FINANCIAL AGGREGATES AS CONDITIONING INFORMATION FOR AUSTRALIAN OUTPUT AND INFLATION

Ellis W. Tallman and Naveen Chandra

Research Discussion Paper
9704

July 1997

Economic Research Department

Reserve Bank of Australia

We thank Will Roberds and Chuck Whiteman for the RATS program for the prediction tests. We thank Gordon de Brouwer, Guy Debelle, Glenn Stevens, David Gruen, Phil Lowe, Troy Swann and Jenny Wilkinson for useful comments on an earlier draft. The opinions expressed, and any remaining errors are ours, and should not be attributed to the Reserve Bank of Australia.

Abstract

This paper examines whether financial aggregates provide information useful for predicting real output growth and inflation, extending the inquiry conducted in Tallman and Chandra (1996).

First, we investigate whether perfect knowledge of the future values of financial aggregates helps improve significantly the forecasting accuracy of output and inflation in a simple vector autoregression framework. The results display only one notable improvement to the forecasts with the addition of perfect information on the financial aggregates – future information on credit growth helps improve the prediction accuracy of real output growth. The improvement is most noticeable during the early 1990s recession.

Second, we test whether the financial aggregates are important explanators within single-equation models that are more rigorously fitted to the data. We find only one instance in which an aggregate helps explain the variation in either real output growth or inflation – that is, the growth in credit helps explain the growth in real output in a particular specification of the output model. This finding, though, is sensitive to the choice of foreign output proxy. In sum, we conclude that while credit may have some useful information in times of financial restructuring it is unlikely that there is information in financial aggregates that is exploitable *systematically* for predicting either real output growth or inflation.

JEL Classification Numbers E40, E44, E51

Table of Contents

FINANCIAL AGGREGATES AS CONDITIONING INFORMATION FOR AUSTRALIAN OUTPUT AND INFLATION

Ellis W. Tallman and Naveen Chandra

1. Introduction

This paper follows on the work in Tallman and Chandra (1996) by investigating further whether financial aggregates explain subsequent fluctuations in real output growth and inflation. In that paper, using the vector autoregression (VAR) methodology, Tallman and Chandra draw the general conclusion that financial aggregates show no exploitable correlations with output growth and inflation that are robust across various time-periods and specifications. However, the paper finds in an out-of-sample setting that some financial aggregates may help forecast inflation. Also, in-sample evidence from their variance decomposition analysis reveals that in certain specifications financial aggregates seem important for determining the forecast error variance of inflation and output growth. These findings, as well as the criticism that all the results rely on the adequacy of the VAR for the real output growth and inflation process, suggest that further research is warranted.

Here, we apply additional empirical methodologies to investigate further the usefulness of financial aggregate data for forecasting output and inflation. In the first method, we test the information value of financial aggregates by employing a VAR to generate a simple, artificial experiment that indicates whether foreknowledge of financial aggregates improves the forecasts of real output growth and inflation. In our study for Australia, the forecast-improvement statistics suggest that financial aggregates are not particularly useful for predicting either real output growth or inflation in the unrestricted VAR setting. The notable exception is the growth in credit as conditional information for improving the prediction of real output growth.

While the above VAR-based approach may uncover meaningful correlations in a relatively unrestricted setting, it has limitations. By limiting the number of included variables, it implicitly imposes exclusion restrictions that may ignore important explanatory relationships found in existing single-equation models. To address this criticism and to provide evidence from an empirical methodology other than the VAR, we analyse the effect of adding financial-aggregate variables to restricted reduced-form single-equation models of real output growth and inflation. To preview the results, we find no evidence that financial-aggregate data improve the fit for inflation. We find in one specification for real output growth that both the contemporaneous and four lags of credit growth explain a significant proportion of growth in real output. However, another specification for real output growth – that using US output instead of OECD output as a measure of world output – shows no evidence of the explanatory power of credit growth. Also, when we restrict the real interest rate coefficients to be zero and leave the financial aggregate as the only financial channel, no aggregate shows significant explanatory power. We suggest these negative results imply that there is a lack of robustness in the positive result for credit growth.

Taking the evidence from both unrestricted VAR prediction tests and the restricted specification, there appears no robust and potentially exploitable correlations between growth in any of the financial aggregates and real output growth and inflation. There is some evidence, however, that in periods of considerable financial restructuring, changes in credit growth may provide useful information regarding the future course of output. Outside such periods, credit growth appears to be simply another corroborating information variable.

2. Background

Estrella and Mishkin (1996) suggest three potential roles for the financial aggregates in the conduct of monetary policy: as information variables, as indicators of policy, and as instruments of policy. These roles require successively stronger and more stable relationships between the aggregates and the final goals of monetary policy in order to perform satisfactorily. The authors find little evidence of the required relationships in the United States and in Germany, suggesting that the monetary aggregates are not good indicators of the stance of policy and have little value as information variables.

In Australia during the late 1970s and early 1980s, financial aggregates, and particularly M3, were a primary focus of monetary policy. As was the case in many countries, there were explicit target rates of growth for money, based on the idea that there was an underlying, stable relationship between the aggregates and the objectives of policy, namely real output growth and inflation. This use of financial aggregates would align with the Estrella and Mishkin idea of financial aggregates as instruments of policy.

Since the mid 1980s, the policy role of financial aggregates, in Australia as in many other industrialised countries, has been de-emphasised. In Australia, 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. Currently, monetary policy in Australia is implemented by direct changes to the short-term rate of interest, with financial aggregates having become just another of the many information variables used in formulating monetary policy.[1]

Tallman and Chandra (1996) review the literature on investigations of whether information on financial aggregates helps predict real output growth or inflation in Australia. The general conclusion from the literature is that there is little evidence supporting financial aggregates as independent explanators of subsequent real output growth and inflation for Australia, and such evidence appears to weaken further as the sample is extended. The implication is that while the financial aggregates might provide some corroborating evidence regarding future developments, they provide little if any information that is not contained in other variables.

In this paper, we investigate further the findings in Tallman and Chandra (1996) and the results in the literature. We focus on the information content of financial aggregates in Australia in two distinct ways. First, we employ a technique introduced by Roberds and Whiteman (1992).[2] In their paper, they examine the observed decline in the predictive value of monetary data for real output and the

---

1 Astley and Haldane (1997) suggest that data for policy analysis in general can either contain incremental information that is not available in other sources or may simply corroborate what other indicators reflect.

2 Roberds and Whiteman (1992) investigate whether monetary aggregates in the United States are useful for explaining real output and price-level fluctuations using a VAR methodology. The prediction exercise was a key test of the relationships in the US data between output, the price level and chosen monetary aggregates.

price level in the United States using VAR techniques. They notice a substantial decline in the information content of specific aggregates for explaining the behaviour of policy targets after the apparent change in Federal Reserve operating procedures in the third quarter of 1979. An innovation in their paper is the technique that allows comparison of conditional versus unconditional forecast accuracy, expanded upon below. We apply this technique to Australian data as an additional method of evaluating the information value of financial aggregate data for policy. The experiment essentially compares the in-sample forecast errors of an unconditional forecast in which each variable in the VAR must be forecast, with the in-sample forecast errors from a conditional forecast that assumes perfect knowledge of the financial aggregate measures eight quarters into the future.

The second method we employ examines whether adding financial aggregate variables to restricted reduced-form single-equation models of real output growth and inflation improves the explanatory power of those single-equation models. These models are re-estimations of existing, rigorously fitted models of Australian output growth (Gruen and Shuetrim 1994) and inflation (de Brouwer and Ericsson 1995). To examine the information content in financial aggregates for these measures, we employ tests of the marginal significance of the aggregates in these single-equation models.

3. The In-sample Prediction Exercise

Five different financial aggregates are used in this investigation: currency (CURR), M1, M3, broad money (BM) and credit of all financial intermediaries (CRED). Real GDP(A) is the output measure, and the underlying CPI is the measure of the price level. The financial aggregates are examined in four-variable VARs which contain inflation, real output growth, the differenced interest rate (90-day bank bill rate) and the growth rate of the relevant financial aggregate. The sample period begins in the fourth quarter of 1977 and ends in the second quarter of 1996. We follow Tallman and Chandra (1996) by using growth rates of the variables in the investigation. Further description of the above data series appears in Appendix A.

Our first empirical method employs a vector autoregressive model that includes four lags each of four variables. The technique involves performing a series of hypothetical in-sample prediction exercises that compare unconditional forecasts with conditional forecasts of real output growth and inflation. In this case, the conditional forecasts assume perfect knowledge of the next eight quarters of a given financial aggregate.

The models are specified in first difference form due to test statistics that suggest non-stationarity 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) and find no substantial differences in the inferences.[3] The model outlined below provides a transparent representation of the VAR that is estimated for the exercise,

$$
\begin{aligned}
p_t &= a_1 + \sum_{i=1}^{4} b_{1i}\, p_{t-i} + \sum_{i=1}^{4} j_{1i}\, y_{t-i} + \sum_{i=1}^{4} g_{1i}\, i_{t-i} + \sum_{i=1}^{4} J_{1i}\, m_{t-i} + u_{1t} \\
y_t &= a_2 + \sum_{i=1}^{4} b_{2i}\, p_{t-i} + \sum_{i=1}^{4} j_{2i}\, y_{t-i} + \sum_{i=1}^{4} g_{2i}\, i_{t-i} + \sum_{i=1}^{4} J_{2i}\, m_{t-i} + u_{2t} \\
i_t &= a_3 + \sum_{i=1}^{4} b_{3i}\, p_{t-i} + \sum_{i=1}^{4} j_{3i}\, y_{t-i} + \sum_{i=1}^{4} g_{3i}\, i_{t-i} + \sum_{i=1}^{4} J_{3i}\, m_{t-i} + u_{3t} \\
m_t &= a_4 + \sum_{i=1}^{4} b_{4i}\, p_{t-i} + \sum_{i=1}^{4} j_{4i}\, y_{t-i} + \sum_{i=1}^{4} g_{4i}\, i_{t-i} + \sum_{i=1}^{4} J_{4i}\, m_{t-i} + u_{4t},
\end{aligned}
\tag{1}
$$

---

[3] Results are available on request from the authors. We also performed a VAR estimation in which only the interest rate was in levels and the remaining variables were in growth rates. The results from that specification were similar to those presented in the paper.

where: p is the inflation rate;
y is the output growth rate;
i is the differenced interest rate; and
m is the growth rate of the financial aggregate.

The VAR model is estimated over the full sample, thus producing one set of coefficient estimates for the entire forecasting procedure. Using the estimates, we produce conditional and unconditional forecasts of real output growth and inflation over an eight-period forecast horizon. All forecasts are dynamic system forecasts, and in this setting they are in-sample. The unconditional forecasts are unconditional in the sense that when forecasting from date t for periods t+1, t+2, t+3, etc., no additional information on any of the variables is available beyond period t. In contrast, the conditional forecasts of real output and inflation use actual values (instead of forecasted values) of the financial aggregates. For example, at period t when forecasting real output growth for period t+5, the *unconditional* forecasts use internal model forecasts of all the right-hand side variables in the VAR, including the financial aggregate, for periods t+1 to t+4. The *conditional* forecast of real output growth in period t+5 made at period t uses *actual* values for the financial aggregate combined with forecasted values of inflation, real output growth and the interest rate for observations dated periods t+1 to t+4. Thus, these forecasts are conditional on knowledge of the financial aggregate.

The forecast errors for the right-hand side variables in the equation for either real output growth or inflation contribute to the measured unconditional forecast error for the policy variable. Knowledge of the future values of one of the right-hand side variables reduces the average forecast error of either real output growth or inflation over the forecast horizon by eliminating one source of the forecast error. Suppose that for the next eight quarters the values of the financial aggregate are known with certainty. Then, the forecast that employs this information is conditional – there is perfect information on one of the variables. As a result, that variable (in our case the financial aggregate) will not contribute forecast errors to the forecasts of either real output growth or inflation because that component is known. What remains is to determine the extent to which this information improves the forecast accuracy for real output growth and inflation by comparing the forecast accuracy of the unconditional versus the conditional forecast. To do this we calculate the measured improvement in the conditional from the unconditional forecast (see Appendix B for details). The ‘improvement’ statistics that we present represent the approximate average reduction, in per cent, of the standard deviations of the one- through eight-step-ahead forecast of the indicated variable that would result from knowledge of the next eight quarters of the given aggregate. This procedure leaves us without a way to judge whether this difference is statistically significant; to overcome this issue, we generate 1 000 draws of a Monte Carlo simulation exercise to produce estimates of the standard deviations of the percentage improvements.

In contrast to out-of-sample evidence, this prediction exercise provides a clearer basis of evaluation for two reasons. First, because Monte Carlo simulation of the forecasts allows calculation of the standard deviation of improvement in forecasting accuracy, we can make statistical inferences about the significance of forecast improvements. Second, the system employs all of the data for the entire sample period to estimate the parameters of the model, so the statistical fit of the model in the forecasting exercises remains the same over the chosen sample. While the prediction exercise is clearly less realistic than out-of-sample forecast evaluations, the results are easier to make inferences from. The information value of each of the aggregates is examined using estimates from both the full sample and a sample that ends in the fourth quarter of 1989. We examine this shortened period to gauge whether inclusion of data from the 1990s has a substantial impact on the results.

The columns in Tables 1 and 2 entitled ‘improvement’ present the percentage reduction in the forecast error measure for either real output growth or inflation given perfect knowledge of the financial aggregates. The numbers in the ‘improvement’ column may be viewed as gauging the level of information content in the financial aggregates for the policy measures.[4]

It is useful to examine how the empirical technique generates the empirical findings. This conditional forecasting exercise hinges on two aspects of financial aggregates in the statistical model:

---

[4] In contrast to the variance decomposition results generated by Tallman and Chandra (1996), this in-sample prediction exercise is not dependent on the structural ordering of the variables in the system. For variance decomposition analysis, researchers investigate the *source* of the forecast errors and hence the structural ordering used is crucial.

1. the importance of financial aggregates in the equations for real output growth and inflation; and

2. the statistical fit for the financial aggregate equation itself.

It is possible that a poor fit in the financial-aggregate equation would imply that perfect information on the financial aggregate would lead to a very large improvement in the forecast accuracy of real output growth. The intuition here is that large errors in the unconditional forecast resulting from a poor fitting financial-aggregate equation are removed when perfect information on the financial aggregate is added. Still, any positive findings would imply that the financial aggregates have a significant correlation with real output growth or inflation.

We note that the only circumstance in which the conditional forecast cannot improve upon the unconditional forecast is when the forecast errors of the financial variable and those of real output growth and inflation are independent.[5] The empirical question then is not whether there is an improvement in the forecast accuracy measure moving from the unconditional to the conditional forecast error covariance matrix, but the degree of (in our case percentage) improvement in the measure.

We consider improvements to be significant if the lower bound of the improvement is above 10 per cent, using a one standard deviation (from the Monte Carlo simulations) criterion to determine the range of likely outcomes. Under this criterion, there is no aggregate that shows a significant improvement in the conditional relative to unconditional forecasts of *inflation* across both samples. The implication is that knowledge of future values of the aggregates would yield

[5] This is a stronger restriction than Granger non-causality (Roberds and Whiteman 1992).

Table 1: Comparison of Unconditional and Conditional Forecasts of Growth in Real GDP and Inflation

Variable forecasted	Aggregate used in forecast	Sample	Improvement[(a)]
Real GDP growth	M3	1977:Q4 – 1989:Q4	8.71 % (2.98)
Real GDP growth	M3	1977:Q4 – 1996:Q2	8.95 % (3.44)
Inflation	M3	1977:Q4 – 1989:Q4	9.39 % (2.76)
Inflation	M3	1977:Q4 – 1996:Q2	5.69 % (1.61)
Real GDP growth	M1	1977:Q4 – 1989:Q4	17.22 % (2.77)
Real GDP growth	M1	1977:Q4 – 1996:Q2	10.88 % (1.51)
Inflation	M1	1977:Q4 – 1989:Q4	6.77 % (3.38)
Inflation	M1	1977:Q4 – 1996:Q2	5.96 % (1.73)
Real GDP growth	Broad money	1977:Q4 – 1989:Q4	7.44 % (3.20)
Real GDP growth	Broad money	1977:Q4 – 1996:Q2	10.79 % (3.99)
Inflation	Broad money	1977:Q4 – 1989:Q4	11.19 % (4.51)
Inflation	Broad money	1977:Q4 – 1996:Q2	9.34 % (3.04)

Note: (a) 'Improvement' denotes approximate average reduction in the standard deviations of the one- through eight-quarter-ahead forecasts. The value of the improvement is the mean value from one thousand Monte Carlo replications. Standard deviations are in parentheses.

Table 2: Comparison of Unconditional and Conditional Forecasts of Growth in Real GDP and Inflation

Variable forecasted	Aggregate used in forecast	Sample	Improvement[(a)]
Real GDP growth	Credit	1977:Q4 – 1989:Q4	17.19 % (3.31)
Real GDP growth	Credit	1977:Q4 – 1996:Q2	16.91 %*[(b)] (2.74)
Inflation	Credit	1977:Q4 – 1989:Q4	3.62 % (1.81)
Inflation	Credit	1977:Q4 – 1996:Q2	5.43 % (1.26)
Real GDP growth	Currency	1977:Q4 – 1989:Q4	9.59 % (3.78)
Real GDP growth	Currency	1977:Q4 – 1996:Q2	4.20 % (1.79)
Inflation	Currency	1977:Q4 – 1989:Q4	5.63 % (2.53)
Inflation	Currency	1977:Q4 – 1996:Q2	10.93 % (1.83)

Notes: (a) 'Improvement' denotes approximate average reduction in the standard deviations of the one- through eight-quarter-ahead forecasts. The value of the improvement is the mean value from one thousand Monte Carlo replications. Standard deviations are in parentheses.

(b) We regard a useful information variable as one where the level of improvement is bounded above 10 per cent in each of the subsamples. * denotes that the aggregate used in the forecast is a useful information variable for the variable forecasted.

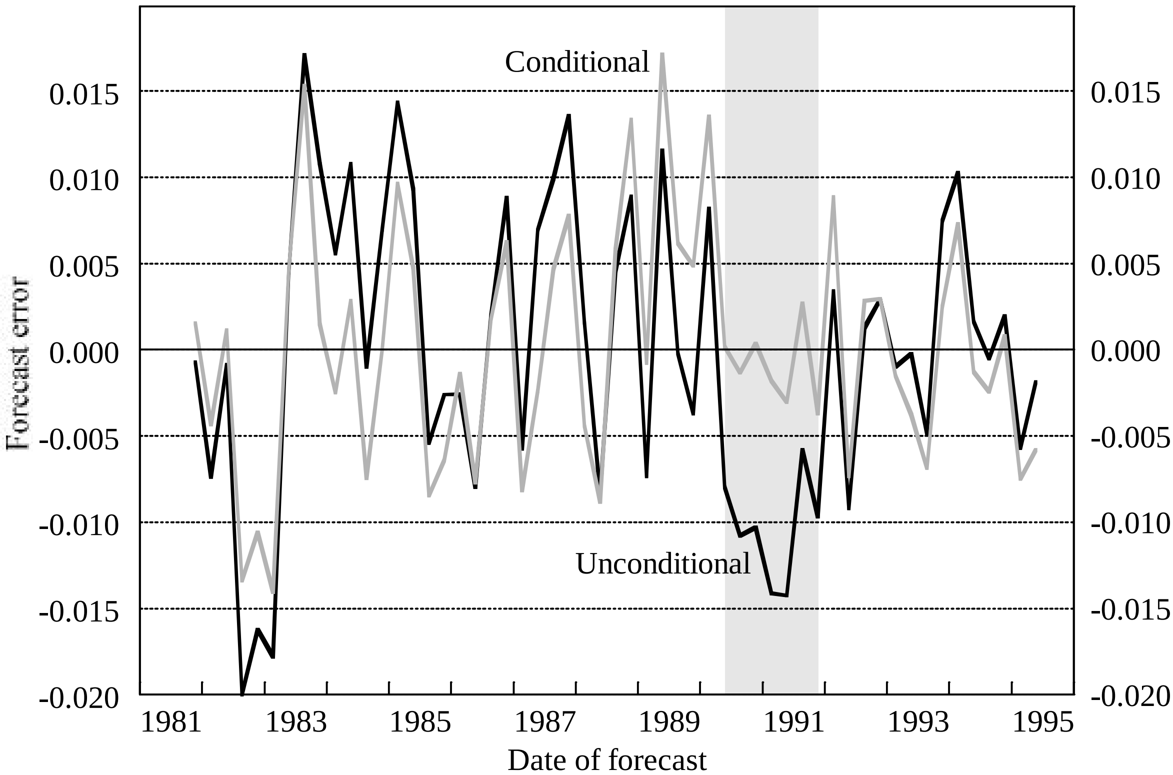
relatively little information about future price changes.[6] Similar results also hold for *real output growth*, with only perfect knowledge of growth in the credit aggregate

[6] These prediction tests provide a 'low hurdle' for monetary aggregates as measures informative for real output growth and inflation due to the unrealistic assumption that we have perfect knowledge of future values of the financial aggregate. Evidence that future financial aggregate information is not helpful for predicting real output growth and inflation is particularly negative considering the strong assumption in the experiment that the future data is known with certainty.

leading to sizeable improvements in the forecast accuracy of output growth in both samples.[7]

Figure 1 shows the errors for the unconditional and conditional forecasts of real output growth. Most of the time, information on future credit growth would have led to only a minor improvement in forecast accuracy. The one important exception is the 1990–91 recession (see shaded area). If one had known the extent of the decline in credit growth, one would have produced much better forecasts of output than those produced by the unconditional VAR.

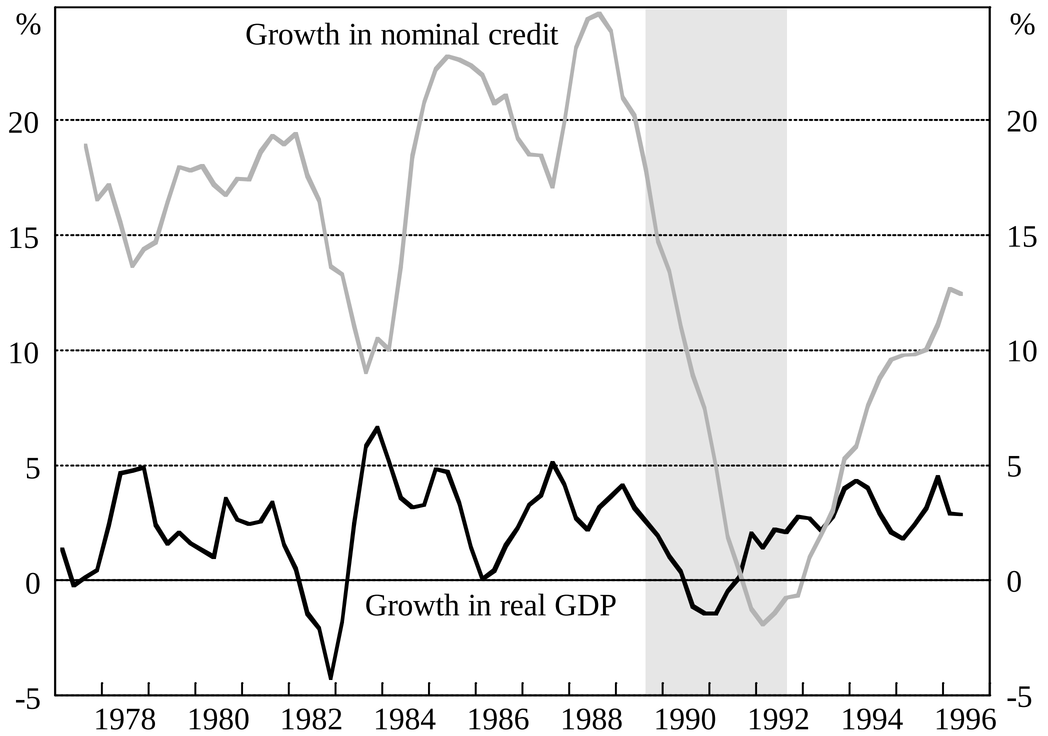
Figure 1: Forecast Errors from Unconditional and Conditional 4-period Ahead Forecasts of Real Output Growth



7 We investigated whether the degree of improvement varied significantly on the basis of forecast horizon. The results are essentially unchanged if the forecast horizon is extended from 8 to 16 periods. However, there is notably less improvement when the forecast horizon is limited to only 4 periods. Because there are fewer periods in which certain information on the credit aggregate can affect the forecasts of the target variables, knowledge of the financial aggregate has diminished influence on the forecasts over the 4-period horizon.

Figure 2, which displays four-quarter-ended growth in real output and credit, helps explain this result. The shading in the figure begins in the June quarter of 1989 because it is the date when forecasts are made for June quarter 1990, the time when the forecasts improve. The important point to note is that the behaviour of credit growth relative to real output growth during the period appears to have been different from other parts of the sample.

Figure 2: Four-quarter-ended Growth in Nominal Credit and Real GDP



The usefulness of actual information on credit over this period reflects two factors. The first is that there was a change in relationship between credit growth and lagged values of credit and output growth; during the early 1990s the forecast errors for credit growth in the VAR were larger than average. Second, the interactions between actual credit growth and output seems to have strengthened in the late 1980s – early 1990s. Not surprisingly, with a stronger link between changes in output and credit, using actual information on credit (as opposed to rather poor forecasts) generates a substantial improvement in the forecasts for output.

Previous research has tended to find that credit is endogenous to output.[8] If this is the case the usefulness of future values of credit growth in predicting output may simply reflect that idea that increases in real output lead to credit growth in the future. If this is the case, then credit is of little use, for if we knew future values of credit we would know future values of output. For credit to be useful it must have some predictive power, independent of the feedback effect from output.

To examine this issue we calculate two forecasts of output growth four periods ahead. Each forecast assumes perfect knowledge of real output growth for the first three forecast periods, but the *conditional* forecast includes perfect information on the growth rate in the credit aggregate, whereas the *unconditional* forecast does not. Thus, the conditional forecasts now include actual data on both output *and* credit, while the unconditional forecast uses actual data on output but model-generated forecasts of credit. If the usefulness of credit reflects the fact that it is endogenous then there should be little difference between these new conditional and unconditional forecasts.

The results are reported in Figure 3. While the differences between these new conditional and unconditional forecasts are smaller than previously, there remains a substantial difference. We note that the improvement in forecast errors for the conditional forecast during the 1990–92 recession period holds up in this experiment. Thus, we can infer that future information on credit growth is not just reflecting information contained in past real output growth. Further, the results suggest that credit growth was particularly important for explaining the behaviour of real output growth during that episode.

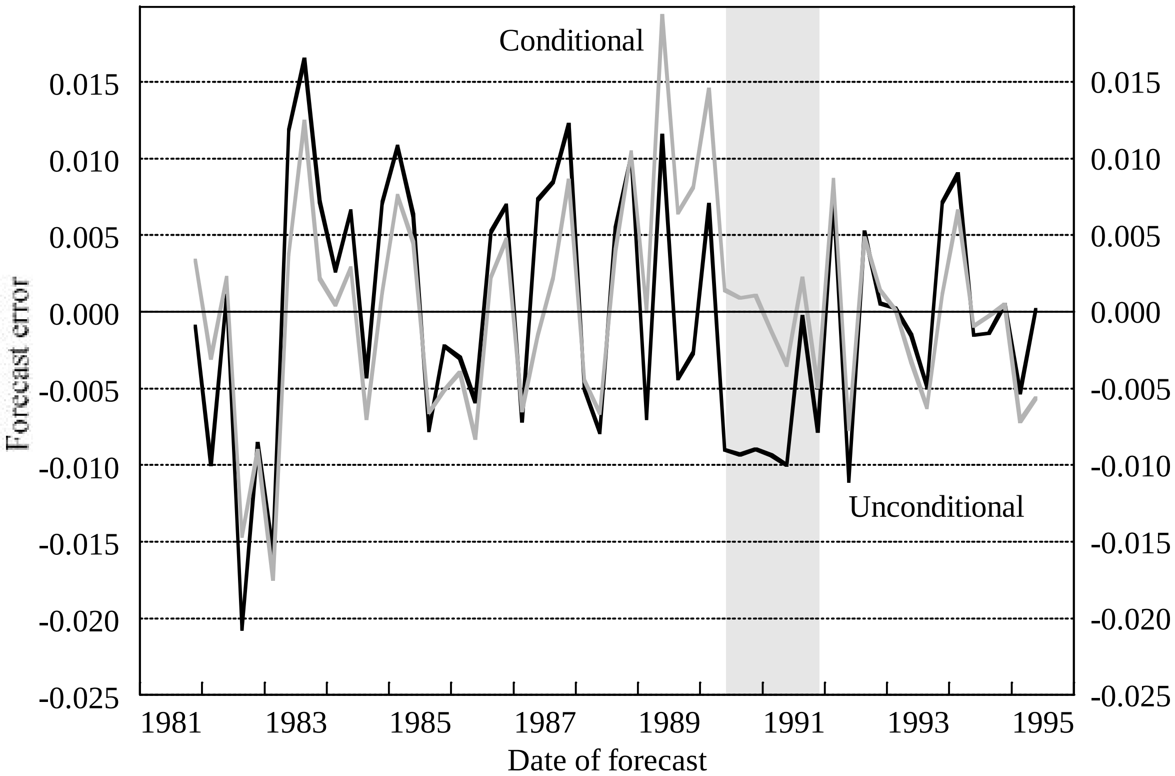
This implies that while credit is partly endogenous to output, changes in credit did have some *independent* information regarding future developments in output. Again, this conclusion appears to be specific to the late 1980s – early 1990s when major financial restructuring of corporate balance sheets was taking place.

These empirical results point out a feature of the Australian economy in the late 1980s that was a focus of monetary policy discussions. Following the 1987 stock

---

8 For example, Stevens and Thorp (1989) who find that output generally leads credit.

Figure 3: Comparing Errors for 4-period Forecast Assuming Knowledge on 3 'Forecast' Periods of Real Output Growth: Conditional (Knowing Credit) versus Unconditional



market crash and throughout most of 1988, there was a notable increase in the growth of nominal credit that was associated with rapid appreciation of asset prices, specifically commercial real estate prices. The rapid credit growth meant that Australian firms were more highly geared than in previous business cycles; the higher gearing made them more sensitive to changes in interest rates and downturns in the business cycle. When the downturn came, considerable balance sheet restructuring was required and this played a role in the protracted nature of the recession (Figure 2). The steep decline in the growth rate of credit from late 1988 to 1992 provided an important indicator of the depth of the contraction in real economic activity.

The conditional forecasting exercise highlights the instrumental role that perfect knowledge of credit would have played in explaining this episode; if one had known the actual path of credit, better forecasts of real output growth could have been made. However, there is little evidence that information on credit is important in other periods where the dynamics of the business cycle are less influenced by financial and balance sheet factors. Aside from that period of financial restructuring, credit appears to be endogenous with little independent information about the future course of real output.

We weigh the preponderance of evidence that refutes the predictive power of the credit aggregate for the real output against the positive suggestions of our prediction exercise. The likely endogeneity of credit to real output in most periods suggests that monitoring credit aggregates is useful for confirming past behaviour of real output growth; however, there appear situations in which the credit aggregate is informative for predicting output, particularly in times of financial distress.[9] Thus, the credit aggregate may be especially useful for predicting real output growth during specific episodes. The challenge is to judge beforehand those episodes in which information on the credit aggregate is likely to be of unusually high importance.

The validity of the prediction exercises, as all the statistical evidence in Tallman and Chandra (1996), is dependent on the adequacy of the four-variable VAR framework to capture the dynamics of inflation and real output growth in Australia. This is not an entirely satisfactory setting given that Australia is a small, open-economy and is heavily influenced by developments in the world economy.[10] In the next section, we extend our analysis by examining the explanatory power of financial aggregates in reduced-form equations of real output growth and inflation.

4. The Single-equation Methodology

The approach here is to examine whether lagged or contemporaneous values of the growth in financial aggregates adds explanatory power to intensively specified single-equation models of inflation and real output growth for Australia. We view a particular financial aggregate as having useful information value if it is statistically

---

[9] We examined whether sub-components of the credit aggregate (business credit, housing credit, and personal credit) as conditioning information improve notably the forecast accuracy for the target variables. Here, we found that business credit appeared the key component, although the results were not notably different from the credit aggregate results.

[10] See Gruen and Shuetrim (1994) for an investigation of the dependence of Australian output on foreign output growth.

significant in either of these models. We employ the same financial aggregate measures as those used in the first section of this paper, and use this exercise as a robustness check of information content across empirical methods.

Our base model for real output growth originates from Gruen and Shuetrim (1994) whereas the model for inflation is a revised version of that used in de Brouwer and Ericsson (1995). The preferred specifications in these papers are the end result of extensive investigation into the determinants of real output growth and inflation over their respective samples and data sets. In this study our concern is not in finding the optimal models for real output growth and inflation; rather, we focus solely on examining whether information on financial aggregates helps predict movements in either real output growth or inflation using the single-equation models as the base case.

Before adding information on financial aggregates, we examine whether the specifications used in both studies were stable after extending the data sample to 1996:Q2. In their original specifications, the estimates for each model employ a shorter dataset. Gruen and Shuetrim (1994) and de Brouwer and Ericsson (1995) estimate their models over the data samples 1980:Q1 to 1993:Q4 and 1977:Q3 to 1993:Q3, respectively. A slightly altered version of the preferred specification from Gruen and Shuetrim (1994) appeared to remain adequate over our full sample 1980:Q3 to 1996:Q2.[11] In contrast, the preferred model in de Brouwer and Ericsson (1995) failed to hold up over the extended sample. Significant revisions in the data used by de Brouwer and Ericsson altered the fit of their preferred specification over their original sample 1977:Q3 to 1993:Q3.

4.1 Model of Real Output Growth

The Gruen and Shuetrim (1994) model is specified as follows,

$$\Delta y_t = a + \sum_{j=2}^{6} b_j r_{t-j} + \sum_{j=1}^{2} g_j \Delta y^f_{t-j} + f y_{t-1} + q w_{t-1} + p \Delta w_t + e_t \,, \tag{2}$$

[11] There was a large outlier in the OECD output measure in 1980:Q2 that made the statistical fit questionable over the entire sample. We dropped the first two observations to establish a satisfactory regression.

where Δy_t is Australian quarterly GDP growth, r_t is the real short-term interest rate, Δy^f_{t-j} is a measure of the growth in the agricultural component of Australian output, y_{t-1} and w_{t-1} are lagged log-levels of Australian and foreign activity, and Dw_t is the contemporaneous quarterly growth rate in foreign activity. The foreign activity variable is used to capture its anticipated positive effect on growth in domestic activity. Gruen, Romalis and Chandra (1997) suggest that US GDP is better than OECD GDP as a proxy for measuring the effect of foreign activity on Australian output. In this paper, OECD GDP and US GDP are used to measure foreign activity in alternative specifications of the output growth equation. The inclusion of the lagged log-level terms is to capture a possible long-run relationship between the levels of domestic and foreign activity.[12] The lags of real short-term interest rate are used to control for the effects of domestic monetary policy and the mean of the coefficients on these terms is expected to be negative. A detailed discussion of the data used in estimation of this equation is in Appendix A.

4.2 Model of Inflation

Given the revisions to the data used in de Brouwer and Ericsson (1995), we search for a comparable model of inflation, using their general model of inflation and a general to specific approach to arrive at the following parsimonious specification,[13]

$$\begin{aligned}\Delta p_t = d + f_1\Delta ulc_t + f_2\Delta ulc_{t-2} + f_3\Delta ulc_{t-4} + f_4\Delta ip_{t-3} + \\ f_5 y^{gap}_{t-1} + f_6 p_{t-1} + f_7 ulc_{t-1} + f_8 ip_{t-1} + f_9 D_t + u_t,\end{aligned} \tag{3}$$

where p is the underlying CPI, ulc is unit labour costs, ip is import prices, y^{gap} is the output gap term and D is a dummy variable included for an increase in indirect taxes in December 1978. Positive movements in the growth rate of both unit labour costs and import prices are expected to increase inflation. The inclusion of lagged level terms is to capture long-run relationships between inflation, unit labour costs, and import prices. The coefficients on all the lagged log-level terms are expected to

---

[12] Refer to Gruen and Shuetrim (1994) for a more detailed explanation of their model specification.

[13] The general model that we use is the same as Equation (11) in de Brouwer and Ericsson (1995) minus the seasonal dummies.

be positive except for the lagged log-level of the dependent variable. A detailed discussion of the data used in estimation of this equation is in Appendix A.

4.3 Empirical Methods

We examine whether past information on financial aggregates is useful for explaining current movements in real output growth or inflation by including four lags of financial aggregate growth in both equations.[14] For the real output growth equation, the appropriate transformation of the financial aggregate is a real growth measure, whereas for the inflation equation, nominal aggregate growth is the relevant measure. We estimate each equation by OLS and then examine F-tests of two restrictions – first, that the coefficients on the financial aggregate terms sum to zero, and second, whether each of the four coefficients for the financial aggregate measure should be restricted to zero. The first restriction implies a prior belief that the net effect of financial aggregate growth should be positive. The second restriction suggests whether the lags of the financial aggregate growth rates are at all related to the policy variables. We employ these tests for the full-sample estimation.

Data for real GDP and CPI are released on a quarterly basis whereas financial aggregate data are released on a monthly basis, and available prior to the release of real GDP and CPI data. Consequently, information available on financial aggregates in the same quarter may be useful for predicting current movements in the policy variables. If there is significant contemporaneous correlation between financial aggregates and growth in the variable, then the first two months of data on the particular financial aggregate could be exploited to predict movement in growth of the relevant variable. To examine this issue, we investigate whether contemporaneous growth in the financial aggregates is significant in estimations of the real output growth and inflation equations.[15] Due to simultaneity problems between the contemporaneous growth in financial aggregates and current movement in real output growth and inflation, we estimate these models by the instrumental variables estimation technique. The first lag of the growth in the relevant financial

[14] We investigated whether the lag length on the aggregate has any impact on the inferences. We found no notable changes in our inferences from changes in the lag length on the aggregates. Results are available upon request from the authors.

[15] As above, we employ real aggregate measures in the real output growth equation and nominal aggregate measures in the inflation equation.

aggregate is used as one of the instruments for the contemporaneous growth in the financial aggregate in these regressions. We then test the exclusion of the contemporaneous growth in the financial aggregate in each respective equation.

Our significance criteria for a useful information variable requires that the relevant restriction be rejected at the 5 per cent significance level. The results are presented in Tables 3 through 6. Using our criteria, we find in no case, either lagged or contemporaneously, that nominal growth in any of the financial aggregates has useful information content for the model of inflation. For output, we find significant results for both lagged and contemporaneous real credit growth as predictors for real output growth in the regressions using OECD output.[16] However, when US GDP is the foreign output proxy, there is no evidence that any of the financial aggregates provide explanatory power to the real output growth regression.

Table 3a presents the results for tests of the significance of lags in the growth rate of the financial aggregates in the real output growth equation using the OECD GDP variable. We focus on the properties of the specification that contains real credit growth. Both restrictions on the lags of the coefficients are rejected at the 5 per cent significance level, and the adjusted R-squared for the regression increases from 0.41 in the base regression to 0.50. Also, the coefficients of most regressors in the base specification remain statistically significant after the addition of the credit variables. Table 4a highlights the fact that the addition of contemporaneous credit growth has comparable effects to those mentioned above.[17]

In Tables 3b and 4b, we present results for the estimations of the real output growth equation using US GDP as the foreign output measure. We find that there is no

---

[16] The results for credit do not hold up if the farm output variable is replaced with the Southern Oscillation Index, the original proxy measure for Australian agricultural output used in Gruen and Shuetrim (1994).

[17] To examine the dynamics of the model with real credit growth, we estimate the impact of a temporary 1 per cent increase in the growth rate of real credit on the level of real output from the model using OECD GDP. The shock to real credit growth is distributed evenly over the first four quarters of the simulation. We find that after six quarters the cumulative impact on the level of real output is approximately 0.6 of a per cent. Results of this exercise are available upon request.

instance in which any of the financial aggregates has a statistically significant impact on real output growth.

Notably, the base regression using US GDP (without lags of a real aggregate growth rate) has comparable explanatory power to the regression containing both OECD output and four lags of real credit growth. One way to interpret this finding is that US GDP conveys the information that both OECD GDP and real credit growth provide for the alternative real output growth specification. Another interpretation is that the result suggesting that real credit growth helps explain real output growth is not robust. Failure of the real credit results to be robust to an alternative measure of agricultural output, and to the exclusion of the real interest rate, support the latter interpretation.[18]

[18] One criticism of the real output growth equation for testing the information from monetary aggregate growth is that the real interest rate may capture much of the potential information that is available for real output growth from the financial sector of the economy. We estimate the real output growth equation (using both OECD and US output as the world output measure) without the real interest rate, and find that no financial aggregate has significant explanatory power for real output growth in this specification.

Table 3a: Gruen and Shuetrim GDP Growth Regression with 4 Lags of Growth in Financial Aggregates 1980:Q3 to 1996:Q2[(a)]

$$\Delta y_t = a + \sum_{j=2}^{6} b_j r_{t-j} + f y_{t-1} + q w_{t-1} + p \Delta w_t + \sum_{p=1}^{2} \Delta y^f{}_{t-p} + \sum_{i=1}^{4} c_i (\Delta finag - \Pi)_{t-i} + e_t$$

Variables	Original model	Model with M3	Model with BM	Model with M1	Model with CRED	Model with CURR
Constant	-1.67** (-3.04)	-1.67 ** (-2.94)	-1.83 (-3.02)	-1.50* (-2.60)	-3.19** (-4.88)	-1.69** (-2.92)
Real cash rate[(b)]	-0.0004 {0.00}**	-0.0004 {0.00}**	-0.0004 {0.00}**	-0.0004 {0.02}**	-0.0006 {0.00}**	-0.0004 {0.00}**
Lagged Australian GDP log level	-0.21** (-2.93)	-0.21** (-2.84)	-0.23** (-2.91)	-0.19* (-2.60)	-0.40** (-4.77)	-0.21** (-2.82)
Lagged OECD GDP log level	0.26** (3.11)	0.26** (3.00)	0.28** (3.09)	0.23* (2.61)	0.49** (4.95)	0.26** (2.99)
OECD GDP growth	1.05** (4.85)	1.02** (4.13)	1.03** (4.05)	0.93** (3.61)	0.79** (3.48)	1.11** (4.74)
Farm GDP growth[(b)]	0.017 {0.09}	0.016 {0.11}	0.016 {0.11}	0.014 {0.22}	0.023 {0.08}	0.016 {0.15}
Growth in aggregate [1]		-0.001 (-0.01)	-0.038 (-0.30)	0.021 (0.35)	0.043 (0.38)	-0.074 (-0.76)
Growth in aggregate [2]		0.060 (0.60)	0.140 (1.23)	0.090 (1.81)	0.078 (0.65)	0.058 (0.61)
Growth in aggregate [3]		0.005 (0.05)	0.070 (0.60)	0.040 (0.72)	0.090 (0.76)	0.068 (0.73)
Growth in aggregate [4]		-0.014 (-0.14)	0.020 (0.18)	-0.030 (-0.54)	0.190 (1.55)	-0.078 (-0.75)
Exclusion of lags of financial aggregate		{0.98}	{0.70}	{0.41}	{0.013}*	{0.76}
Test of sum of lags of financial aggregate		{0.75}	{0.37}	{0.22}	{0.00}**	{0.87}
Adjusted R^2	0.41	0.37	0.39	0.41	0.50	0.38
LM test for 1st order autocorrelation	0.31 {0.58}	0.41 {0.52}	0.55 {0.46}	0.71 {0.40}	0.31 {0.58}	0.48 {0.49}

Notes: (a) The models are estimated by OLS. Numbers in square brackets [ ] are lags. Numbers in parentheses ( ) are t-statistics. Numbers in braces {} are p-values. Items marked with *(**) are significantly different from zero at the 5%(1%) level. All variables in log levels (except for real interest rate).

(b) The mean coefficient is reported for the real cash rate and farm growth. The p-values for the real interest rate and farm growth are derived from F-tests of the joint significance of the lags.

Table 3b: Gruen and Shuetrim GDP Growth Regression with 4 Lags Of Growth in Financial Aggregates 1980:Q3 to 1996:Q2[(a)]

$$\Delta y_t = a + \sum_{j=2}^{6} b_j r_{t-j} + f y_{t-1} + q w_{t-1} + p \Delta w_t + \sum_{p=1}^{2} \Delta y^f{}_{t-p} + \sum_{i=1}^{4} c_i (\Delta finag - \Pi)_{t-i} + e_t$$

Variables	Original model	Model with M3	Model with BM	Model with M1	Model with CRED	Model with CURR
Constant	-1.25**	-1.23 **	-1.21	-1.17**	-1.41**	-1.28**
	(-5.04)	(-4.69)	(-4.64)	(-4.16)	(-5.26)	(-4.77)
Real cash rate[(b)]	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005	-0.0004
	{0.00}**	{0.00}**	{0.00}**	{0.02}**	{0.00}**	{0.00}**
Lagged Australian GDP log level	-0.28**	-0.27**	-0.27**	-0.26**	-0.31**	-0.28**
	(-4.98)	(-4.65)	(-4.58)	(-4.19)	(-5.17)	(-4.71)
Lagged US GDP log level	0.33**	0.33**	0.32**	0.31**	0.38**	0.34**
	(5.19)	(4.80)	(4.76)	(4.15)	(5.42)	(4.89)
US GDP growth	0.35**	0.34**	0.37**	0.31*	0.33**	0.35**
	(2.92)	(2.71)	(2.82)	(2.38)	(2.71)	(2.77)
Farm GDP growth[(b)]	0.018	0.018	0.018	0.014	0.018	0.019
	{0.03}*	{0.04}*	{0.04}*	{0.16}	{0.024}*	{0.04}*
Growth in aggregate [1]		-0.002	-0.038	0.033	-0.120	-0.069
		(-0.02)	(-0.35)	(0.61)	(-1.09)	(-0.76)
Growth in aggregate [2]		0.050	0.080	0.053	-0.090	-0.006
		(0.54)	(0.79)	(1.06)	(-0.75)	(-0.07)
Growth in aggregate [3]		0.019	-0.010	0.007	0.100	0.075
		(-0.20)	(-0.11)	(0.15)	(0.87)	(0.88)
Growth in aggregate [4]		-0.004	-0.020	-0.060	0.190	-0.023
		(-0.04)	(-0.19)	(-1.10)	(1.66)	(-0.24)
Exclusion of lags of financial aggregate		{0.99}	{0.95}	{0.70}	{0.22}	{0.86}
Test of sum of lags of financial aggregate		{0.86}	{0.94}	{0.71}	{0.28}	{0.88}
Adjusted R^2	0.50	0.46	0.46	0.48	0.52	0.47
LM test for 1st order autocorrelation	0.68	0.92	0.61	1.76	0.86	0.89
	{0.41}	{0.34}	{0.44}	{0.19}	{0.35}	{0.35}

Notes: (a) The models are estimated by OLS. Numbers in square brackets [ ] are lags. Numbers in parentheses ( ) are t-statistics. Numbers in braces {} are p-values. Items marked with *(**) are significantly different from zero at the 5%(1%) level. All variables in log levels (except for real interest rate).

(b) The mean coefficient is reported for the real cash rate and farm growth. The p-values for the real interest rate and farm growth are derived from F-tests of the joint significance of the lags.

Table 4a: Gruen And Shuetrim GDP Growth Regression with Contemporaneous Growth in Financial Aggregates 1980:Q3 to 1996:Q2[(a)]

$$\Delta y_t = a + \sum_{j=2}^{6} b_j r_{t-j} + f y_{t-1} + q w_{t-1} + p \Delta w_t + \sum_{p=1}^{2} \Delta y^f{}_{t-p} + c(\Delta finag - \Pi)_t + e_t$$

Variables	Original model	Model with M3	Model with BM	Model with M1	Model with CRED	Model with CURR
Constant	-1.67**	-1.61**	-1.61	-1.02	-2.44**	-2.25
	(-3.04)	(-2.68)	(-1.88)	(-0.27)	(-3.92)	(-1.78)
Real cash rate[(b)]	-0.0004	-0.0004	-0.0005	-0.0004	-0.0003	-0.0005
	{0.00}**	{0.00}**	{0.52}	{0.02}*	{0.00}**	{0.03}*
Lagged Australian GDP log level	-0.21**	-0.20*	-0.20	-0.13	-0.31**	-0.28
	(-2.93)	(-2.63)	(-1.70)	(-0.31)	(-3.82)	(-1.73)
Lagged OECD GDP log level	0.26**	0.25**	0.25*	0.16	0.37**	0.35
	(3.11)	(2.71)	(2.04)	(0.26)	(3.98)	(1.81)
OECD GDP growth	1.05**	1.00**	1.14	0.84	0.71**	1.21**
	(4.85)	(3.29)	(1.43)	(0.66)	(2.78)	(3.15)
Farm GDP growth[(b)]	0.017	0.017	0.016	0.012	0.017	0.018
	{0.09}	{0.09}	{0.13}	{0.29}	{0.06}	{0.15}
Growth in aggregate		0.05	-0.14	0.26	0.30*	-0.35
		(0.22)	(-0.11)	(0.17)	(2.31)	(-0.54)
Exclusion of financial aggregate		{0.82}	{0.91}	{0.86}	{0.02}*	{0.59}
Adjusted R^2	0.41	0.41	0.31	0.19	0.46	0.17
LM test for 1st order autocorrelation	0.31	0.34	8.75	17.18	1.10	15.04
	{0.58}	{0.56}	{0.00}**	{0.00}**	{0.30}	{0.00}**

Notes: (a) The models are estimated by instrumental variables. Numbers in square brackets [ ] are lags. Numbers in parentheses ( ) are t-statistics. Numbers in braces {} are p-values. Items marked with *(**) are significantly different from zero at the 5%(1%) level. All variables in log levels (except for real interest rate).

(b) The mean coefficient is reported for the real cash rate and farm growth. The p-values for the real interest rate and farm growth are derived from F-tests of the joint significance of the lags.

Table 4b: Gruen and Shuetrim GDP Growth Regression with Contemporaneous Growth in Financial Aggregates 1980:Q3 to 1996:Q2[(a)]

$$\Delta y_t = a + \sum_{j=2}^{6} b_j r_{t-j} + f y_{t-1} + q w_{t-1} + p \Delta w_t + \sum_{p=1}^{2} \Delta y^f{}_{t-p} + c(\Delta finag - \Pi)_t + e_t$$

Variables	Original model	Model with M3	Model with BM	Model with M1	Model with CRED	Model with CURR
Constant	-1.67**	-1.22**	-1.32**	-0.72	-1.27**	-1.73*
	(-3.04)	(-4.00)	(-3.33)	(-0.40)	(-4.00)	(-2.02)
Real cash rate[(b)]	-0.0004	-0.0004	-0.0005	-0.0004	-0.0004	-0.0005
	{0.00}**	{0.00}**	{0.20}	{0.04}*	{0.00}**	{0.02}*
Lagged Australian GDP log level	-0.21**	-0.27**	-0.29**	-0.17	-0.28**	-0.39
	(-2.93)	(-4.01)	(-3.33)	(-0.43)	(-3.94)	(-1.99)
Lagged US GDP log level	0.26**	0.33**	0.35*	0.19	0.34**	0.45*
	(3.11)	(4.00)	(3.24)	(0.36)	(4.11)	(2.06)
US GDP growth	1.05**	0.34*	0.39	0.33	0.35**	0.27**
	(4.85)	(2.50)	(1.85)	(1.85)	(2.89)	(3.15)
Farm GDP growth[(b)]	0.017	0.018	0.018	0.012	0.018	0.019
	{0.09}	{0.03}	{0.05}	{0.20}	{0.03}	{0.08}
Growth in aggregate		0.035	-0.16	0.33	-0.01	-0.39
		(0.17)	(-0.24)	(0.30)	(-0.13)	(-0.60)
Exclusion of financial aggregate		{0.87}	{0.81}	{0.77}	{0.90}	{0.55}
Adjusted R^2	0.41	0.49	0.41	0.07	0.46	0.27
LM test for 1st order autocorrelation	0.31	0.50	11.79	29.54	0.87	20.96
	{0.58}	{0.48}	{0.00}**	{0.00}**	{0.35}	{0.00}**

Notes: (a) The models are estimated by instrumental variables. Numbers in square brackets [ ] are lags. Numbers in parentheses ( ) are t-statistics. Numbers in braces {} are p-values. Items marked with *(**) are significantly different from zero at the 5%(1%) level. All variables in log levels (except for real interest rate).

(b) The mean coefficient is reported for the real cash rate and farm growth. The p-values for the real interest rate and farm growth are derived from F-tests of the joint significance of the lags.

Table 5: de Brouwer and Ericsson Inflation Equation with 4 Lags of Growth in Financial Aggregates 1977:Q3 to 1996:Q2[(a)]

$$\Delta p_t = d + f_1\Delta ulc_t + f_2\Delta ulc_{t-2} + f_3\Delta ulc_{t-4} + f_4\Delta ip_{t-3} + f_5 y^{gap}_{t-1} + f_6 p_{t-1} + f_7 ulc_{t-1} + f_8 ip_{t-1} + f_9 D_t + \sum_{i=1}^{4} b_i\, finag_{t-i} + u_t$$

Variables	Original model	Model with M3	Model with BM	Model with M1	Model with CRED	Model with CURR
Constant	-0.005 (-0.63)	-0.003 (-0.38)	-0.002 (-0.23)	-0.0008 (-3.08)	-0.003 (-0.34)	-0.004 (-0.45)
Growth in ULC [0]	0.063** (3.65)	-0.060** (3.35)	0.062** (3.31)	0.056** (2.98)	0.060** (3.59)	0.062** (3.35)
Growth in ULC [2]	0.052** (2.99)	0.050** (2.67)	0.051** (2.73)	0.051** (2.74)	0.056** (3.10)	0.053** (2.87)
Growth in ULC [4]	0.035* (2.15)	0.036* (2.20)	0.036* (2.12)	0.035 (1.99)	0.023 (1.29)	0.035* (2.07)
Growth in import prices [3]	0.036** (3.70)	0.040** (3.72)	0.040** (3.59)	0.035** (3.22)	0.030** (3.22)	0.040** (3.35)
Output gap [1]	0.073** (6.06)	0.093** (5.23)	0.079** (3.78)	0.072** (5.65)	0.055 (3.01}	0.073** (5.80)
Lagged CPI log level	-0.073** (-7.65)	-0.075** (-7.57)	-0.073** (-6.90)	-0.069** (-6.18)	-0.067** (-6.86)	-0.073** (-6.89)
Lagged ULC log level	0.042** (4.21)	0.042** (4.18)	0.041** (3.91)	0.036** (2.89)	0.039** (3.93)	0.040** (3.98)
Lagged import price log level	0.034** (10.25)	0.036** (9.72)	0.034** (8.49)	0.035** (9.29)	0.030** (6.21)	0.030** (8.75)
Dummy	-0.005* (-2.03)	-0.005 (-1.81)	-0.005* (-2.01)	-0.005* (-2.09)	-0.005* (-2.09)	-0.005 (-1.98)
Growth in aggregate [1]		-0.059* (-2.19)	-0.007 (-0.22)	-0.013 (-0.79)	0.002 (0.07)	0.017 (0.55)
Growth in aggregate [2]		0.004 (0.12)	-0.019 (-0.53)	-0.006 (-0.36)	-0.060 (-1.47)	-0.020 (-0.70)
Growth in aggregate [3]		0.021 (0.21)	0.015 (0.39)	-0.009 (-0.52)	0.050 (1.31)	-0.005 (-0.15)
Growth in aggregate [4]		-0.007 (-0.23)	-0.009 (-0.26)	0.003 (0.17)	0.050 (1.47)	0.002 (0.06)
Exclusion of lags of financial aggregate		{0.27}	{0.97}	{0.91}	{0.17}	{0.94}
Test of sum of lags of financial aggregate		{0.11}	{0.75}	{0.45}	{0.24}	{0.87}
Adjusted R^2	0.90	0.90	0.89	0.89	0.90	0.89
LM test for 1st order autocorrelation	0.37 {0.55}	0.92 {0.34}	0.35 {0.55}	0.30 {0.58}	0.34 {0.56}	0.57 {0.45}

Note: (a) The models are estimated by OLS. Numbers in square brackets [ ] are lags. Numbers in parentheses ( ) are t-statistics. Numbers in braces {} are p-values. Individual coefficients marked with *(**) are significantly different from zero at the 5%(1%) level. All variables in log levels .

Table 6: de Brouwer and Ericsson Inflation Equation with Contemporaneous Growth in Financial Aggregates 1977:Q3 to 1996:Q2[(a)]

$$\Delta p_t = d + f_1 \Delta ulc_t + f_2 \Delta ulc_{t-2} + f_3 \Delta ulc_{t-4} + f_4 \Delta ip_{t-3} + f_5 y_{t-1}^{gap} + f_6 p_{t-1} + f_7 ulc_{t-1} + f_8 ip_{t-1} + f_9 D_t + f_{10} finag_t + u_t$$

Variables	Original model	Model with M3	Model with BM	Model with M1	Model with CRED	Model with CURR
Constant	-0.005	0.0009	-0.004	-0.012	-0.005	-0.009
	(-0.63)	(0.08)	(-0.28)	(-3.08)	(-0.63)	(-0.63)
Growth in ULC [0]	0.063**	0.046	0.062**	0.064**	0.060**	0.063**
	(3.65)	(3.35)	(2.61)	(2.72)	(3.61)	(3.01)
Growth in ULC [2]	0.052**	0.051*	0.052**	0.072	0.053**	0.056*
	(2.99)	(2.37)	(2.93)	(1.60)	(2.98)	(2.39)
Growth in ULC [4]	0.035*	0.040	0.036*	0.030	0.036	0.032
	(2.15)	(1.97)	(2.05)	(1.28)	(2.09)	(1.54)
Growth in import prices [3]	0.036**	0.021	0.040**	0.056	0.040**	0.050
	(3.70)	(1.38)	(3.60)	(1.37)	(3.66)	(1.37)
Output gap [1]	0.073**	0.098**	0.075**	0.110	0.072**	0.081**
	(6.06)	(4.57)	(3.08)	(1.56)	(4.74}	(3.14)
Lagged CPI log level	-0.073**	-0.076**	-0.073**	-0.082**	-0.073**	-0.064*
	(-7.65)	(-6.38)	(-7.50)	(-3.72)	(-7.47)	(-2.40)
Lagged ULC log level	0.042**	0.038**	0.041**	0.059	0.042**	0.040**
	(4.21)	(3.05)	(3.52)	(1.62)	(4.10)	(2.56)
Lagged import price log level	0.034**	0.040**	0.034**	0.027	0.030**	0.030*
	(10.25)	(7.33)	(7.33)	(1.81)	(6.99)	(2.00)
Dummy	-0.005*	-0.007*	-0.005*	-0.004	-0.005*	-0.004
	(-2.03)	(-2.13)	(-1.86)	(-0.93)	(-2.00)	(-1.20)
Growth in aggregate [0]		-0.130	-0.010	0.110	0.004	0.130
		(-1.62)	(-0.10)	(0.51)	(0.12)	(0.39)
Exclusion of lags of financial aggregate		{0.11}	{0.92}	{0.61}	{0.91}	{0.70}
Adjusted R^2	0.90	0.84	0.89	0.81	0.90	0.85
LM test for 1st order autocorrelation	0.37	-29.13	-8.48	29.3	0.34	-1 386.9
	{0.55}	{n.a.}	{n.a.}	{0.00}**	{0.56}	{0.70}

Note: (a) The models are estimated by OLS. Numbers in square brackets [ ] are lags. Numbers in parentheses ( ) are t-statistics. Numbers in braces {} are p-values. Items marked with *(**) are significantly different from zero at the 5%(1%) level. All variables in log levels.

5. Conclusions

This paper tests whether financial aggregates are useful as information variables for policy makers in two distinct frameworks. The first technique employs a liberal criterion to examine this issue, seeing if completely certain information on the future course of financial aggregates improves in-sample forecasts of real output growth and inflation. The aggregates in general do not satisfy this criterion, with one exception: certain knowledge of future credit growth could have improved the prediction of real output growth, particularly in 1990 and 1991. This of course begs the question of whether credit can be accurately forecast. Further analysis of the results suggests, as has been found in other research, that credit growth is typically endogenously determined by real output growth. However, in the 1990–92 period, credit appears to have been more informative than simply a variable moving in response to real output growth. This suggests that credit growth is more informative in periods of financial restructuring.

The second method that we employ examines the information content of the financial aggregates in single-equation frameworks for predicting real output growth and inflation. In this exercise, using well-specified models of inflation and real output growth, we find a statistically significant contribution from the growth in credit to real output growth in a specification using OECD GDP as the foreign output measure. Results using US GDP as a foreign output measure offer no significant results for any of the financial aggregates.

We suggest that a financial aggregate is useful for policy-making if it provides significant information for real output growth and/or inflation that is robust across empirical methods. Our results suggest that while financial aggregates contain some information about future growth in real output, that information is generally captured more precisely by other variables. Once we control for these other variables, there appears to be no robust relationship between real output growth and inflation and any of the financial aggregates that can be exploited in a regression framework for policy analysis. In general, the financial aggregates become just another set of corroborating information variables. The one exception to this conclusion is that in periods of major financial restructuring, changes in credit growth may provide important information in assessing the pace of future output growth.

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*

M1

Definition: Currency plus total current deposits with banks, excluding Commonwealth and State government deposits and interbank deposits. Seasonal adjustment by the Australian Bureau of Statistics.

Source: Reserve Bank of Australia *Bulletin*

M3

Definition: Currency plus bank deposits of the private non-bank sector, 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. Seasonal adjustment by the Australian Bureau of Statistics.

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*

Credit from all financial intermediaries (CRED)

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)

Definition: Seasonally adjusted by the Australian Bureau of Statistics. Values are constant in 1989/90 prices. Both the non-farm and farm GDP series are components of this series.

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

Real Australian cash rate

Definition: Australian cash rate less underlying inflation over the previous 12 months.

OECD GDP

Source: Datastream, OCDGDP..D

US GDP

Source: Datastream, USGDP...D

Southern oscillation index

Definition: The Southern Oscillation Index measures the sea level barometric pressure differential between Darwin and Tahiti.

Source: Bureau of Meteorology

Unit labour costs (ULC)

Definition: RBA's measure of underlying unit labour costs per wage and salary earner.

Source: Reserve Bank of Australia, unpublished data.

Import prices

Definition: Tariff-adjusted import price index of merchandise imports, excluding exogenous imports, computers, and other lumpy import items.

Source: The constant and current price series of merchandise imports less exogenous items are taken from *Balance of Payments, Australia*, ABS Cat. No. 5302.0, Tables 13 and 14. The constant and current price series of computers are unpublished data provided by the Australian Bureau of Statistics. The constant and current price series of other lumpy items are unpublished data provided by the Department of Treasury. Taxes on international trade are drawn from *Australian National Accounts*, ABS Cat. No. 5206.0, Table 40.

Petrol prices

Definition: Automotive fuel price index.

Source: *Consumer Price Index*, ABS Cat. No. 6401.0, Table 7

Private final demand

Definition: Private final consumption expenditure and private gross fixed capital expenditure, excluding net second-hand purchases of gross equipment and non-dwelling construction from the public sector.

The variable y^{gap} is the output gap term used in the estimation of the inflation equation. y^{gap} is the residual of the log of the private final demand regressed on a constant and trend for the period 1977:Q3-1996:Q2.

Units Private final demand is measured in $A millions, 1989/90 prices.

Source: *Australian National Accounts*, ABS Cat. No. 5206.0, Table 59

Appendix B: Technical Description of the Conditional Forecasting Exercise

In each exercise, we use a four-variable VAR to calculate an estimated forecast error covariance matrix of one- through eight-quarter-ahead forecasts of the indicated policy variable.[19] We denote this forecast error covariance matrix as Ω_{pp}, where p refers to policy variable.[20] The forecast error covariance matrix summarises the degree of variation in either real output growth or inflation not explained within the model using information up to period t. The diagonal elements of the error covariance matrix are the variance terms of the one- through eight-step-ahead forecast error of the policy variable, whereas the off-diagonal elements are the covariances between the forecast errors across the one- through eight-period forecast horizons. The log determinant of this covariance matrix is used as a measure of unconditional forecast accuracy for either real output growth or inflation, given by log $\left|\Omega_{pp}\right|$.[21] For example, if the forecasts become more accurate, then the forecast errors become smaller as does the log determinant of the forecast error covariance matrix. The predominant contributors to the measure of forecast accuracy are typically the own error variance terms, that is, the diagonal terms. The log determinant of the error covariance matrix would get successively smaller as more values of the other three variables in the VAR became available as certain information.[22]

---

[19] The following description relies heavily on pages 148–49 of Roberds and Whiteman (1992).

[20] This matrix measures forecast error covariances calculated within the sample using a model with parameters estimated employing the entire sample data period. Thus, the forecast errors are in-sample forecast errors; this artificial test of in-sample forecast improvement is distinct from the out-of-sample tests in Tallman and Chandra (1996).

[21] Log determinant measures are used in standard likelihood ratio tests in VAR analyses. For our purposes, the log determinant measure is somewhat analogous to a mean squared error measure in a single-equation forecasting statistic, but it is more general because of the covariance terms among the eight-period horizon forecasts.

[22] This formulation of forecast error variance is comparable to the variance decomposition in VAR analysis, whereby the forecast errors in a variable are associated with innovations in each variable in the system. Unlike the variance decomposition, this technique need not orthogonalise innovations.

This prediction exercise focuses on the covariance between forecast errors of financial aggregates and of real output growth and inflation. We use the same full-sample estimation of the VAR model to derive an estimate of the covariance matrix of the same forecast, conditioned on certain knowledge of the next eight quarters of the given financial aggregate. In order to examine the contribution of information on financial aggregates, we must create a measure of conditional forecast accuracy. For the succeeding eight quarters of a given financial aggregate *a*, we define Ω_{aa} similarly to the unconditional forecast error covariance matrix of the policy variables, but allow it to represent the (unconditional) forecast error covariance of the financial aggregate for the eight-period forecast horizon. Separately, we define Ω_{ap} and let it represent the forecast error covariance matrix between the financial aggregate and the policy variable of interest (either output growth or inflation). In this covariance matrix, the diagonal terms represent the covariance between the forecast errors of the financial aggregate and those of either real output growth or inflation at the same forecast horizon. For example, the first diagonal term represents the covariance of the financial aggregate with a policy variable at the one-period forecast horizon, and so on until the last diagonal term reflecting the correlation at the eight-period forecast horizon. The off-diagonal terms represent the covariance between forecast errors of the financial aggregate and the policy variable across different forecast horizons.

Unconditional forecast errors for the policy variable in this setting implicitly contain covariation in errors from forecasting the other variables in the system with the errors in forecasting the policy variable. Comparable to a variance decomposition, we can measure the contribution of each variable in the system to the forecast error in the policy variable. Eliminating forecast errors in the financial aggregate series (that is, providing perfect knowledge of future values of the variable) is like removing the covariation of forecast errors in the financial aggregate with those in the policy variable (either real output growth or inflation) and the related contribution to the unconditional forecast error of real output growth or inflation. That is the intuitive motivation behind Equation (B1) below.

By manipulating the estimated forecast error covariance matrixes, we essentially compare how the contribution of certain knowledge of the aggregates reduces the measure of forecast accuracy. Defining Ω_c as the conditional error covariance matrix,

$$\Omega_c = \Omega_{pp} - \Omega_{pa}\Omega_{aa}^{-1}\Omega_{ap}, \tag{B1}$$

we subtract the component of the forecast error covariance in the variable of interest that is removed when the financial aggregate for the next eight periods is known with certainty. Here, we eliminate the component of forecast error covariance of the policy variable that knowledge of the financial aggregates will remove. That is, knowing the measure of the financial aggregate removes the forecast error variance of these measures over the eight-period forecast horizon from the system, and thus removes the contribution of that forecast error variance to the forecast error variance for the policy variables. Thus, the log determinant of Ω_c, given by $\log\left|\Omega_c\right|$, becomes our measure of conditional forecast accuracy. The focus of our attention then become the difference between the measures of conditional and unconditional forecast accuracy, denoted as,

$$\text{Forecast Accuracy Improvement} = \log\left|\Omega_{pp}\right| - \log\left|\Omega_c\right|. \tag{B2}$$

References

Astley, M.S. and A.G. Haldane (1997), 'The Information in Money', The Bank of England *Quarterly Bulletin*, 37(2), May, pp. 174–180.

de Brouwer, G. and N.R. Ericsson (1995), 'Modelling Inflation in Australia', Reserve Bank of Australia Research Discussion Paper No. 9510.

Estrella, A. and F.S. Mishkin (1996), 'Is there a Role for Monetary Aggregates in the Conduct of Monetary Policy', NBER Working Paper No. 5845.

Gruen, D., J. Romalis, and N. Chandra (1997), 'The Lags of Monetary Policy', Reserve Bank of Australia Research Discussion Paper No. 9702.

Gruen, D. and G. Shuetrim (1994), 'Internationalisation and the Macroeconomy', in P. Lowe and J. Dwyer (eds), *International Integration of the Australian Economy*, Proceedings of a Conference, Reserve Bank of Australia, Sydney, pp. 309–363.

Roberds, W. and C.H. Whiteman (1992), 'Monetary Aggregates as Monetary Targets: A Statistical Investigation', *Journal of Money, Credit and Banking*, 24(2), pp. 141–161.

Stevens, G.R. and S.J. Thorp (1989), 'The Relationship between Financial Indicators and Economic Activity: Some Further Evidence', Reserve Bank of Australia Research Discussion Paper No. 8903.

Tallman, E.W. and N. Chandra (1996), 'The Information Content of Financial Aggregates in Australia', Reserve Bank of Australia Research Discussion Paper No. 9606.