under consideration actually worsens forecasting performance of the system.[21] If the ratio is less than one, the statistic suggests that the addition of the financial aggregate to the system can add to the forecasting ability of the VAR for the variable of interest. One shortcoming of this statistic is that it does not involve a decision rule criterion for rejecting the null hypothesis that the two forecasts are approximately equivalent. Like the Theil-U statistic that it is patterned from, the statistic instead relies on ‘rules of thumb’ about forecast improvement. For example, the ratio may be .92, but it is unclear whether the difference in the accuracy of the separate models is significant.

The other measure we use is the Theil-U statistic of the VAR including the aggregate. This measure is included to indicate whether the larger VAR systems improve or worsen out-of-sample performance relative to the random walk forecast. Often, the addition of variables to a VAR reduces the forecast accuracy of the system for the variables of interest because the forecast errors of the additional variables add noise. This problem is particularly noticeable for variables that are hard to predict, like the change in the exchange rate or in the differenced interest rate.

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[21] The ratios of the root mean squared error (RMSE) is comparable to the Theil-U statistic used in forecast evaluation that compares a forecast RMSE to that of a random walk forecast. In our case, if the financial aggregates add no value to the forecast, the two VAR model alternatives should have comparable RMSE for forecasting output growth and inflation. In that case, the ratio values should be close to one.

5.2 Out-Of-Sample Forecasting Results

The detailed out-of-sample forecasting results for systems containing the aggregates are presented in Appendix B, Tables B1 to B8. All forecast statistics for the aggregates are listed in these tables in the Appendix. A summary of the results is presented below in Tables 3 and 4. For the inflation forecasts, we also

Table 3: Out-Of-Sample Forecasts of Output Growth

Performance of models containing the financial aggregates relative to the corresponding model without the financial aggregate

Model[(a)]	Ratio statistic
2VM3	Slight improvement over steps 2-6[(b)]
3VM3	Slight improvement over steps 5-8
4VM3	Slight improvement at steps 7 and 8
5VM3	Worse over 7 of 8 steps
2VCU	Uniformly worse
3VCU	Uniformly worse
4VCU	Uniformly worse
5VCU	Uniformly worse
2VBM	Uniformly worse
3VBM	Worse over 6 of 8 steps
4VBM	Worse over 7 of 8 steps
5VBM	Slight improvement at steps 6 and 8 Notable improvement at step 5[(c)]
2VCR	Uniformly worse
3VCR	Uniformly worse
4VCR	Uniformly worse
5VCR	Uniformly worse

Notes: (a) The prefix in this column refers to the number of variables in the system eg 2VM3 is the two-variable system containing M3.
(b) Slight improvement refers to those cases where the average improvement across horizons is less than 5%.
(c) Notable improvement refers to those cases where the average improvement is greater than 5%.

Table 4: Out-Of-Sample Forecasts of Inflation

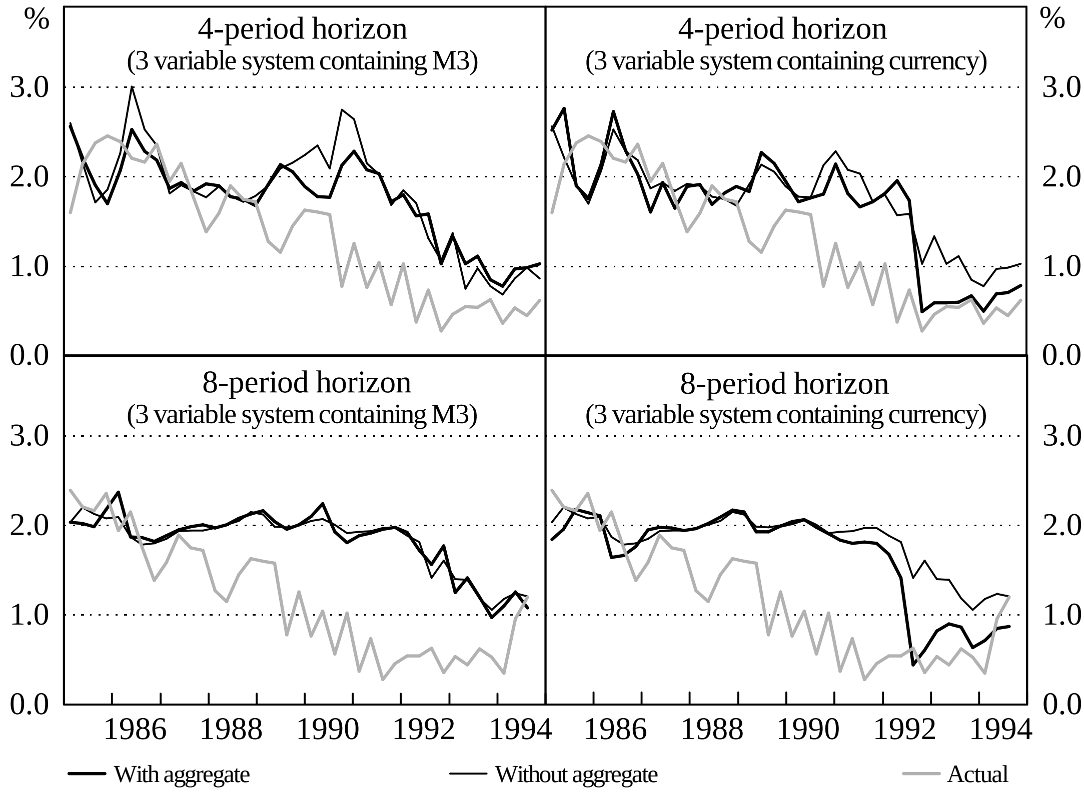
Performance of models containing the financial aggregate relative to the corresponding model without the financial aggregate

Model[(a)]	Ratio statistic
2VM3	Slight improvement over steps 4-8[(b)]
3VM3	Uniformly worse
4VM3	Uniformly worse
5VM3	Uniformly worse
2VCU	Notable improvement over steps 4-8 [(c)]
3VCU	Slight improvement over steps 5-8
4VCU	Slight improvement over steps 5-8
5VCU	Uniformly worse
2VBM	Notable improvement over steps 5-8
3VBM	Slight improvement over steps 5-8
4VBM	Slight improvement over steps 6-8
5VBM	Uniformly worse
2VCR	Uniform notable improvement
3VCR	Uniform improvement. Notable improvement at steps 6-8
4VCR	Slight improvement over steps 2,4 and 5 Notable improvement at steps 6-8
5VCR	Slight improvement over steps 6-8

Notes: (a) The prefix in this column refers to the number of variables in the system eg 2VM3 is the two-variable system containing M3.
(b) Slight improvement refers to those cases where the average improvement across horizons is less than 5%.
(c) Notable improvement refers to those cases where the average improvement is greater than 5%.

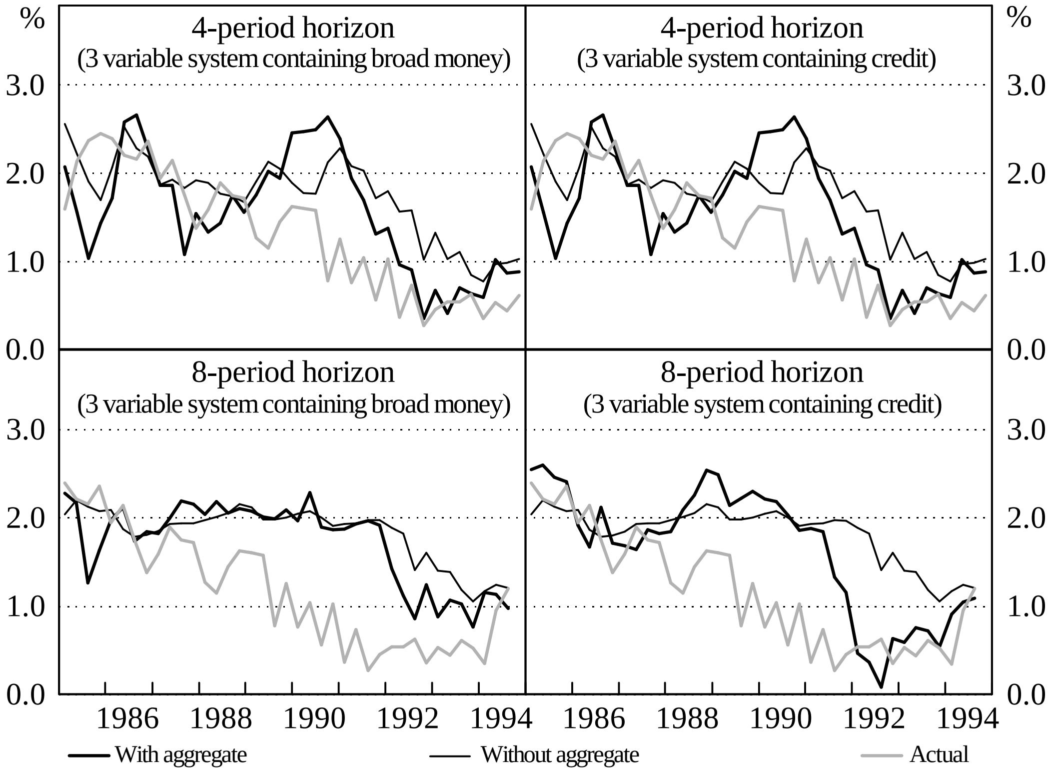
present Figures (6 and 7) of the forecasts for the 4 and 8-period horizons for models with each aggregate to identify whether any improvement in the forecasting accuracy is consistent over the entire forecast sample.

Figure 6: Inflation Forecasts For Systems Containing M3 and Currency



As was the case for the in-sample tests, the results are mixed. There appears little evidence that the inclusion of any of the financial aggregates improves the out-of-sample forecasts of real GDP growth. For inflation forecasting, the results appear somewhat more positive, although they do not seem to be robust over the entire sample. Currency shows some contribution to improving the forecasting accuracy for inflation relative to the model without currency, consistent with some of the in-sample evidence. Broad money also shows some improvement in the forecasts of inflation in the latter quarters of the forecast horizon, but only in the two-variable VAR is there evidence of notable improvement. Inclusion of credit in the VAR improves forecast accuracy for inflation towards the end of the forecast horizon, but the improvement is strongest in the two and three-variable VARs. M3 appears to make no contribution to out-of-sample forecasting performance.

Figure 7: Inflation Forecasts for Systems Containing Broad Money and Credit



To keep these results in perspective, it should be noted that none of the models yields particularly good out-of-sample inflation forecasts. Figures 6 and 7 illustrate that the forecasts from both VAR models generally overpredict inflation over the forecast sample. In cases where some forecast improvements do occur, Figures 6 and 7 illustrate that the improvement to the forecast of inflation is confined to the latter part of the forecast sample. As discussed above in the data section, the forecast improvement may be reflecting the dramatic decline of the growth of the aggregates along with inflation after 1990, and does not appear to be a general result applicable to the sample as a whole.

6. Discussion of Results

We interpret our evidence as indicating that there are no large and obvious correlations between financial aggregates and the variables of interest that can be exploited by policymakers in forecasts using simple VARs. Across the numerous systems we examine, the in-sample and out-of-sample tests do not provide consistent support for the idea that growth rates in financial aggregates contain significant information for explaining subsequent fluctuations in output growth and inflation.

There are isolated instances where certain aggregates contain information in an in-sample setting; however, in no case do we find that any single aggregate bears significant explanatory power across all of the in-sample tests. One example of this finding is the variance decomposition results for the broader aggregates. For the full sample, the placement of the financial aggregate in the causal ordering is crucial to the findings of significance. Specifically, when the aggregate follows the policy targets in the causal ordering, the importance of the aggregates for explaining inflation disappears.

The out-of-sample forecast results indicate that none of the aggregates appear to improve the prediction of real output growth in a real-time setting. On the other hand, the out-of-sample results suggest that some of the financial aggregates may improve the prediction of inflation. The RMSE ratio statistics indicate that models containing either broad money, credit, or currency improve the forecasting of inflation in the two and three-variable systems (and also for the four-variable systems containing credit and currency).[22]

We suspect that the relationship between inflation and the growth in the financial aggregates has become stronger in the latter part of the sample. This apparent correlation appears to be driving the improvement in the forecasts of inflation in the models where financial aggregates are included. However, figures of the forecasts of

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[22] When the exchange rate is included in the system, then models with the financial aggregate actually perform worse that the restricted VAR that excludes the aggregate. Because of the poor out-of-sample forecast results for systems that include the exchange rate (those with and without a financial aggregate), we are hesitant to place much importance on results from these systems. We attribute these results to the random nature of exchange rate changes and the inability of the unrestricted VAR to forecast it adequately.

inflation 4 periods and 8 periods out of sample (for all aggregates except M3) show obvious improvement in the forecast from the VAR with the aggregate *only* at the end of the sample. The lack of degrees of freedom prevents us from exploring the out-of-sample forecast performance of these models using only the data from the latter period. The key question is whether these correlations indicate the emergence of a more stable and meaningful relationship between financial aggregates and inflation, or are characteristic only of a particular episode.

Further research is necessary to explore this issue. Aside from waiting for more data, one way to proceed in further examining the usefulness of the aggregates might be to examine forecasting models that employ mixed frequency intervals in order to test whether financial data can improve real-time forecasts of inflation.[23] Data for real GDP and the CPI are published on a quarterly basis, whereas monetary data are published on a monthly frequency, and released prior to the publication of output and inflation measures. This may give these variables information value that is not captured in a quarterly VAR.

[23] The availability of financial aggregate figures on a monthly basis may allow the use of a state-space filter as used by Zadrozny (1990) to use higher frequency data to forecast lower frequency variables. This issue is left for future research.

Appendix A: Data

Currency (Curr)

Definition: Holdings of notes and coins by the non-bank private sector. Seasonal adjustment by the Australian Bureau of Statistics.

Source: Reserve Bank of Australia *Bulletin*.

M3

Definition: Currency plus total current deposits with banks, excluding Commonwealth and State Government deposits and interbank deposits. Seasonally-adjusted M3 adjusted for breaks due to the transfer of non-bank financial intermediary (NBFI) business to banks or the establishment of new banks.

Source: Reserve Bank of Australia *Bulletin*.

Broad Money (BM)

Definition: M3 plus borrowings from the private sector by NBFIs less the latter's holdings of currency and bank deposits. Borrowings by NBFIs include borrowings by permanent building societies, credit co-operatives, finance companies, authorised money market dealers, pastoral finance companies, money market corporations, general financiers and cash management trusts, less borrowings by authorised money market dealers from those non-bank intermediaries.

Source: Reserve Bank of Australia *Bulletin*.

Lending by All Financial Intermediaries (Credit, CR)

Definition: Bank lending plus lending (including bills discounted) to the private sector by non-bank financial corporations.

Source: Reserve Bank of Australia *Bulletin*.

The 90-Day Bank Accepted Bill Rate (BAB)

Definition: Three-month average of the average nominal 90-day bank accepted bill rate for the week ending last Wednesday of the month.

Source: Reserve Bank of Australia *Bulletin*.

Real Gross Domestic Product – GDP (A)

Definition: Average of income, expenditure and production measures of GDP. Seasonally adjusted by the Australian Bureau of Statistics. Values are constant in 1989/90 prices.

Source: Quarterly Estimates of National Income and Expenditure, ABS Cat. No. 5206.0.

Consumer Price Index (CPI)

Definition: The underlying consumer price index.

Units 1989/90 = 100. (NSA)

Source: Consumer Price Index, ABS Cat. No. 6410, Table 11.

Trade-Weighted Index (TWI)

Definition: Quarterly average of the $A in relation to the currencies of Australia's trading partners.

Source: Reserve Bank of Australia *Bulletin*.

Figure A1: Log Differences of Aggregates

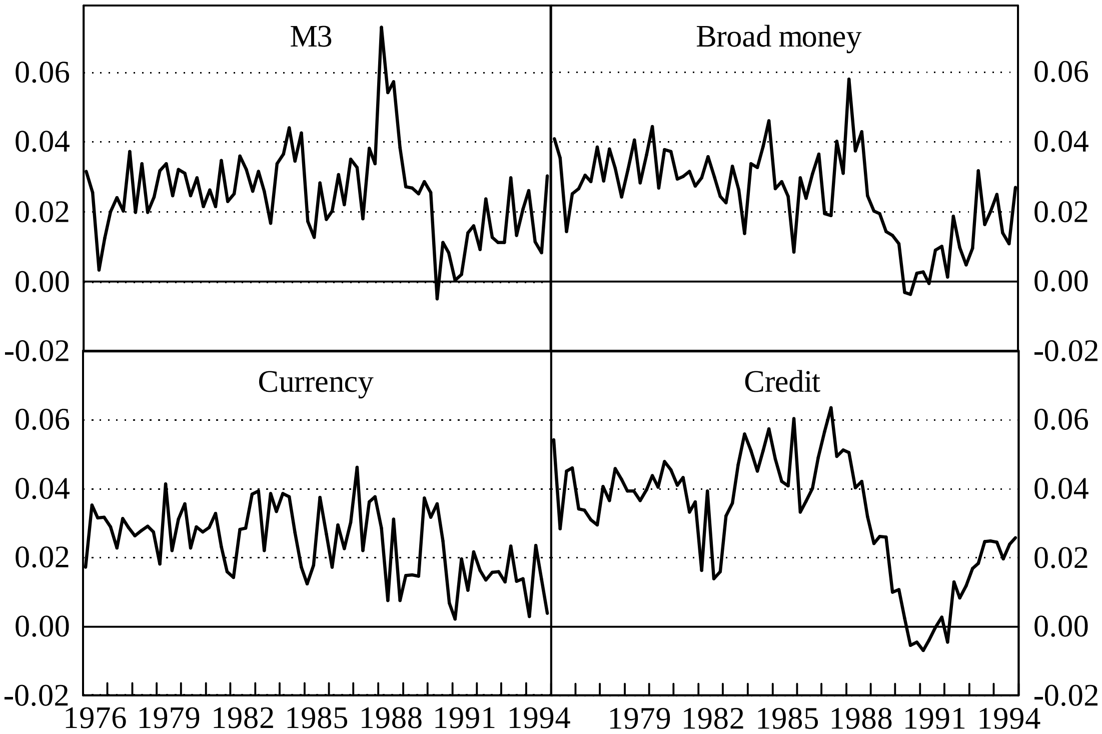
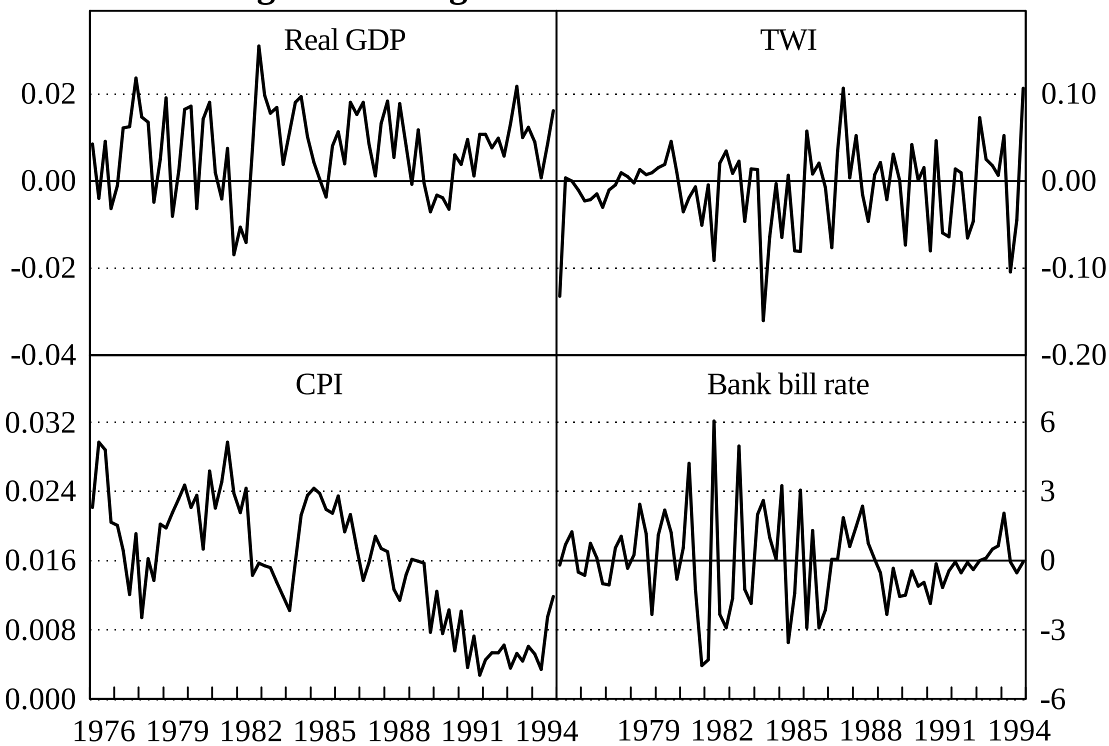


Figure A2: Log Differences of Other Data



Appendix B: Detailed Out-Of-Sample Results

Table B1: Out-Of-Sample Forecasts of Output Growth

Forecast error statistics

Model	Measure	Step 1	2	3	4	5	6	7	8
2VM3	Ratio[(a)]	1.110	0.958	0.969	0.960	0.976	0.957	1.003	1.006
	Theil U[(b)]	0.965	0.815	0.856	0.738	0.731	0.683	0.649	0.687
3VM3	Ratio	1.057	1.007	1.045	1.010	0.987	0.896	0.957	0.964
	Theil U	1.130	1.021	1.020	0.846	0.763	0.601	0.579	0.628
4VM3	Ratio	1.165	1.019	1.069	1.036	1.081	1.008	0.984	0.928
	Theil U	1.345	1.119	1.201	0.993	0.831	0.645	0.593	0.662
5VM3	Ratio	1.143	1.242	1.254	1.167	0.780	1.003	1.549	1.034
	Theil U	1.751	1.699	1.823	1.322	0.978	1.229	1.286	0.980

Notes: (a) This ratio is the ratio of the root mean square error of the forecast of output growth in the model with the financial aggregate relative to the root mean square error of the forecast of output growth in the corresponding model without the financial aggregate.

(b) This is the Theil U statistic for the output growth forecast in the model with the financial aggregate under consideration.

Table B2: Out-Of-Sample Forecasts of Inflation

Forecast error statistics

Model	Measure	Step 1	2	3	4	5	6	7	8
2VM3	Ratio[(a)]	1.047	1.034	1.021	0.997	0.972	0.981	0.959	0.960
	Theil U[(b)]	1.157	1.245	1.235	1.297	1.290	1.424	1.351	1.346
3VM3	Ratio	1.063	1.086	1.094	1.077	1.042	1.043	1.015	1.009
	Theil U	1.180	1.307	1.280	1.317	1.281	1.396	1.353	1.341
4VM3	Ratio	1.154	1.216	1.233	1.260	1.222	1.183	1.109	1.088
	Theil U	1.342	1.405	1.357	1.468	1.472	1.587	1.498	1.461
5VM3	Ratio	1.249	1.385	1.271	1.273	1.257	1.261	1.255	1.222
	Theil U	2.059	1.902	1.571	1.840	1.764	1.922	1.875	1.724

Notes: (a) This ratio is the ratio of the root mean square error of the forecast of inflation in the model with the financial aggregate relative to the root mean square error of the forecast of inflation in the corresponding model without the financial aggregate.

(b) This is the Theil U statistic for the inflation forecast in the model with the aggregate under consideration.

Table B3: Out-Of-Sample Forecasts of Output Growth

Forecast errror statistics

Model	Measure	Step 1	2	3	4	5	6	7	8
2VCU	Ratio[(a)]	1.307	1.310	1.306	1.210	1.150	1.188	1.166	1.166
	Theil U[(b)]	1.136	1.115	1.154	0.929	0.862	0.848	0.755	0.796
3VCU	Ratio	1.250	1.252	1.246	1.191	1.127	1.112	1.149	1.212
	Theil U	1.337	1.269	1.215	0.997	0.870	0.747	0.695	0.789
4VCU	Ratio	1.200	1.213	1.106	1.063	1.124	1.137	1.106	1.162
	Theil U	1.385	1.332	1.242	1.019	0.864	0.727	0.667	0.829
5VCU	Ratio	1.326	1.597	1.154	1.332	1.400	1.546	1.424	1.509
	Theil U	2.032	2.185	1.678	1.508	1.755	1.895	1.183	1.430

Notes: (a) This ratio is the ratio of the root mean square error of the forecast of output growth in the model with the financial aggregate relative to the root mean square error of the forecast of output growth in the corresponding model without the financial aggregate.
(b) This is the Theil U statistic for the output growth forecast in the model with the financial aggregate under consideration.

Table B4: Out-Of-Sample Forecasts of Inflation

Forecast error statistics

Model	Measure	Step 1	2	3	4	5	6	7	8
2VCU	Ratio[(a)]	1.031	0.993	0.938	0.888	0.908	0.894	0.894	0.891
	Theil U[(b)]	1.139	1.196	1.134	1.156	1.207	1.297	1.259	1.249
3VCU	Ratio	1.125	1.026	1.006	0.959	0.947	0.913	0.918	0.903
	Theil U	1.248	1.234	1.177	1.172	1.165	1.221	1.225	1.200
4VCU	Ratio	1.224	1.024	1.014	1.009	0.971	0.925	0.935	0.912
	Theil U	1.423	1.184	1.116	1.174	1.170	1.240	1.263	1.225
5VCU	Ratio	1.120	1.198	1.205	1.164	1.124	1.073	1.038	1.062
	Theil U	1.848	1.647	1.490	1.682	1.578	1.636	1.550	1.500

Notes: (a) This ratio is the ratio of the root mean square error of the forecast of inflation in the model with the financial aggregate relative to the root mean square error of the forecast of inflation in the corresponding model without the financial aggregate.
(b) This is the Theil U statistic for the inflation forecast in the model with the aggregate under consideration.

Table B5: Out-Of Sample Forecasts of Output Growth

Forecast error statistics

Model	Measure	Step 1	2	3	4	5	6	7	8
2VBM	Ratio[(a)]	1.192	1.072	1.142	1.120	1.117	1.123	1.120	1.093
	Theil U[(b)]	1.037	0.912	1.009	0.860	0.836	0.801	0.725	0.746
3VBM	Ratio	1.100	0.989	1.094	1.029	1.005	1.008	1.033	0.978
	Theil U	1.176	1.002	1.067	0.861	0.776	0.677	0.625	0.637
4VBM	Ratio	1.320	1.017	1.060	0.953	1.116	1.088	1.036	1.089
	Theil U	1.524	1.118	1.191	0.913	0.858	0.696	0.624	0.777
5VBM	Ratio	1.101	1.610	1.051	1.259	0.827	0.950	1.333	0.944
	Theil U	1.686	2.202	1.527	1.426	1.037	1.164	1.107	0.895

Notes: (a) This ratio is the ratio of the root mean square error of the forecast of output growth in the model with the financial aggregate relative to the root mean square error of the forecast of output growth in the corresponding model without the financial aggregate.
(b) This is the Theil U statistic for the output growth forecast in the model with the financial aggregate under consideration.

Table B6: Out-Of Sample Forecasts of Inflation

Forecast error statistics

Model	Measure	Step 1	2	3	4	5	6	7	8
2VBM	Ratio[(a)]	1.035	0.997	0.969	0.946	0.894	0.868	0.878	0.890
	Theil U[(b)]	1.143	1.200	1.171	1.231	1.187	1.259	1.237	1.247
3VBM	Ratio	1.040	1.040	1.044	1.040	0.968	0.924	0.921	0.919
	Theil U	1.154	1.252	1.222	1.271	1.191	1.236	1.228	1.221
4VBM	Ratio	1.359	1.092	1.073	1.074	1.066	0.950	0.962	0.964
	Theil U	1.436	1.325	1.224	1.279	1.224	1.246	1.259	1.270
5VBM	Ratio	1.410	1.865	1.175	1.043	1.623	1.238	1.152	2.113
	Theil U	2.325	2.563	1.452	1.507	2.277	1.887	1.721	2.983

Notes: (a) This ratio is the ratio of the root mean square error of the forecast of inflation in the model with the financial aggregate relative to the root mean square error of the forecast of inflation in the corresponding model without the financial aggregate.
(b) This is the Theil U statistic for the inflation forecast in the model with the aggregate under consideration.

Table B7: Out-Of Sample Forecasts of Output Growth

Forecast error statistics

Model	Measure	Step 1	2	3	4	5	6	7	8
2VCR	Ratio[(a)]	1.169	1.178	1.158	1.135	1.154	1.098	1.044	1.053
	Theil U[(b)]	1.017	1.002	1.024	0.872	0.865	0.784	0.676	0.719
3VCR	Ratio	1.016	1.004	1.096	1.103	1.224	1.212	1.166	1.141
	Theil U	1.087	1.018	1.069	0.923	0.946	0.814	0.706	0.743
4VCR	Ratio	1.480	1.180	1.057	1.164	1.432	1.553	1.281	1.321
	Theil U	1.708	1.294	1.187	1.116	1.101	0.994	0.772	0.943
5VCR	Ratio	1.398	1.594	0.986	1.284	0.998	1.037	1.450	1.839
	Theil U	2.142	2.181	1.433	1.453	1.251	1.271	1.204	1.743

Notes: (a) This ratio is the ratio of the root mean square error of the forecast of output growth in the model with the financial aggregate relative to the root mean square error of the forecast of output growth in the corresponding model without the financial aggregate.
(b) This is the Theil U statistic for the output growth forecast in the model with the financial aggregate under consideration.

Table B8: Out-Of Sample Forecasts of Inflation

Forecast error statistics

Model	Measure	Step 1	2	3	4	5	6	7	8
2VCR	Ratio[(a)]	0.937	0.898	0.874	0.860	0.854	0.826	0.805	0.798
	Theil U[(b)]	1.035	1.081	1.057	1.118	1.134	1.199	1.133	1.118
3VCR	Ratio	0.962	0.926	0.940	0.938	0.915	0.862	0.825	0.804
	Theil U	1.068	1.114	1.010	1.147	1.125	1.153	1.100	1.069
4VCR	Ratio	1.052	0.977	1.052	0.957	0.961	0.866	0.854	0.846
	Theil U	1.223	1.130	1.157	1.114	1.157	1.161	1.153	1.136
5VCR	Ratio	1.199	1.135	1.354	1.009	1.053	0.977	0.992	0.931
	Theil U	1.978	1.559	1.674	1.457	1.477	1.490	1.482	1.314

Notes: (a) This ratio is the ratio of the root mean square error of the forecast of inflation in the model with the financial aggregate relative to the root mean square error of the forecast of inflation in the corresponding model without the financial aggregate.
(b) This is the Theil U statistic for the inflation forecast in the model with the aggregate under consideration.

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