Forecasting Australian GDP Growth: A Mixed-Frequency Approach

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Introduction

- Paper explores whether forecasts of Australian economic growth can be improved by employing recently-developed techniques of mixed-frequency modelling.
- Mixed Data Sampling Model (MIDAS) developed by Ghysels, Santa-Clara and Valkanov (2004).
- An alternative to other mixed-frequency models (e.g. temporal aggregation).
- Can this be beneficial in improving short-term forecasts in an Australian context?

Motivation

- Unbalanced datasets are relatively common in macroeconomic forecasting.
- Can arise due to sampling frequency of variables and/or missing values. Some economic data are reported at lower frequencies (e.g. quarterly) while others are reported at higher frequencies (e.g. monthly and daily).
- Mixed-frequency samples have traditionally been a challenge for economists and policymakers undertaking macroeconomic forecasting.

Motivation

- In previous empirical applications, solution to mixed-frequency samples was to pre-filter the data such that the left-and-right-hand side variables were sampled at the same frequency.
- For instance, to convert monthly to quarterly data, the forecaster could simply take the average of the three months in the quarter.
- Other solutions include interpolation of missing data and bridge equations.

Motivation

- Trade-off from these methods, however, is the loss of potentially useful information and mis-specification of the model.
- The MIDAS set of models have been introduced in volatility predictions and, more recently, macroeconomic modelling and forecasting.
- Previous studies have found that there are benefits to incorporating higher-frequency data in short-term economic forecasting models (e.g. Bai, Ghysels and Wright (2013); Armesto, Owyang and Piger (2010); Macrcellino and Schumacher (2009)).
- None, however, have been applied to the Australian economy.

The Model: Basic MIDAS Model

- The MIDAS models of Ghysels et al. (2004) are closely related to the distributed lag models but with key adjustments.

- The MIDAS models are essentially tightly parameterised, reduced form regressions that involve processes sampled at different frequencies.

- The response to the higher-frequency explanatory variable is modelled using highly parsimonious distributed lag polynomials to prevent the proliferation of parameters that might otherwise result (Ghysels et al. 2004).

- One primary advantage of the MIDAS approach is that the lag polynomial is used to weight the lags of the explanatory variable - this only requires a few parameters to be estimated, resulting in a parsimonious model.

The Model: Basic MIDAS Model

- One of the key features of the MIDAS model is the parameterisation of the lagged coefficients B(k;θ) in a parsimonious way. This is achieved by restricting the lag coefficients to lie on a polynomial function.
- There are various alternatives for the polynomial specification. The two more flexible specifications that parameterise the weights into a two parameter vector are the exponential Almon lag and Beta lag.
- In their paper, Ghysels, Sinko and Valkanov (2007) provide a discussion of the Beta lag specification, Almon lag and exponential Almon lag specification as well as the Step functions (see Ghysels, Sinko and Valkanov (2007) for a detailed description).
- We explore all four specifications of polynomials in this paper.

The Model: Basic MIDAS Model

- MIDAS model is similar to the distributed lag model but with few variations.

- Distributed lag model that takes the form:

$$y_t = \alpha + B(L)x_t + \epsilon_t$$

where B(L) is a finite or infinite lag polynomial operator.

The Model: Basic MIDAS Model

- Basic MIDAS model for single explanatory variable, and one-step-ahead forecasting is given by:

$$y_t = \beta_0 + \beta_1 B(L^{1/m}; \theta) x_{t-1}^m + \epsilon_t^m$$

where y_t is the regressand and x_{t-1}^m is the regressor sampled at frequency m. The polynomial lag operator is given by B($\mathrm{L}^{1/m}$;θ) which can take various specifications. As mentioned earlier, we explore four functional forms (Almon lag, Exponential Almon lag, Beta lag and Step Function).

The Model: AR-MIDAS Model

- When y_t is serially correlated, normally the case in time-series variables, the simple model is extended to a dynamic linear regression or autoregressive distributed lag (ADL) model. This gives:

$$y_t = \beta_0 + \lambda y_{t-1} + \beta_1 B(L^{1/m};\theta)x_{t-1}^{m} + \epsilon_t^{m}$$

Data Description

- Data set used in this paper has been compiled from the ABS, RBA and private institutions like NAB.
- Our sample set uses a window from 1990 Q1 to 2015 Q4.
- First in-sample starts from 1990 Q1 to 2013 Q4.
- First out-of-sample forecasts starts from 2014 Q1 to 2015 Q4 (i.e. 8 quarters).
- The following table presents a list of the variables utilised in the model.

Data Description

Table: Model Variables

Data Series	Frequency	Transformation
Real GDP	Quarterly	Log Differences
NAB Business Conditions	Monthly	None (deviation from mean)
AUD/USD	Monthly	None
Employment	Monthly	Log Differences
M1	Monthly	Log Differences
M3	Monthly	Log Differences

Results and Discussion

- Results from the MIDAS models are compared with the traditional Auto-regressive distributed lag models.
- We use the Root Mean Square Error (RMSE) to compare the accuracy of the forecasts.
- The dependent variable is quarterly real GDP.

Results and Discussion

Table: 1-Quarter Ahead Forecasts

Variable	Almon	Exp. Almon	Beta	Step	ADL
NAB Business Conditions	**0.090**	0.145	0.124	0.136	0.236
Employment	**0.147**	0.170	0.170	0.183	0.255
AUD/USD	0.171	**0.129**	0.166	2.500	0.277
M1	0.170	0.203	0.170	**0.167**	0.219
M3	0.151	0.143	0.152	0.141	**0.137**

Results and Discussion

Table: 2-Quarter Ahead Forecasts

Variable	Almon	Exp. Almon	Beta	Step	ADL
NAB Business Conditions	0.446	0.435	0.379	**0.136**	0.506
Employment	**0.147**	0.170	0.170	0.182	0.255
AUD/USD	0.171	**0.129**	0.166	2.500	0.277
M1	0.171	0.203	0.170	**0.167**	0.219
M3	0.151	0.143	0.152	0.141	**0.137**

Results and Discussion

Table: 1-Year Ahead Forecasts

Variable	Almon	Exp. Almon	Beta	Step	ADL
NAB Business Conditions	0.389	0.405	**0.329**	0.398	0.469
Employment	0.424	0.419	0.456	0.456	**0.392**
AUD/USD	0.443	**0.389**	0.437	2.790	0.489
M1	0.426	0.450	0.422	**0.421**	0.421
M3	0.400	0.409	0.404	**0.399**	0.407

Concluding Remarks

- MIDAS model with Almon lag presents the most accurate forecasts for business conditions and employment indicators.
- Overall, findings suggests MIDAS models provide better short-term forecasts, lower RMSE, in comparison to traditional mixed-frequency models.
- Results imply higher-frequency data contains useful information that are important in the forecast of lower-frequency macroeconomic variables and should be incorporated in macroeconomic forecasting.
- Exploratory exercise. Avenue for future research using MIDAS-VAR or other larger macroeconometric models.

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