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Forecast and Forecast Evaluation of the Australian inflation rate - Does adding more variables improve the forecast's accuracy?

I. Introduction. The inflation rate is a major economic variable. Various interest groups pay close attention to the development of prices in goods and services. It serves as an input for government budget planning, central bank policy making and business decisions. Thus, these groups rely on inflation rate forecasts as guidance.

Fritzer, Moser and Scharler (2002) finds that the forecast's accuracy of the Austrian inflation rate for longer horizons of 8 to 12 months estimated by a Vector Autoregressive Model is superior compared to a univariate ARIMA. Canova (2007) tests multiple VAR models and performs recursive forecasts for G7 countries 4 and 8 quarters ahead. It finds for the US that the VAR models do not improve the forecast's accuracy against a univariate ARIMA. Additionally, no consistent improvements of the accuracy are found for the multivariate models of the other countries. Thus, the research on inflation forecasts is mixed and no consensus exists if multivariate models do improve the forecast's accuracy. This paper seeks to extend the literature with the example of the Australian inflation rate. It wants to establish if a multivariate approach to forecast inflation rate translate to higher forecast's accuracy for 2, 4 and 8 quarters ahead.

Section 2 discusses briefly the dataset, while section 3 explains the estimation strategy of the univariate and multivariate models and the pseudo-out-of-sample forecast using recursive and rolling techniques. Section 4 interprets the results from tests used to assess the precision of the forecasts related to the models and section 5 closes the paper with a conclusion and a note on limitations of the findings.

II. Dataset. The dataset consists of quarterly inflation rate, quarterly seasonally adjusted real GDP growth rate, monthly 3-month business inflation rate expectation, converted into quarterly data, and quarterly unemployment rate from 1989 Q3 to 2019 Q4. It covers a total of 122 observations. The source of these data is the Reserve Bank of Australia. The real GDP growth rate and the unemployment rate are activity-based variables of the business cycle which could have an impact on the inflation rate. The 3-month business inflation rate expectation is an indicator of what businesses expect inflation to be and thereby affect their behaviour and thus affecting the inflation rate. The inflation expectations are a commonly used predictor. The following section 3 discusses the estimation strategy.

III. Estimation strategy. The data period to estimate the models of interest range from 1989 Q3 to 2012 Q1, covering 91 observations. It is used to identify and fit an ARIMA model and three VAR models. The difference in the VAR models is an increase by one predictor per model, meaning the VAR3 model has three additional variables. In order to fit the models, the Bayesian information criteria (BIC) is always chosen because it punishes more complex models and leads to asymptotically better short-term forecasts. The remaining observations are used to evaluate the pseudo-out-of-sample forecast with horizons 2, 4 and 8 quarters. These forecasts are performed by recursive and rolling techniques. Furthermore, the results are tested for unbiasedness and equal accuracy using a bias test and the Diebold-Mariano (DM) test. The focus is thereby on the DM test to infer if the ARIMA model tested against the multivariate models does not rejects the null hypothesis of equal loss differences and thereby infers that the forecasts have the same accuracy.

The variables are correlated and thus are suitable as predictors. The APPENDIX graphic 1 highlight that the process for inflation rate, the 3-month business inflation rate expectation and the unemployment rate might not be stationary because the variance and mean seems time variant. The picture for the real GDP growth rate is less clear. The variables are tested for stationary. The Augmented Dickey-Fuller (ADF) test and the KPSS test are performed and the variables are stationary and integrated of order 1.

An ARIMA model is fitted of the inflation rate. APPENDIX graphic 2 shows that the autocorrelation function damps off and the partial autocorrelation function spikes which is a sign for autoregression. Using information criterion to fit the model, the BIC prefers ARIMA(1,1,0) model (ARIMA). It has no autocorrelation and the residuals are normally distributed according to the Ljung-Box test (LB) and the Jarque-Bera test (JB). Thus, the differenced inflation is an autoregressive process with lag order 1, meaning that the current value is based on the preceding value. The VAR1 is a VAR model where the real GDP growth rate is added. The inflation rate and the real GDP growth rate are integrated of order 1 and thus could be cointegrated. The Engle-Granger test suggests that the variables are indeed cointegrated and the VAR1 model is estimated in levels because a long-term relationship seems to exist which is stationary. The BIC prefers a lag order of 2. The multivariate LB and JB test suggest that the model has no autocorrelation and that the residuals are normally distributed. Furthermore, the model is stable due to distinct and real eigenvalues inside the unit interval. Hence, a VAR(2) model is estimated for the VAR1. VAR2 is a VAR model that considers the real GDP growth rate and the unemployment rate in addition to the inflation rate. In order to assess cointegration the Johansen Procedure is performed using the trace test and the maximum eigenvalue test and one cointegrated relationship is found suggesting a long-term relationship between those variables. Thus, a Vector Error Correction Model (VECM) with two lags is constructed using the variables in levels. The VECM is transformed to a VAR model and LB and JB suggest that VAR2 is well defined. The last VAR model (VAR3) considers all variables. The Johansen procedure is performed and one cointegrated relationships is found underscoring a long-term relationship that is stationary. A VECM with lag order 2 is estimated and transformed to a VAR model which has no autocorrelation and normally distributed residuals according to LB and JB.

The above-mentioned models are used to perform rolling and recursive pseudo-out-of-sample forecasts 2, 4 and 8 quarters ahead. To perform a recursive forecast, the number of observations used to forecast the inflation rate grows with each forecast origin. The rolling forecast technique, however, fixes the number of observations so that at each origin one observation enters and one exits the period. The rolling forecast technique, thus, has a stronger emphasize on new information while the recursive forecast technique utilizes all information available. The ARIMA is re-estimated on each forecast origin and the VECM of VAR2 and VAR3 is also estimated on each origin while keeping the lag order and the number of cointegrated relationships constant. The forecast errors are calculated as the actual value subtracted from the forecasting value. The bias test and the Diebold-Mariano test are then performed on these forecast errors. Section 4 discusses and explains the test results.

IV. Interpretation of the forecast's precision. After performing the pseudo-out-of-sample forecast in the period from 2012 Q2 to 2019 Q4, the forecast errors are calculated for each horizon respectively. The bias test is performed on these forecast errors. An optimal forecast is unbiased and the expected forecast errors are zero considering a symmetric cost function. The cost function for inflation rate is likely to be symmetric. A systematically overestimation and underestimation of the future inflation rate might cost the various interest groups probably equally. Central banks would wrongly promote a hawkish or dovish policy while fixed income investors would allocate the funds to investments that yield inappropriately. The results of the bias test, shown in APPENDIX table 1, illustrate that the forecasts of the ARIMA, VAR2 and VAR3 are unbiased because the null hypothesis of biasedness are rejected and thus the expected forecast errors are zero. The results for VAR1 are less clear. While the forecasts estimated using the recursive technique do unbiased forecasts, the rolling technique for horizon 4 and 8 perform biased forecast. APPENDIX graphic 3 illustrates the

VAR1 forecast compared to the actual inflation rate and the forecasts of the other models. The VAR1 using rolling technique for horizon 4 and 8 seems to have a lower variance than the other models. The forecast has the tendency to underestimate the actual inflation rate. These forecasts are not optimal given a symmetric cost function because it violates the property of unbiasedness of an optimal forecast. Adjusting the VAR1 for biasedness would be subject to future research.

The Diebold-Mariano (DM) test of equal forecast accuracy is performed and the models are tested pairwise for equal loss difference, meaning that the forecast variance equals the expected loss of the compared models. APPENDIX table 2 illustrates the results of testing the 28 combinations. This paper seeks to investigate if increasing the number of predictors lead to more accurate predictions. Therefore, the main focus is on the ARIMA test-statistics as the baseline model with only one predictor. No rejection of the DM test against the multivariate models would suggest that differences in accuracy are not statistically significant and models with more predictors do not outperform the ARIMA in terms of accuracy in the evaluation period. The ARIMA tested against the VAR1 for rolling and recursive techniques rejects the null of equal forecast accuracy at nearly every horizon. By investigating the APPENDIX graphic 3, it seems that the distance of the ARIMA to the actual inflation rate is smaller suggesting that ARIMA might have the lower loss difference. Furthermore, the results of VAR1 are to some extend biased which might interfere with the results. Nevertheless, it seems that ARIMA with only one predictor forecasts more precise. The results for ARIMA against VAR2 show that both models forecast equally accurate. The null hypothesis is not rejected and thus it can be inferred that the two additional predictors of the VAR2 led to no increase in accuracy. Moreover, it can be inferred from the test of VAR3 against ARIMA that the forecasts have mostly the same accuracy except testing both models using the rolling technique for 4 quarters ahead. In general, VAR3 is not superior in forecast's accuracy to ARIMA which emphasizes that the three additional predictors did not yield in more accuracy. Furthermore, there seems to be no consistent improvement within the multivariate models except that the accuracy is not the same between VAR1 and the other multivariate models. In conclusion, these results question that an increased number of predictors yield into more precise forecasts. Thus, the forecast precision for the Australian inflation rate is predominantly equal whether using ARIMA with the lagged inflation as a predictor or models with additional predictors. Furthermore, these results are in line with the findings of Canova (2007) that multivariate models did not outperform the univariate ARIMA. Section 5 concludes the paper and underscores the limitation of the results.

V. Conclusion and Limitations. The purpose of the paper is to assess if models with more predictors yield in forecasts with higher accuracy for the Australian inflation rate. The DM test-statistic shows that using multiple predictors does not enhance the accuracy of the forecasts. Hence, performing forecasts with an ARIMA model achieves an equal forecast's accuracy compared to multivariate models in the evaluation period. These findings are in line with the results of Canova (2007) but extend the results for Australia. However, the findings cannot be inferred for a different country, different horizons or different set of predictors. Furthermore, any higher number of predictors or increasing horizons could yield to more accurate forecasts. Thus, the results in this paper are bound to the three additional predictors used. Moreover, the predictors assigned in each step were chosen arbitrarily, meaning the VAR1 could have also been estimated using a different variable. It could be that the choice of a different variable in the VAR1 would lead to different results. Incrementally increasing the additional variables to a higher set of variables, e.g. 10, 20 and 50, or the horizons are subject to future research. Finally, using a recombination approach for multivariate models might be interesting to test how a different variable for VAR1 would affects the results and thereby allowing to check if more correlated variables change the forecasts results.

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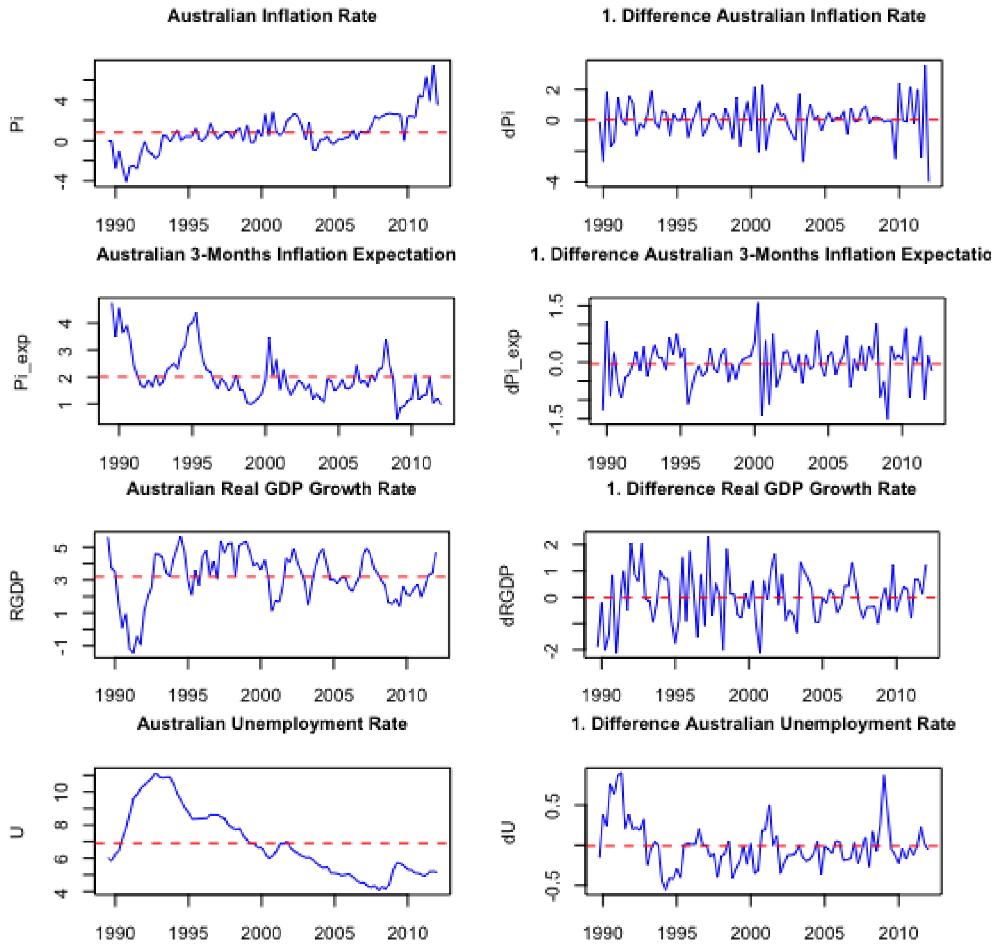
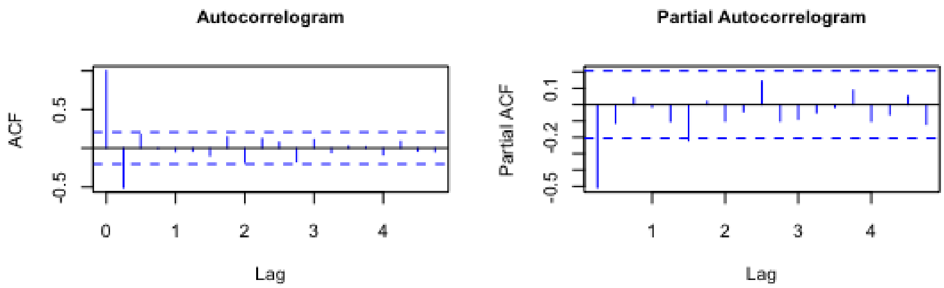
APPENDIX

Graphic 1: Processes in level and in first difference



Graphic 2: ACF and PACF of the Australian inflation rate



Graphic 3: Forecasts of the ARIMA, VAR1, VAR2 and VAR3 with h = 2, 4 and 8

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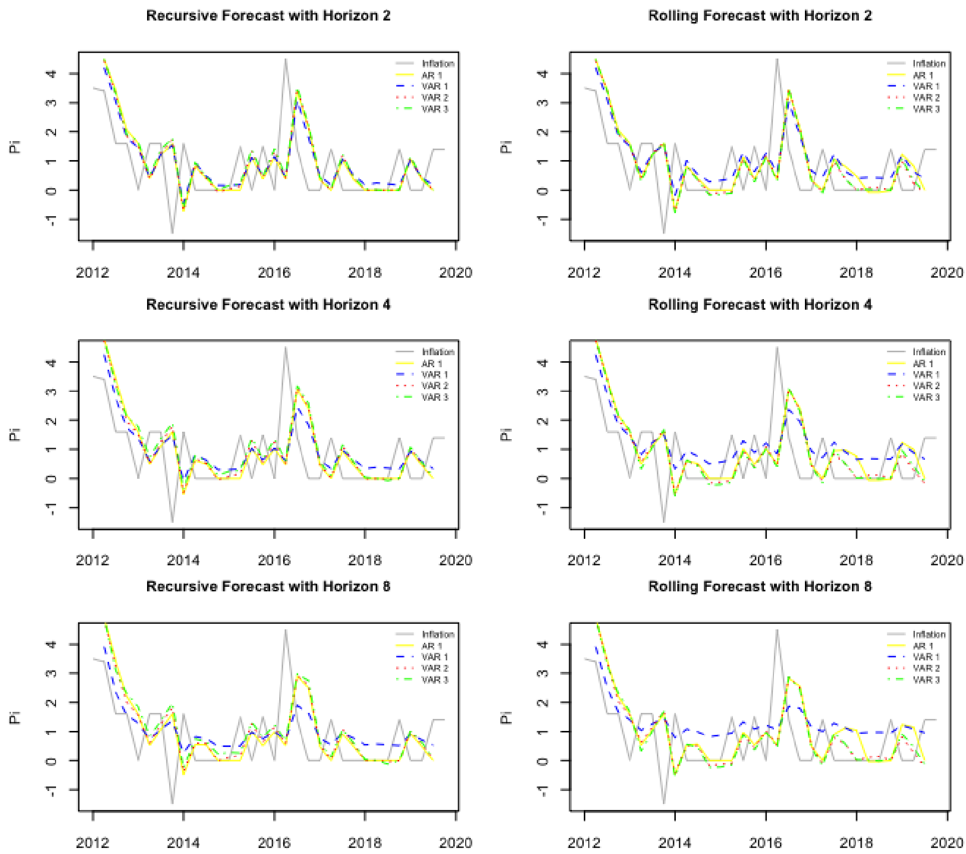

Table 1: Results of the bias test

	AR.RE.2p	AR.RO.2p	VAR1.RE.2p	VAR1.RO.2p	VAR2.RE.2p	VAR2.RO.2p	VAR3.RE.2p	VAR3.RO.2p
Horizon 2	0.50	0.41	0.37	0.14	0.43	0.56	0.32	0.58
Horizon 4	0.32	0.24	0.17	0.03	0.24	0.36	0.16	0.40
Horizon 8	0.35	0.27	0.19	0.03	0.27	0.39	0.17	0.42

Table 2: Results of the Diebold-Mariano test

	Horizon 2	Horizon 4	Horizon 8
AR.RE vs. AR.RO	0.43	0.27	0.79
AR.RE vs. VAR1.RE	0.06	0.00	0.00
AR.RE vs. VAR1.RO	0.04	0.00	0.00
AR.RE vs. VAR2.RE	0.56	0.51	0.57
AR.RE vs. VAR2.RO	0.71	0.89	0.42
AR.RE vs. VAR3.RE	0.80	0.80	0.60
AR.RE vs. VAR3.RO	0.17	0.16	0.59
AR.RO vs. VAR1.RE	0.03	0.00	0.01
AR.RO vs. VAR1.RO	0.01	0.01	0.00
AR.RO vs. VAR2.RE	0.34	0.82	0.77
AR.RO vs. VAR2.RO	0.48	0.43	0.74
AR.RO vs. VAR3.RE	0.60	0.61	0.22
AR.RO vs. VAR3.RO	0.72	0.04	0.16
VAR1.RE vs. VAR1.RO	0.49	0.83	0.31
VAR1.RE vs. VAR2.RE	0.13	0.01	0.00
VAR1.RE vs. VAR2.RO	0.07	0.00	0.00
VAR1.RE vs. VAR3.RE	0.16	0.02	0.00
VAR1.RE vs. VAR3.RO	0.02	0.00	0.00
VAR1.RO vs. VAR2.RE	0.09	0.00	0.00
VAR1.RO vs. VAR2.RO	0.06	0.00	0.00
VAR1.RO vs. VAR3.RE	0.12	0.00	0.00
VAR1.RO vs. VAR3.RO	0.02	0.00	0.00
VAR2.RE vs. VAR2.RO	0.57	0.55	0.92
VAR2.RE vs. VAR3.RE	0.57	0.21	0.20
VAR2.RE vs. VAR3.RO	0.18	0.29	0.43
VAR2.RO vs. VAR3.RE	0.90	0.87	0.41
VAR2.RO vs. VAR3.RO	0.01	0.09	0.07
VAR3.RE vs. VAR3.RO	0.47	0.81	0.92