Forecasting house price inflation: a model combination approach*

Sarah Drought and Chris McDonald†
Reserve Bank of New Zealand

DRAFT - NOT FOR CITATION
June 18, 2010

Abstract

In this paper, we use a range of statistical models to forecast New Zealand house price inflation. We address the issue of model uncertainty by combining forecasts using weights based on out-of-sample forecast performance. We consider how the combined forecast for house prices performs relative to both the individual model forecasts and the Reserve Bank of New Zealand's house price forecasts. We find that the combination forecast is on par with the best of the models at each horizon, and has produced lower root mean squared forecast errors than the Reserve Bank's forecasts.

*The views expressed in this paper are those of the authors and do not necessarily represent those of the Reserve Bank of New Zealand. The authors would like to thank Özer Karagedikli for his helpful comments and suggestions.

†Reserve Bank of New Zealand, 2 The Terrace, Wellington, Email: Sarah.Drought@rbnz.govt.nz; Chris.McDonald@rbnz.govt.nz

1 Introduction

Forecasting house prices is important for monetary policy, particularly in New Zealand. This is because house prices play a significant role in the evolution of business cycles in the New Zealand economy. De Veirman and Dunstan (2008) found significant wealth effects on consumption in New Zealand, arising from housing wealth. As such, house prices are an important leading indicator of inflationary pressures. For an inflation targeting central bank, this is important.

In recent years, many developed and emerging countries have experienced very strong increases in house prices. Corresponding wealth and housing collateral effects on consumption have been widely investigated.[1] Housing wealth can also have an inflationary effect via private investment. As house prices increase relative to the value of housing-related construction costs (i.e. Tobin's q for residential investment), new housing becomes relatively more profitable. Moreover, as the value of assets that can be used as collateral increase (value of houses and land), the ability of firms to borrow and finance their business investment increases. As a result, one would expect a strong correlation between house prices and private investment.

Given the importance of house prices, there have been many studies that investigate 'fundamental house prices' in New Zealand, including Fraser et al (2008) and Herring (2006). Furthermore, O'Donovan and Rae (1997), and Briggs and Ng (2009) model the short-run dynamics of New Zealand house prices around their fundamental level, using error correction models. However, there can be considerable uncertainty surrounding the fundamental level of house prices and also what drives the short run dynamics. Nonetheless, to our knowledge there has been little published research that attempts to forecast house prices outside of the equilibrium-type framework.

In light of this, we use a range of time series models to forecast house price inflation, including an autoregressive model (our benchmark model), a single equation indicator model, four variations of Bayesian vector autoregression models, a factor model, and an error correction model. Though we consider many models, this is not an exhaustive list. That is, there are many other models that we could develop.

The motivation behind using these models is to capture a large range of empirical time series approaches. Also, we have tried to include a wide

[1] For example see Muellbauer (2007), Dvornak and Kohler (2007) and, for the case in New Zealand, De Veirman and Dunstan (2008).

range of indicators. However, having such a range of models presents a problem. That is, which forecast do we focus on? Or, perhaps, is an average better still? To investigate, we consider two types of combination: a simple average, and a weighted average (where weights are based on inverse mean squared errors). We find that these approaches produce similar root mean squared forecast errors. Further, we compare the performance of these combination methods to a model selection approach. Model selection involves forecasting with the best model in real time for each horizon. We find that an average outperforms a selection approach over our sample.

Lastly, we consider how this combined forecast for house prices performs relative to both the individual models and the Reserve Bank of New Zealand's (RBNZ) house price forecasts.[2] We find that the combination forecast always beats the AR(1) benchmark model and is on par with the best of the models at each horizon. The combination forecast has also produced lower root mean squared errors than the RBNZ's published forecasts.

The remainder of the paper is structured as follows. Section 2 outlines the data that we used to produce real time forecasts. Section 3 introduces the eight models that we have developed. Section 4 discusses combination methods. Section 5 presents results and, finally, section 6 concludes.

2 Data

To produce historic house price forecasts we have tried to use real time data. That is, the data that was available at the time when the forecast would have been made. For key variables used in the RBNZ forecast process (such as GDP, CPI and house prices), real time data has been stored at the time of each quarters publication. However, for many other variables this real time data is not available. As such, we use the most recent series and crop it back to what would have been available at the time of the forecast (quasi-realtime). For these variables, we have assumed that revisions are relatively small or non-existent.[3] It is our opinion that these

[2] We use the RBNZ forecasts as a comparison because to our knowledge there are no house price forecasts published by an alternative source each quarter. Also, the RBNZ does not publish its house price forecasts on a regular basis, however, real time forecasts are produced each quarter for internal use.

[3] In New Zealand, the real variables from the National Accounts are subject to the largest revisions. Generally, other data is not revised or the revisions are relatively small.

unaccounted for revisions would have little effect on the results presented in this paper.

The house price series that we forecast in this paper is the Quotable Value (QV) quarterly house price index. This series has been forecast at the RBNZ for the last decade. This house price series is generally considered New Zealand's most robust, though it is somewhat untimely (four-month lag).

The untimely nature of the QV house price index is its weakness. As such, in much of our analysis we have used the REINZ monthly house price index, which only has a two week lag, to forecast the first quarter.[4] We considered forecasts both with and without the REINZ monthly data. As this additional information was found to improve forecast performance, we have included this data where possible in our models.[5] We forecast annual house price inflation so any improvement in the root mean squared errors (RMSEs) in the first quarter, will improve the RMSEs in the first four quarters. The REINZ index was only developed in 2009, so comparing the forecast performance of the models and the RBNZ in the first four quarters should be done with care. Although, the information incorporated in the REINZ index has essentially been available to the RBNZ for a number of years.

3 Models

To forecast house prices we use a range of empirical time series approaches. We started with models as simple as an AR process and simple equations, but have developed more dynamic models, some of which are fairly data rich. We have produced four Bayesian VARs, with the number of variables ranging from four to 50. We also developed a factor model, which uses 500 data series, and an error correction model. While this is a fairly broad range of models this is not an exhaustive list and further model development is likely.

AR(1)

We started with a simple AR(1) forecast of quarterly house price inflation (Δhp_t). This can be thought of as a benchmark model. We considered

[4] See McDonald and Smith (2009) for information on the REINZ house price index.

[5] For a comparison of results see appendix A, figure 7 and table 1.

other AR processes, but the Bayesian information criteria suggested that adding more lags was not worthwhile.

$$\Delta hp_t = \gamma_0 + \gamma_1 \Delta hp_{t-1} + \epsilon_t \tag{1}$$

Migration and Mortgage Rate indicator (MM indicator)

This indicator model uses just one equation. Using OLS we regress quarterly house price inflation against the 5-year mortgage rate, permanent and long-term (PLT) arrivals and PLT departures.[6] This type of indicator has been considered in the RBNZ's forecasting process for a while.

$$\Delta hp_t = \gamma_0 + \gamma_1 \Delta PLTA_{t-2} + \gamma_2 \Delta PLTD_{t-2} + \gamma_3 R_{t-2} + \varsigma_t \tag{2}$$

To produce house price forecasts this equation relies on forecasts for both components of PLT migration and the 5-year mortgage rate. We use the published RBNZ forecasts for these.[7]

Bayesian Vector Autoregression (Small BVAR)

This four variable Bayesian VAR uses the same variables as the simple indicator equation above. Its advantage is that it does not require exogenous forecasts. This VAR is in the form shown below (equation 3), and includes four lags for each of the explanatory variables.

Consider a VAR(p) model:

$$Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + ...B_P Y_{t-p} + v_t \tag{3}$$

We use Bayesian techniques to estimate this VAR, in part because of few degrees of freedom. We use Minnesota priors which assume the mean of prior distribution is a random walk. The specification of the standard deviation of the prior imposed on variable j in equation i at lag k is:

[6] Both migration series are de-trended using working aged population and all explanatory variables are lagged two quarters.

[7] There is no 5-year mortgage rate forecast so this is proxied by 5-year swap rates plus a margin which is held constant over the forecast.

$$\sigma_{ijk} = \theta w(i,j) k^{-\phi} \left(\frac{\hat{\sigma}_{uj}}{\hat{\sigma}_{ui}} \right) \quad (4)$$

Where θ is the 'overall tightness' parameter, reflecting the standard deviation of the prior on the first lag of the dependent variable. The $k^{-\phi}$ term is the lag decay parameter. Increasing ϕ reduces the standard deviation of the priors on lags greater than one. Also, $w(i,j)$ allows us to weight the priors on variables differently. For a good summary of the priors see LeSage (1999)

In regards to the BVAR we estimate, we have set θ to one and made $w(i,j)$ a scalar also equal to one (thus we do not weight variables differently). However, we made ϕ equal to 100. This gives us very tight priors on coefficients of lags greater than one, such that coefficients on longer lags tend to be close to zero, unless a strong relationship exists in the data. This, in part, combats the problem we face with having relatively few degrees of freedom.[8]

Bayesian Vector Autoregression (BVAR)

This model is similar to the Bayesian VAR described above, but with five additional variables. We have included terms of trade, quarterly GDP growth, the 90-day interest rate, the New Zealand dollar TWI, and the Australian unemployment rate. We have aimed to include variables that have some leading information for house prices, or are key macroeconomic indicators. For example, we use the Australia unemployment rate because it seems to help predict the number of PLT departures to Australia. The structure of the model is very similar to the small BVAR above, with four lags and tight priors on those lags greater than one.

Bayesian Vector Autoregression (Big BVAR)

This is a large Bayesian VAR developed by Bloor and Matheson (2009) using the conditional forecasting estimation techniques of Waggoner and Zha (1999). The model includes 50 domestic and international variables including house prices. There are four lags in the model and they also use Minnesota priors. To overcome the problem of having a short sample and

[8] We use the LeSage MATLAB package to estimate this Bayesian VAR and iterate the Gibbs sample 10000 times. For further details on these functions see LeSage (1999).

few degrees of freedom they also apply tight priors. Further, they incorporated some structural aspects to the VAR. Notably, they treat the lags of foriegn variables as exogenous to the domestic variables. Though this model was not developed to forecast house prices, it is worthwhile considering because the forecasts were easily accessible. Unlike the BVARs above, this model is estimated using log-levels data (not in differences).

Monthly Vector Autoregression (REINZ VAR)

While the other models use the monthly REINZ housing price index to forecast the first quarter, there is typically an extra month's data not considered by these other models. This REINZ monthly VAR fully uses this timely data, and was developed for its ability to forecast near-term house price inflation.

This model has two stages. The first stage estimates a small four variable Bayesian VAR using monthly data. We include the REINZ housing price index, house sales de-trended using working aged population, median days to sell, and the 90-day interest rate. We use the Bayesian information criteria to choose the lag length. In this case, we apply fairly loose random walk priors (again Minnesota priors). In particular, the overall tightness hyperparameter is set to three. For coefficients on longer lags, we have applied tighter priors so that coefficients will tend to be close to zero. Using this VAR, we forecast each of the four monthly variables.

In the second stage of this model, we forecast quarterly house price inflation using a simple equation. We use OLS to regress quarterly QV house price inflation (Δhp) on the quarterly change in the REINZ housing price index (Δrhp) and de-trended house sales (HS) .

$$\Delta hp_t = \gamma_0 + \gamma_1 \Delta rhp_t + \gamma_2 HS_t + \varsigma_t \tag{5}$$

Using the forecasts produced in the first stage, collapsed to quarterly frequency, we can apply the coefficients estimated in this equation to generate a quarterly QV house price inflation forecast.

Error Correction Model

This is a simple two-step error correction model. The first step estimates the fundamental house price level. The second step uses the error correction term, amongst other data, to forecast quarterly house price inflation.

In our long-run equation, fundamental house prices are driven by nominal GDP, population and a user cost term. Nominal GDP is designed to capture the income effect on housing demand. The user cost is an effective mortgage rate less the expected capital gain (proxied by the most recent 3-year moving average of house price inflation).[9]

Long-run equation:

$$hp_t = \alpha_0 + \alpha_1 gdp_t + \alpha_2 pop_t + \alpha_3 UC_t + \epsilon_t \tag{6}$$

The short-run equation uses the error correction term (difference of house prices from their fundamental level) to forecast house price inflation.[10] The lag of house price inflation and population are also included in this equation.

Short-run equation:

$$\Delta hp_t = \beta_0 + \beta_1 \epsilon_{t-1} + \beta_2 \Delta gdp_{t-1} + \beta_3 \Delta pop_{t-1} + \varsigma_t \tag{7}$$

where hp is the log of house price, gdp is the log of nominal GDP, pop is the log of population, and UC is the user cost.

Factor model

The most data-rich model in our suite is a dynamic factor model. This model uses factors from as many as 500 series. It was developed by Matheson (2006) and is used at the RBNZ to forecast other macroeconomic variables (for example GDP and CPI inflation). As such, the included series were not specifically chosen to forecast house prices.

This model forecasts using factors from four different subsets of the data. It takes factors from the entire data set, then repeats this with the 25, 50 and 75 percent best fitting series. The forecasts are made using the following equation, where Δhp_{t+h} is the quarterly house price inflation forecast at horizon h, f_t is a matrix of factors, Δhp_t is the end point

[9] The series we have used is the floating first-mortgage new customer rate.

[10] We have used a linear error correction term. However, O'Donovan and Rae (1997) find evidence that the error correction term for New Zealand house prices may be asymmetric. We plan to investigate this further.

for quarterly house price inflation, and (L) denotes the variations on lag lengths.

$$\Delta hp_{t+h} = \phi + \beta(L)\Delta hp_t + \gamma(L)f_t + \vartheta_{t+h} \tag{8}$$

Further to varying the size of the data set, this factor model allows for many variations in its structure, similar to Stock and Watson (2002). In particular, it allows for variations in the number of factors, lags of the dependent variables, and lags of the factors. It uses the Bayesian information criteria to choose between different structures.

4 Combination approach

Using many forecasting models can make it difficult to know which forecast to focus on. Furthermore, because the data generating process is unknown, model uncertainty will also be an issue. Combining the forecasts may provide a solution to these issues. As such, forecast combination is becoming increasingly popular in central banks. The Reserve Bank of New Zealand currently uses a suite of statistical models to produce forecasts for key macroeconomic variables. The combined forecast is used to highlight any potential risks around the central projection.[11] Other central banks that use forecast combination include the Bank of England, the Riksbank (Sweden), Norges Bank (Norway) and the Bank of Canada, see Bjørnland et al (2009) for an overview.

Timmermann (2006) provides a survey of the large literature on forecast combination. Two motivations for undertaking a combination approach are: (i) combination forecasts may be more robust to unknown instabilities (structural breaks) than forecasts from an individual model; and (ii) individual models may be subject to misspecification bias and these biases may be averaged out in the combination forecast.

In empirical studies, combination forecasts have been found to frequently outperform forecasts from the best-performing model in real time. Timmermann (2006) highlights that simple combination schemes (using equal weights or inverse mean squared error weights) are hard to beat.

[11] Combination forecasts are produced for GDP, CPI, tradable CPI, non-tradable CPI, the 90-day interest rate and the NZD TWI.

4.1 Our method

We consider two combination approaches and a model-selection approach to produce point forecasts at each horizon. The combination approaches that we consider use equal weights and mean squared error weights. When using equal weights, each model receives a 1/N weighting, where N is the number of models. Mean squared error (MSE) weights are calculated using the inverse of the model's mean squared error. Hence, the model with the lowest average forecast error receives the highest weight for the combination forecast.

MSE weights:

$$MSE_i = \frac{1}{T}\sum_{t=1}^{T}(y_{t+h} - \hat{y}_{t+h})^2 \tag{9}$$

$$MSEweight_i = \frac{\frac{1}{MSE_i}}{\sum_{i=1}^{N}(\frac{1}{MSE_i})} \tag{10}$$

Where T refers to the number of forecasts h-horizons ahead and N to the number of models.

In addition to the two combination methods, we also consider a model selection approach. This method forecasts using the model with the lowest mean squared error up until that point in time, for each horizon. The fact that a model has forecast accurately in the past, does not mean that this will be true in the future.

Initially, all models are estimated on data up to 2000Q1 and the models forecast the annual percent change (apc) of house prices up to two years ahead.[12][13] All models are then re-estimated each quarter using new data to produce a new set of forecasts. This process is repeated until 2010Q1 which is the final estimation period.

All models are evaluated in each forecast horizon using actual data. The relative performance of the individual models can vary across forecast horizons (some models are good for near-term forecasting and others are better for medium-term forecasting), so our weights are horizon-specific. The weights are calculated recursively and are updated each period. Using these weights combination forecasts are generated from

[12] Due to data limitations the simpleHP, smallBVAR and BVAR models produce their first set of forecasts from 2001Q1.

[13] Because of the four-month lag in house price outturns, the first forecast horizon is in the past.

2002Q2. As such, the evaluation period for all results presented in this paper is 2002Q2-2010Q1.

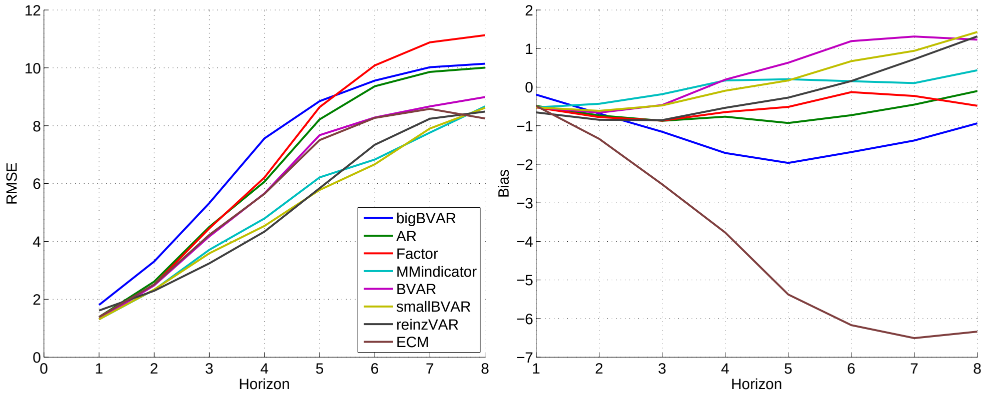
5 Results

In this section we describe the main results. First, we look at the forecast performance of the individual models. Then we compare the performance of the combination approaches against a model selection approach. Finally, our preferred combination forecast, which uses MSE weights, is compared to both the individual model forecasts and the Reserve Bank of New Zealand's forecasts of house price inflation.

5.1 Individual model results

Figure 1 shows the root mean squared errors (RMSEs) and biases of the individual model forecasts. It seems there is no dominant model for forecasting house price inflation over all horizons. However, all models, with the exception of the big BVAR and factor models, produce more accurate forecasts than our AR(1) benchmark.

Figure 1: Root mean squared errors (left) and biases (right) of individual forecasts



For forecasting two to four quarters ahead the REINZ VAR has the lowest RMSE. This model uses monthly housing-specific data, whereas a majority of the data used by the other models is general macroeconomic data measured at a quarterly frequency. Thus, the use of higher frequency and more timely housing-specific data is beneficial for forecasting house price inflation in the near term.

The small BVAR and the MM indicator models use the same data and both have low RMSEs for forecasts five to seven quarters ahead. Thus, it seems that net migration and mortgage rates are important indicators for predicting house price inflation at these horizons.

The error correction model (ECM) is the most accurate model for forecasting house price inflation eight quarters ahead (the longest horizon we look at). This suggests that house prices may revert back towards some fundamental level in the medium term.

While performing well at longer horizons, the ECM has had a large negative bias for all forecast horizons. Though, many of the other models also have a negative bias for most of the forecast horizons. In recent years there have been many studies that have found New Zealand house prices to be above their fundamental levels.[14] The negative bias of the ECM is consistent with this idea.

The small BVAR and the BVAR are the only models to have a positive bias when averaged over all horizons.[15] These models are not influenced by the level of house prices relative to other variables.

Figure 2: Root mean squared errors of individual models over time

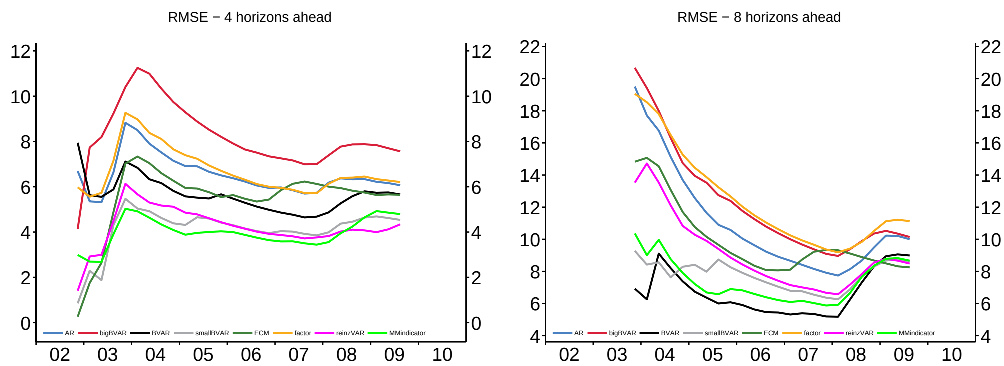


Figure 2 illustrates how the performance of the models has changed over time. The RMSE is on the vertical axis and the forecast date on the horizontal axis. Once the RMSEs have stabilised (after a couple of years) the model rankings do not change much. At least, not until the sharp downturn in house price inflation in 2007/08.

Before the downturn, the relative performance of the ECM was deteriorating. But subsequently the ECM forecast the downturn in house price

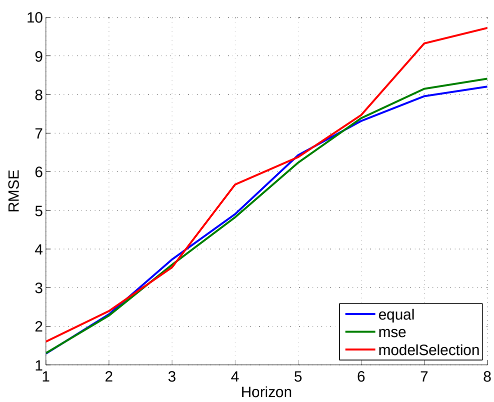
[14] These include Briggs and Ng (2009), Fraser et al (2008) and Herring (2006).
[15] Appendix B, table 3

inflation better than other models, causing an improvement in its relative performance. Looking at the RMSE four quarters ahead, the MM indcator model performed relatively badly during the downturn in house price inflation.

5.2 Combination results

We combine the individual forecasts using equal and MSE weights. Figure 3 shows the RMSE of these combination forecasts compared to the forecasts produced using a model selection approach.

Figure 3: Root mean squared errors of forecasts using different weighting methods

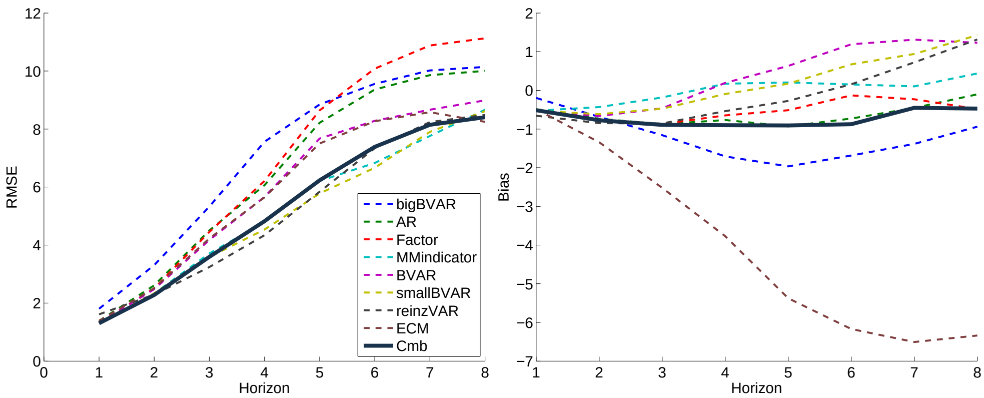


The performance of the different combination methods varies across forecast horizons. For all forecast horizons the difference in the RMSEs of the combination forecasts using equal weights or MSE weights is marginal.

For most horizons our combination forecasts have produced more accurate out-of-sample forecasts than forecasting using the best-performing model (model selection). This result highlights the value of placing weight on a number of different forecasting models. This may reflect that the good forecasting performance of a model in the past does not guarantee good performance in the future.

Figure 4 graphs the RMSE and bias of the MSE-weighted combination forecast (solid black line) against the individual model forecasts. The combination forecasts for house price inflation for one and two quarters ahead have a lower RMSE than any of the individual model forecasts. For the other forecast horizons, there is at least one individual model with better forecast accuracy. However, the combination forecast is still reasonably accurate over these horizons. That is, the RMSE of the combination forecast is only marginally greater than the best individual model at each horizon.

Figure 4: Root mean squared errors (left) and biases (right) of individual and combination forecasts



Do the combination forecasts outperform the Reserve Bank of New Zealand's forecasts?

We now compare the performance of the combination forecasts with the RBNZ's forecasts.[16] The combination forecasts use MSE weights rather than equal weights because MSE weights can vary over time and the models with lower forecast errors are given higher weights. The RMSEs and biases of both forecasts are shown in figure 5. Over this evaluation period, the combination forecasts have been considerably more accurate than the RBNZ forecasts for all horizons. The increased accuracy of the combination forecasts is particularly pronounced for forecasting house price inflation between four and eight quarters ahead.

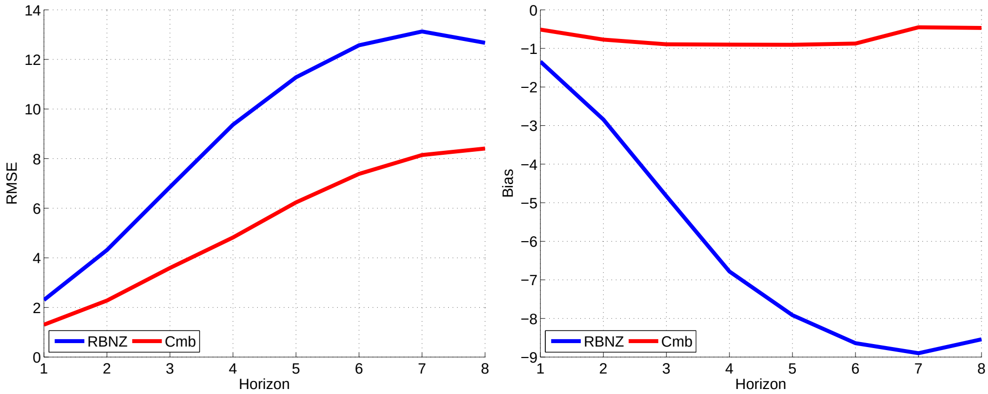
Over recent years the RBNZ has held the view that house prices were above their fundamental values.[17] Consequently, they were forecasting house prices to decrease. This is apparent in RBNZ forecasts for more than 4 quarters ahead. Figures 6 shows the RBNZ and combination forecasts graphed against actual outturns.[18] Before the recent downturn in the housing market (2007/08), the RBNZ's long-run forecasts for annual

[16]The RBNZ forecasts are used as a comparison because to our knowledge there are no house price forecasts published by an alternative source each quarter.

[17]Reserve Bank of New Zealand (2005) and Reserve Bank of New Zealand (2008).

[18]Forecasts for all horizons can be found in appendix C, figures 8 and 9.

Figure 5: Root mean squared errors (left) and biases (right) of combination and Reserve Bank forecasts

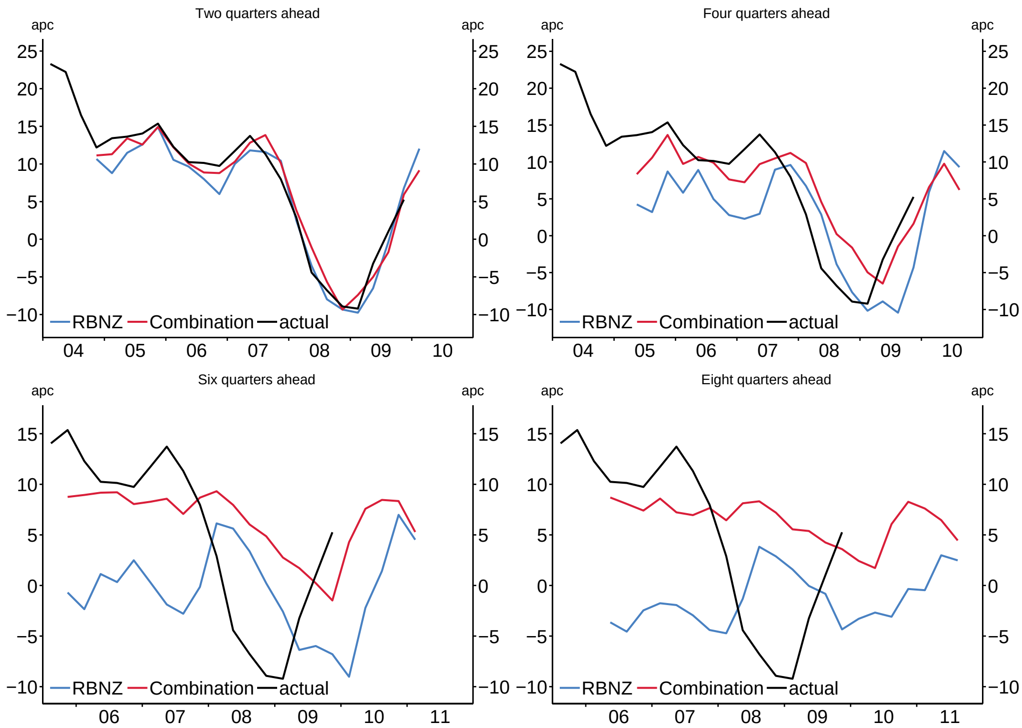


house price inflation were consistently below 5 percent and often negative. However, house price inflation was persistently above 10 percent.

The strong negative bias of the RBNZ's forecasts highlights that the RBNZ has tended to place a lot of weight on the fundamental level of house prices. With the exception of the ECM, and in part the big BVAR, the models used in the combination do not have a 'fundamental house price value'. Hence, the combination forecasts tended to be higher than the RBNZ forecasts and consequently were closer to actual house price inflation.

The ability of models to forecast turning points is important. Evaluating a model using only the RMSE and bias does not capture this. Looking at the four quarter ahead forecast, the RBNZ did well, relative to the combination, in forecasting the downturn in house price inflation in 2007/08. The combination forecasts predicted a downturn to house price inflation but the predicted magnitude was too small. This highlights a weakness of using a pure statistical model approach. It seems our statistical models struggle to forecast extreme events in house price inflation. A further weakness of our combination approach is the relatively short sample, as the results may differ over a longer sample.

Figure 6: Combination and RBNZ Forecasts



6 Conclusion

In this paper we developed a range of statistical models to forecast house price inflation. The best-performing models (based on RMSEs) were those that used small housing-specific data sets, such as the REINZ VAR, the small BVAR and the MM indicator model. All models that were developed to specifically forecast house price inflation (that is, all models except the big BVAR and factor models), outperformed our AR(1) benchmark.

We generate a summary forecast using three approaches: equal weights, MSE weights and model selection. We found that the averaging methods had lower forecast errors than the model selection approach. This result is consistent with the empirical evidence, outlined in Timmermann (2006), that simple averages often produce more accurate out-of-sample forecasts than the best-performing model in real time.

We also evaluated the combination forecast against both the individual models' and the RBNZ's forecasts of house price inflation. Over our evaluation period, the combination forecast is on par with the best of the individual models at each horizon, and has produced lower RMSEs than the RBNZ's forecasts. However, the combination forecast struggled to capture turning points and was outperformed by the RBNZ during the strong downturn in house price inflation in 2007/08.

Nonetheless, these results suggest statistical model forecasts for house price inflation should be considered in the forecast process. Further, a combined forecast is beneficial in that it produces low RMSEs and is a clear communication tool. However, while the results are somewhat striking, we recognise that the sample is relatively short.

References

Bjørnland, H C, K Gerdrup, A S Jore, C Smith, and L A Thorsrud (2009), "Does forecast combination improve Norges Bank inflation forecasts?" *Norges Bank*, *Working Paper*, 2009/01.

Bloor, C and T Matheson (2009), "Real-time conditional forecasts with Bayesian VARs: An application to New Zealand," *Reserve Bank of New Zealand*, *Reserve Bank of New Zealand Discussion Paper Series*, DP2009/02.

Briggs, P and T Ng (2009), "Trends and cycles in New Zealand house prices," *Centre for Housing Research, Aotearoa New Zealand*, *Paper for CHRANZ workshop*.

De Veirman, E and A Dunstan (2008), "How do housing wealth, financial wealth and consumption interact? evidence from New Zealand," *Reserve Bank of New Zealand*, *Reserve Bank of New Zealand Discussion Paper Series*, DP2008/05.

Dvornak, N and M Kohler (2007), "Housing wealth, stock market wealth and consumption: A panel analysis for Australia," *The Economic Record*, 83(261), 117–130.

Fraser, P, M Hoesli, and L McAlevey (2008), "House prices and bubbles in New Zealand," *The Journal of Real Estate Finance and Economics*, 37(1), 71–97.

Herring, R J (2006), "Booms and busts in housing markets: How vulnerable is New Zealand?" Available from: http://www.rbnz.govt.nz/research/fellowship/3324563.pdf.

LeSage, J P (1999), *Applied Econometrics using MATLAB*.

Matheson, T D (2006), "Factor model forecasts for New Zealand," *International Journal of Central Banking*, 2(2).

McDonald, C and M Smith (2009), "Developing stratified housing price measures for New Zealand," *Reserve Bank of New Zealand*, *Reserve Bank of New Zealand Discussion Paper Series*, DP2009/07.

Muellbauer, J N (2007), "Housing, credit and consumer expenditure," *Proceedings*, 267– 334.

O'Donovan, B and D Rae (1997), "The determinants of house prices in New Zealand: An aggregate and regional analysis," *New Zealand Economic Papers*, 31(2), 175–198.

Reserve Bank of New Zealand (2005), "Financial Stability Report, November 2005," *Reserve Bank of New Zealand*.

Reserve Bank of New Zealand (2008), "Monetary Policy Statement, March 2008," *Reserve Bank of New Zealand*.

Stock, J H and M W Watson (2002), "Macroeconomic forecasting using diffusion indexes," *Journal of Business & Economic Statistics*, 20(2), 147–62.

Timmermann, A (2006), *Forecast Combinations*, vol 1 of *Handbook of Economic Forecasting*, chap 4, 135–196, Elsevier.

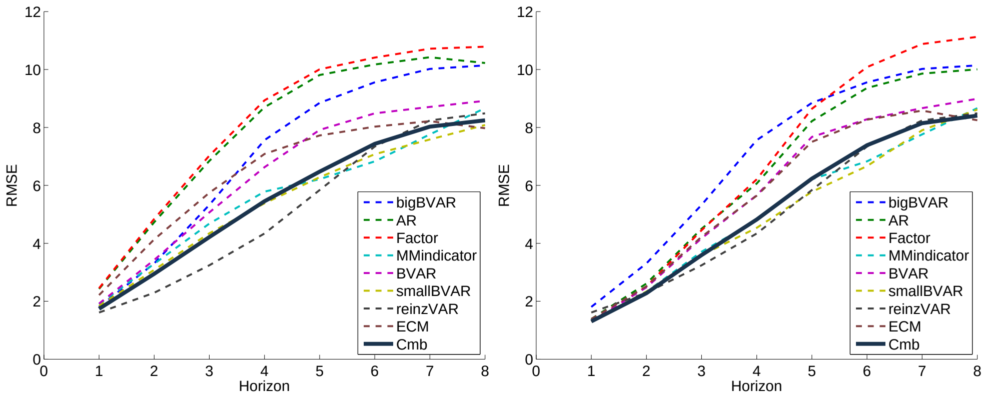
Waggoner, D F and T Zha (1999), "Conditional forecasts in dynamic multivariate models," *The Review of Economics and Statistics*, 81(4), 639–651.

Appendices

A. First forecast horizon

Because there is a two quarter lag in the QV house price index, all results in this paper use the more timely REINZ housing index for the first forecast horizon.[19] Figure 7 shows the RMSEs of the model forecasts with and without this data.

Figure 7: No REINZ data (left), including REINZ data (right)



Using the REINZ index decreases the RMSE of all models. Further, table 1 shows that the REINZ index improves the RMSE for more than just the first horizon, in part because this is based on forecasts of annual house price inflation. The improvement is the largest for the models that contain a lot of persistence, for example the AR and Factor models.

Table 1: Difference in RMSE when the REINZ housing index is used for the first horizon forecast

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Mean**
AR	1.039	2.116	2.342	2.630	1.591	0.813	0.566	0.219	1.414
Factor	1.140	2.338	2.574	2.727	1.361	0.328	-0.163	-0.341	1.245
MMindicator	0.591	0.964	0.972	0.993	0.000	0.000	0.000	0.000	0.440
BVAR	0.610	0.946	0.894	0.966	0.241	0.205	0.040	-0.071	0.479
smallBVAR	0.530	0.748	0.758	0.845	0.505	0.410	-0.318	-0.534	0.368
ECM	0.825	1.619	1.518	1.441	0.221	-0.241	-0.365	-0.276	0.593
Cmb	0.436	0.669	0.621	0.630	0.240	0.048	-0.119	-0.161	0.295

[19]This is true for all models except the big BVAR and the REINZ VAR. These models generate their own first horizon forecast.

B. Model Evaluation

Tables 2 and 3 outline the RMSE and bias of each model over all horizons. Table 4 shows the RMSE of forecasts produced using equal weights, MSE weights and model selection.

Table 2: Root mean squared error

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Mean**
bigBVAR	1.803	3.306	5.326	7.563	8.846	9.557	10.020	10.143	7.070
AR	1.387	2.612	4.501	6.066	8.218	9.361	9.858	10.004	6.501
Factor	1.308	2.505	4.450	6.210	8.644	10.082	10.881	11.128	6.901
MMindicator	1.308	2.327	3.708	4.793	6.214	6.828	7.761	8.667	5.201
BVAR	1.308	2.479	4.172	5.660	7.672	8.283	8.667	8.989	5.904
smallBVAR	1.308	2.336	3.586	4.536	5.777	6.665	7.902	8.617	5.091
reinzVAR	1.610	2.291	3.241	4.341	5.837	7.341	8.240	8.487	5.173
ECM	1.387	2.514	4.226	5.644	7.501	8.267	8.582	8.249	5.796
Cmb	1.304	2.277	3.593	4.820	6.234	7.385	8.147	8.408	5.271
RBNZ	2.301	4.315	6.854	9.368	11.278	12.571	13.127	12.669	9.061

Table 3: Mean forecast error (bias)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Mean**
bigBVAR	-0.197	-0.685	-1.159	-1.708	-1.966	-1.685	-1.385	-0.940	-1.216
AR	-0.488	-0.734	-0.872	-0.767	-0.930	-0.729	-0.454	-0.103	-0.635
Factor	-0.526	-0.778	-0.870	-0.647	-0.513	-0.131	-0.230	-0.483	-0.522
MMindicator	-0.526	-0.432	-0.183	0.172	0.203	0.153	0.104	0.436	-0.009
BVAR	-0.526	-0.662	-0.464	0.194	0.632	1.192	1.310	1.231	0.363
smallBVAR	-0.526	-0.615	-0.475	-0.094	0.172	0.673	0.942	1.429	0.188
reinzVAR	-0.657	-0.849	-0.856	-0.536	-0.273	0.156	0.724	1.316	-0.122
ECM	-0.488	-1.341	-2.521	-3.772	-5.375	-6.171	-6.507	-6.339	-4.064
Cmb	-0.513	-0.773	-0.893	-0.901	-0.907	-0.875	-0.452	-0.471	-0.723
RBNZ	-1.341	-2.844	-4.829	-6.783	-7.914	-8.642	-8.900	-8.541	-6.224

Table 4: Root mean squared errors of forecasts using different weighting methods

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Mean**
Equal	1.291	2.311	3.729	4.903	6.429	7.315	7.955	8.204	5.267
MSE	1.304	2.277	3.593	4.820	6.234	7.385	8.147	8.408	5.271
ModelSelection	1.602	2.394	3.524	5.668	6.380	7.467	9.323	9.723	5.760

C. Forecasts

Figure 8 shows the combination and RBNZ forecasts for 1, 3, 5 and 7 horizons ahead. These forecasts tell a similar story to the forecasts that were shown in section 5. Namely, that the RBNZ consistently under-predicted annual house price inflation. However, the RBNZ was more accurate, relative to the combination method, in forecasting the strong downturn in house price inflation in 2007/08.

Figure 8: Combination and Reserve Bank Forecasts

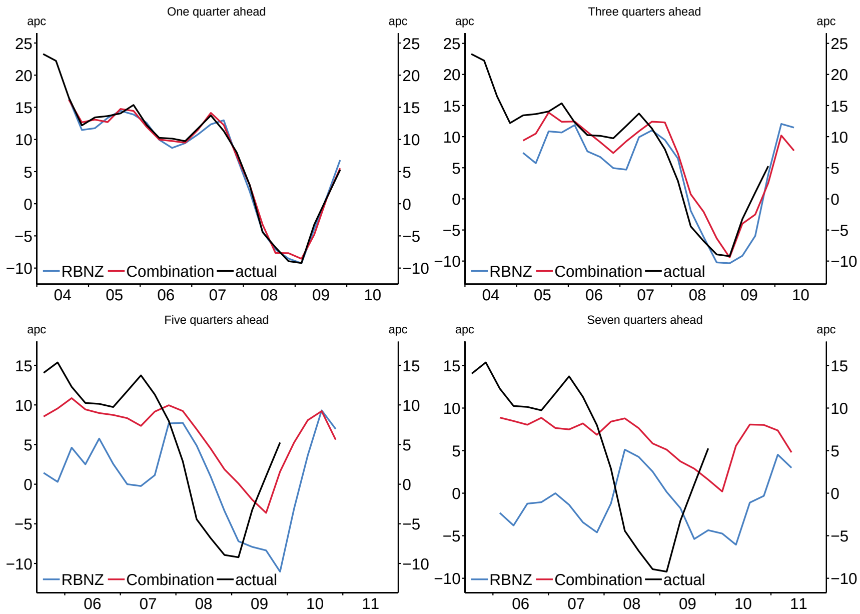


Figure 9 shows the RBNZ and combination forecasts made at a particular date. The title provides the date that the forecast was made and the vertical black line shows the date of the latest house price outturn.

Figure 9: Combination and RBNZ Forecasts