
The use of statistical forecasting models at the Reserve Bank of New Zealand

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Economic forecasts, in particular the forecasts for inflation, are an important part of the monetary policy formulation process at the Reserve Bank. The forecasts from a range of statistical models provide an important cross check for the forecasts produced by the main policy model that supports the policy deliberation process. This article describes the suite of statistical models used at the Reserve Bank and how these models fit into the forecasting process.

1 Introduction

The Policy Targets Agreement (PTA) sets out that the goal of monetary policy in New Zealand is to keep future inflation between 1 to 3 percent on average over the medium term. A key requirement for achieving this aim is forecasting the medium-term path of inflation. At the Reserve Bank of New Zealand, the forecasts underlying policy decisions are formed as part of a rigorous forecasting process. The forecasts from economic models are an important part of this process.

There are many different ways to model the economy, and the choice of model can result in materially different forecasts. Modelling approaches at the Reserve Bank can be split into two broad categories. The first are so-called structural models, where the model is based on theory about how agents in the economy operate. The existing policy model at the Reserve Bank (FPS) and the new policy model described in an accompanying article in this issue (KITT; Lees, 2009b) are both of this form.

Structural models offer many advantages to the model user. As the relationships in the model are based on economic theory, it is possible to tell rich stories about the particular drivers of the forecasts. The forecaster can incorporate important known features of the economy, such as the inflation target, into these models which may improve medium-term forecast accuracy. It is also possible to judgementally adjust these forecasts in a consistent way, usually to incorporate information not captured by the model, so that judgement to one part of the model will have implications for other parts of the model. These features make structural models ideal as the main policy model at a central bank.

However, these models require the model builder to make very strong assumptions about the nature of the economy. These assumptions are often critical to the behaviour of the model, but are highly uncertain in practice. In many cases it is difficult to check the validity of these assumptions empirically, and choices are often made to achieve desired theoretically-motivated properties in the model rather than on the basis of strong supporting evidence in favour of one choice over another.

An alternative approach is to use forecasting methodologies that rely more on the statistical patterns in the data. These techniques generally require the modeller to make fewer assumptions about the structure of the economy. At the Reserve Bank, forecasts from this class of model are used as a cross check for the central forecasts produced with the help of the main policy model, and can provide a basis for incorporating judgement into the final published forecasts.

This article proceeds as follows: Section 2 outlines the motivation for using statistical models. Section 3 discusses the actual models used for medium-term forecasting. Section 4 discusses the historical forecast accuracy of these models. Section 5 discusses other modelling techniques used as near-term indicators, while section 6 discusses areas for future work. Section 7 concludes.

2 Why use statistical models?

Statistical models allow the user to estimate the historic relationships between macroeconomic variables, while remaining relatively agnostic about the true structure of the economy.

However, since the estimated relationships are based on historical correlations, rather than causal relationships based on formal assumptions about the behaviour of households and firms, it can be hard to decipher the drivers of a particular forecast. For example, a particular model may pick up that interest rates and the exchange rate have tended to move in the same direction over time, but cannot distinguish the direction in which the causality runs.

Nevertheless, statistical models generally produce forecasts of similar accuracy to judgementally adjusted forecasts from structural models. The former thus provide a useful cross check to the latter. Statistical models are used in the forecasting process at a number of central banks. (See, for example, Kapetanios *et al.* (2007) for the Bank of England, and Bjornland *et al.* (2009) for the Norges Bank.)

Generally statistical models are designed to forecast medium-term movements in the economy – roughly two to eight quarters into the future. This is the major focus of the statistical modelling work at the Reserve Bank. However, there are some techniques for forecasting shorter-term movements in the economy. These are discussed in more detail in section 5.

3 The Reserve Bank’s medium-term statistical forecasting models

While statistical models generally remain agnostic about the structure of the economy, the model builder does still have to make a number of choices about what information to incorporate in their model. Models differ in terms of how much data enters into them (both the amount of historical data and the number of data series), what lag structure is allowed in the model, and what the functional relationship between data is.

The Reserve Bank’s statistical model suite contains a range of different models that vary across each of these dimensions. For example, the smallest models in the suite use a single indicator to forecast the variable of interest, while the largest model contains around 400 series.

The statistical models used for medium-term forecasting

at the Reserve Bank can be usefully split into four different groupings, ordered from the most data-driven to the least data-driven: factor models, bi-variate indicator models, vector autoregressive models, and Bayesian vector autoregressive models.

The forecasts from these models are one input into the forecasting and policy process at the Reserve Bank.

Factor models

Factor models are useful for summarising large quantities of data. The ability to forecast using large quantities of data means that the model builder does not have to make strong assumptions about which particular series are important for forecasting the variable of interest.

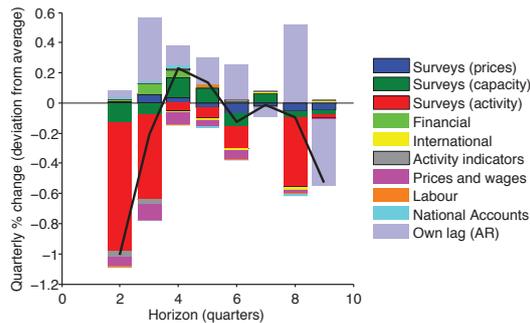
Factor models generally use principal components, a statistical technique, to estimate the underlying “common factors” generating fluctuations across a wide range of data. These factors are the linear combinations of all of the data in the model that explain the highest proportion of the variance in the data. These factors can thus be thought of as picking up the underlying movements in the economy that show through in a large number of series. These estimated factors are used as predictors in a linear regression on the forecast variable of interest.

Matheson (2006) developed a factor model of the New Zealand economy that is estimated with a panel of around 400 macroeconomic indicators. This model forms part of the Reserve Bank’s statistical modelling suite.

A common criticism of factor models is that their “black-box” nature makes it hard to interpret their forecasts. One technique to mitigate this is to split out the contributions of various classes of data to the forecasts. An example of the contributions to the factor model forecast for quarterly GDP growth at the end of 2008 is shown in figure 1. The black line shows that GDP growth was projected to be below average over the entire forecast horizon. The coloured bars show the contribution of each class of data to that forecast. They indicate that the low near-term GDP forecast at that time was primarily due to weakness exhibited in surveys of business conditions such as National Bank’s Business Outlook

and NZIER's Quarterly Survey of Business Opinion (the red bars on the graph). The own lag term picks up the portion of the GDP forecasts that is explained by the past history of GDP movements.

Figure 1
Contributions to factor model forecasts of GDP in 2008Q4



Bi-variate indicators

Rather than combining a large number of series into a small number of factors, an alternative approach is to use each series individually to forecast the variable of interest. Another type of forecast in our suite uses the factor model data panel to estimate a series of bi-variate regressions. A weighted average of the resulting forecasts is then created, with the weight determined by the in-sample fit of that particular indicator.

Since this methodology is averaging a large number of forecasts, each of which have relatively small predictive power, the resulting forecasts tend to be close to the historical average of that particular series.

Vector autoregressions (VARs)

In contrast to the previous two approaches, which are agnostic about which data provides predictive power, VARs require stronger assumptions to be made about the structure of the economy. While the forecaster need not specify the exact relationship between data, strong assumptions have to be made about which particular variables to include in the model, as these models typically include a dozen or fewer variables.

A VAR model is a system of equations where each variable

is modelled as a function of contemporaneous and lagged values of the other variables in the system. Since each variable in the system enters the right hand side of each equation with a number of lags, the number of estimated parameters grows very quickly as the model size increases. As a consequence, these models tend to overfit the data and forecast poorly if too many variables or lags are included.¹

Therefore, VARs tend to be estimated with a relatively small number of variables, requiring the model builder to decide which variables are particularly important.

Nevertheless, this approach has some advantages over pure data driven approaches like factor models. In VAR models, the forecasts for each variable influence the forecasts for other variables in the system. This consistency between model variables makes it easier to interpret the economic story underlying the forecasts than in factor models or bi-variate indicators.

At the Reserve Bank we estimate a large number of VARs, and then average the forecasts across these models. This allows us to incorporate the information from a larger number of series without over-fitting any particular model.

Bayesian vector autoregressions (BVARs)

The use of Bayesian techniques is another way to overcome the problem of overfitting in standard VAR analysis. BVARs do this by imposing prior beliefs on parameter values. Generally these priors are a-theoretical in nature and are of a simple form, such as that all variables will remain at their current levels or grow at their average growth rates. These priors act to shrink the parameter estimates away from what would be obtained from an unrestricted VAR, and hence act to limit the signal that is allowed to be extracted from the data.

Using this approach it is possible to build models that forecast using a very large panel of data without exhibiting signs of overfitting. As is the case with VAR models the

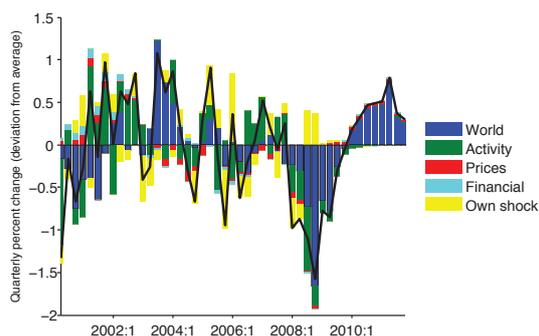
¹ **Overfitting occurs when too many parameters are estimated relative to the quantity of data available. An estimated model can achieve an arbitrarily close fit to the data over history as more parameters are included, but the estimated parameters will tend be inaccurate. As a result, an overfitted model will tend to forecast poorly.**

forecasts for each variable are internally consistent, allowing the economic story to be disentangled.

Recently this modelling technique has been used to develop a 35 variable BVAR for the New Zealand economy, details of which are available in Bloor and Matheson (2009). This particular model employs conditional forecasting techniques that are usually associated with structural models like FPS or KITT. In other words, one can form forecasts that are conditional on certain events happening. For example, the forecasts from this model are often produced assuming that a certain outlook for the world economy will eventuate. Using these techniques, it is also possible to consider alternative scenarios, where assumptions about the path of exogenous variables are altered.

These techniques make this model more effective in the policy environment, as forecast stories can be effectively communicated, and differences from central forecasts can be more easily disentangled. For example, it is possible to decompose historical observations and the forecasts to the originating shocks that have hit the economy. While it would require very strong assumptions to allocate these shocks to particular variables, it is possible to allocate them to broader blocks of variables using relatively weak identifying assumptions. Figure 2 shows an example of the shock decomposition for GDP from the BVAR at the end of 2008. At that time the BVAR interpreted the 2008 recession as being due to a combination of world and domestic activity shocks. The assumed outlook for the world economy was interpreted as consistent with an improvement in the domestic economy over 2009.

Figure 2
BVAR shock decomposition for GDP in 2008Q4



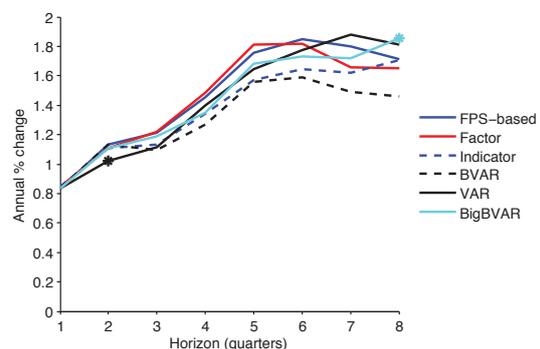
4 Forecast accuracy

Since forecasts play an integral part to the policy process at the Reserve Bank, regular work is done to evaluate the forecasting performance of both the published forecasts and the various inputs into those forecasts. An example of this work is Turner (2008), which evaluated the Reserve Bank's forecasting performance against Consensus Forecasts, an average of forecasts produced by reputable forecasters.

Figures 3 and 4 show the historical forecasting accuracy of the medium-term forecasting models in the statistical model suite compared with internal forecasts based on the Reserve Bank's core structural model of the New Zealand economy, FPS, over the period 2000 to 2008. These are used as the main projections to inform the Reserve Bank's policy discussions, and the projections published in each *Monetary Policy Statement*.²

In these graphs, the measure of forecast accuracy used is the root mean squared forecast error (RMSFE) statistic, which is a measure of the average forecast error over time. It shows that many of the models in the statistical model suite have been able to produce more accurate forecasts than the main internal forecasts for GDP over the time period considered. However, only one model in the suite has been able to outperform the internal forecasts for CPI inflation.

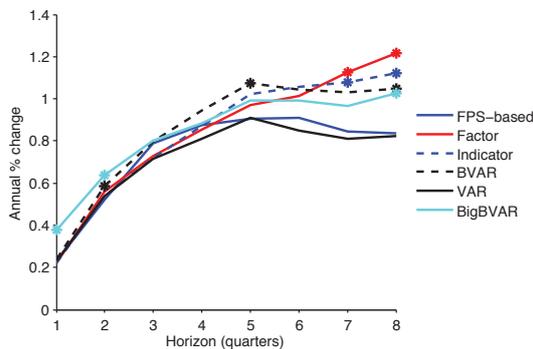
Figure 3
Forecast accuracy for GDP (RMSFE)³



² See RBNZ (2004) for further details on how these forecasts are produced.

³ Forecast errors that are marked with an asterisk are statistically different from FPS-based forecasts at the 10 percent level. Big BVAR in these charts refers to the model described in the BVAR section of this paper, while the BVAR model is a smaller model which uses similar techniques.

Figure 4
Forecast accuracy for CPI inflation (RMSFE)



While statistical models have been shown to produce similar forecast accuracy to the more sophisticated internal FPS-based forecasts over this particular time period, this may not always be the case. Stock and Watson (2007) show that over the period of low macroeconomic volatility labelled the Great Moderation, forecasting became easier, and it became increasingly difficult for more sophisticated models to outperform relatively simple statistical models. If this period of relative stability has come to an end, more complicated structural models of the economy may again show superior forecasting ability.

5 Near-term forecasting models

The Reserve Bank's forecasts for the very near-term economic outlook are produced largely judgementally, taking into account large quantities of information. Generally statistical models struggle to match the accuracy of these short-horizon forecasts. This is often due to information available to the near-term forecaster that is difficult to incorporate into models, such as announced increases in electricity prices. However, there are an additional three models in the suite that are designed to pick up shorter-run fluctuations in specific areas of the economy. All three models are applications of the factor model methodology.

Factor augmented vector autoregression (FAVAR)

Matheson (2007) applied a variant of a factor model to New Zealand using around 2000 economic indicators. This particular model is designed to forecast using the most

timely pieces of data that have been released, which makes the model particularly good at short-term forecasting. Historically it has produced more accurate forecasts for near-term GDP than the judgemental forecasts produced at the Reserve Bank. This model is an important input for the near-term GDP forecasts.

Factor model core inflation indicator

Measures of calculating core inflation are often employed by central banks to gauge the likely persistence of movements of inflation away from target. The first common factor extracted from a dataset of all sub-indexes in the CPI regimen is one measure of the underlying movements in inflation. This factor-model-based indicator of core inflation is described in more detail in Giannone and Matheson (2007) and Holden (2006).

QSBO cyclical indicator

A third short-term model is a factor model that is estimated only on data from NZIER's Quarterly Survey of Business Opinion. The first factor from this model correlates well with capacity pressures in the economy, and is used as an indicator of the current cyclical position. This indicator has tended to give a one-year lead on movements in non-tradable inflation.

6 Frontiers of statistical modelling

In November the Reserve Bank held a conference on Nowcasting and Model Combination, a summary of which is available in Lees (2009a). This conference highlighted some of the frontiers of statistical modelling, and suggested some areas for future work at the Reserve Bank. Already underway is an evaluation of the benefits of model averaging compared to the forecasts from individual forecasts. Possible areas for future development include greater use of probabilistic forecasting, rather than forecasting the single most likely outcome, as well as modelling techniques that are more robust to structural change in the economy.

7 Conclusion

The forecasts from statistical models form an important part of the forecasting and policy process at the Reserve Bank. These techniques have tended to produce forecasts with similar accuracy to the Reserve Bank's internal forecasts. While forecasts from statistical models often lack the richness of those produced by more structural models, techniques have been developed to improve the story telling ability of these models.

The continued development of statistical forecasting models represents part of the continued evolution of forecasting practice at the Reserve Bank. We regularly analyse our historical forecast performance, and this has provided impetus for the continued development of forecasting techniques.

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