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Factor model forecasts for New Zealand

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Abstract[1]

This paper focuses on forecasting four key New Zealand macroeconomic variables using a dynamic factor model and a large number of predictors. We compare the (simulated) real-time forecasting performance of the factor model with a variety of other time series models and gauge the sensitivity of our results to alternative variable selection algorithms. We find that the factor model performs particularly well at longer horizons.

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1 Introduction

Each quarter, the Reserve Bank of New Zealand assesses the state of the economy and publishes forecasts in its *Monetary Policy Statement*. The Bank has a multitude of economic and financial data at its disposal (over 6000 series), all of which can be used to glean information about the economy. Yet, experience suggests that the usefulness of these data varies widely, both across the different series and over time. Indicators with good predictive ability over history may break down when used in forecasting, while indicators not so useful in the past may prove to be the most useful in future. Forecasting is thus fraught with difficulties; the informational content of each piece of data is small and, importantly, unknown to the forecaster in real time.

The time series models used in forecasting typically only incorporate a small handful of variables, chosen using a variety of different selection procedures. The final variables selected are thus considered representative of a larger population of potentially useful series. Recently, however, methods have been developed to distil information from a very large data set into a few variables (called factors). Forni et al (2000, 2004) and Stock and Watson (1998), for example, examine the properties of generalized dynamic factor models, based on the dynamic factor models of Sargent and Sims (1977) and Geweke (1977). In a series of papers, Stock and Watson (1998, 1999, 2002) use factor models to combine information from large panels of macroeconomic data in the US, and then use the estimated factors to forecast future realisations of a variety of macroeconomic series. In factor models a huge variety of series are used to identify the latent drivers – the factors – that are common to all of the series. These factors can then be used to forecast particular series of interest, such as GDP and inflation. Stock and Watson find that this two-step procedure yields forecasts that compare favourably to a large number of other univariate, bivariate, and multivariate benchmarks (according to comparisons of mean squared forecast errors, MSFEs). Stock and Watson's (1999) results are particularly striking when forecasting inflation.

With similarly impressive results, Forni et al (2001) and Marcellino et al (2003) use factor models to analyse large panels of Euro-area data, while Artis et al (2001) use factor models to forecast economic and financial variables for the United Kingdom.

In this paper, we examine – for the first time – the forecasting performance of factor models in the New Zealand context. We also analyse the forecasting performance of a range of other univariate, bivariate and multivariate forecasts. Forecasts are made for four key macroeconomic variables (the consumer price index, gross domestic product, the 90 day interest rate and the trade weighted nominal exchange rate), and the performance of competing models is tested using fully recursive real-time out-of-sample forecast simulations. In all cases, our forecasts are compared with a relatively sophisticated benchmark – the real-time forecasts published by the Reserve Bank of New Zealand.

The transformations made to the indicators entering into the factor model ultimately influence the model's forecasting performance. Thus, we also gauge the sensitivity of our forecasting results to assumptions made in transforming the data. Specifically, we compare the case where each series determines its own transformation (to maximise in-sample fit) with the case where the data transformations are imposed exogenously (as is commonplace in the empirical literature).

The size of the data set from which factors are extracted may also be important for forecasting. Boivin and Ng (2003) show that extracting factors from larger data sets does not always yield better forecasting performance. Instead, they propose some ad hoc rules to reduce the size of their data set before factors are extracted. They show that forecasting performance can be improved by reducing the size of the data set based on removing (or down-weighting) series with highly cross-correlated errors in the factor model, and rules based on categorising the data into sub-groups with an economic interpretation (real and nominal variables, for example). We propose another approach, which has the added feature of linking the data to the particular variable and the particular horizon being forecast. We effectively group series together based on their past predictive performance, thereby tailoring our data-reduction rule to the particular task at hand – forecasting.

We find that the factor model performs well and can serve as a useful complement to the Reserve Bank's current forecasting methodologies, especially at longer horizons. We also find that choosing data transformations based on past predictive performance generally

deteriorates our forecasting performance, but that our data-reduction rule yields superior forecasts at some horizons.

The paper proceeds as follows. We begin with a general description of the factor model. This is followed by a description of our raw data, and a description of two different data sets which we analyse separately (each with different assumptions regarding how the raw data are transformed). We then outline an algorithm that we use to vary the size of the data set from which the factors are extracted. In section 4 we lay out our forecasting models, and section 5 describes our out-of-sample forecasting exercise. Section 6 contains our empirical findings, and we conclude in section 7.

2 An approximate dynamic factor model

2.1 The factor model

In this section, we outline the generalised factor model. For a more detailed description of factor models, their estimation, and their use in forecasting, see Stock and Watson (1998).

Let X_{it} be the observed data for the ith macroeconomic time series at time t, for $i = 1, \cdots, N$ and $t = 1, \cdots, T$. Now suppose X_{it} has an approximate linear dynamic factor representation with $\bar{r}$ common dynamic factors (f_t):

$$X_{it} = \lambda_i(L) f_t + e_{it} \tag{1}$$

where e_{it} is an idiosyncratic disturbance with limited cross-sectional and time series dependence, and $\lambda_i(L)$ are polynomials of non-negative powers of the lag operator L, where $Ly_t = y_{t-1}$. This model is the dynamic factor representation of the data; see, for example, Geweke (1977), Sargent and Sims (1977) and Forni et al (2000, 2004). If the lag polynomials $\lambda_i(L)$ are assumed to have finite orders of at most q, (1) can be written in static form:

$$X_t = \Lambda F_t + e_t \tag{2}$$

In the above equation $X_t = (X_{1t}, X_{2t}, \cdots, X_{Nt})'$, $\Lambda = (\lambda_1, \lambda_2, \cdots, \lambda_N)'$, $F_t = (f_t^{'}, \cdots, f_{t-q}^{'})'$, and $e_t = (e_{1t}, e_{2t}, \cdots, e_{Nt})'$ (Stock and Watson, 1998). Note that the factors F_t, the loadings Λ, and the disturbances e_t are not observable. When the idiosyncratic components e_t are allowed to exhibit some cross-correlation, the model is said to have an approximate factor structure. Approximate factor models are more general than the strict factor model used in classical factor analysis, which assumes that e_{it} is uncorrelated across i (Bai and Ng, 2002).

2.2 Estimation

When N is small, factor models are often expressed in state space form and estimated using the Kalman Filter (Stock and Watson, 1989). The drawback with this is that the number of parameters to be estimated, and the difficulty of the estimation problem, increases with N. Stock and Watson (1998), however, show that common factors can be consistently estimated in large panels using asymptotic principal components. The number of factors that can be estimated using this method is then min{N,T} – much larger than is permitted by state space models.

When k factors are allowed for in the estimation, where $k <$ min{N,T}, estimates of λ^k and F^k are obtained by solving the following optimization problem:

$$V(k) = \min_{\Lambda, F^k} (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \lambda_i^k F_t^k)^2 \qquad (3)$$

If

$$\frac{F^{k'} F^k}{T} = I^k \qquad (4)$$

is imposed, then the estimated factor matrix $\tilde{F}^k$ is simply $\sqrt{T}$ times the eigenvectors corresponding to the k largest eigenvalues of the $T \times T$ matrix XX' (Bai and Ng, 2002). Given $\tilde{F}^k$, $\tilde{\Lambda}^k$ is then:

$$\tilde{\Lambda}^k = \frac{\tilde{F}^{k'} X}{T} \qquad (5)$$

But this solution is not unique, even though the sum of squared residuals *V(k)* is. Another solution, for example, can be found by imposing:

$$\frac{\overline{\Lambda}^{k'} \overline{\Lambda}^k}{N} = I^k \qquad (6)$$

$\overline{\Lambda}^k$ is then constructed as $\sqrt{N}$ times the eigenvectors corresponding to the k largest eigenvalues of the $N \times N$ matrix $X'X$.[2]

Bai and Ng (2002) propose several information criteria for estimating the number of factors in (3). However, in preliminary work, we found that these criteria typically retained a large number of factors, too many to include in the forecasting equation without running low on degrees of freedom. Instead of using the Bai and Ng criteria, we thus extract a fixed number of factors from the data, and allow the final number of factors to be determined by a criterion that minimises the MSFEs, as in Stock and Watson (1998, 2002).

3 Data

This section describes the macroeconomic variables that we forecast. It also describes two different variants of the data set, which we analyse separately. One data set fixes the transformations performed on the raw data, as is typical in the literature. The other data set is constructed in a more agnostic fashion, allowing the transformations of the variables to be determined by the data. In both cases, we vary assumptions regarding the size of the data sets, based on the past predictive ability of the indicators (explained below).

3.1 The forecast series

[2] The second set of calculations is computationally less costly when $T>N$, while the first is less intensive when $T<N$.

We forecast four series (z_t): the growth rate of the Consumer Price Index excluding credit charges (CPI); the growth rate of real Gross Domestic Product (GDP); the level of 90 day bank bill interest rate; and the growth rate of the nominal trade weighted exchange rate index. All data are analysed at a quarterly frequency. Our sample period ranges from 1992:2 to 2004:3. We forecast at horizons between 1 and 8 quarters ahead, $h = (1,\dots,8)$.

3.2 The raw indicators

The raw indicator set contains 386 series drawn from a variety of sources (appendix A). The set of indicators is compiled from the Reserve Bank's databases and consists of both monthly and quarterly data. All monthly data are aggregated into quarterly data using monthly averages.

Both forward-looking and backward-looking indicators of economic activity and prices are incorporated into the data set, although special attention is given to activity-related, forward-looking variables.[3] Some of the series were included at the finest level of dis-aggregation possible, as well as in aggregate form, while other series were only included as aggregates. Broadly speaking, the forward-looking series are included at their finest level of dis-aggregation and the backward-looking variables are included only as aggregates. Series considered to display excessive volatility in dis-aggregate form were only included as aggregates.

The raw data are pre-processed into two different data sets: a 'fixed' data set and a 'flexible' data set. The forecasting experiments that follow are performed on each of these data sets.

3.1.1 Fixed data set

In the fixed data set, all series are seasonally adjusted using X12 (additive). The series are then transformed to account for stochastic and

[3] Stock and Watson (1999) found that data relating to real activity performed well when forecasting inflation.

deterministic trends; the I(1) series are logged and then differenced, and the I(0) series are left as levels.

3.1.2 Flexible data set

In the flexible data set, *the transformations on the base data are chosen to maximise past predictive performance,* and can vary over forecast horizons. All series are first seasonally adjusted using X12. The raw, unseasonally adjusted data and the seasonally adjusted data are then transformed using the same 5 transformations: quarterly differences; seasonal differences, log quarterly differences; log seasonal differences; and a one-sided Hodrick-Prescott (HP) filter (see Harvey and Jaeger, 1993).[4] This means that a single 'root' series (subscript i) has 12 possible variants (superscript j) – the raw and seasonally adjusted series in levels, plus the 5 different transformations of each. For each forecast horizon, the flexible data set thus initially contains over 4000 series, but only 386 untransformed 'base' series. We then introduce an algorithm to reduce this data set, using past predictive performance to determine which transformation of each indicator enters into the final data set.

For each forecast horizon h, each stationary forecast variable y_t, and each potential indicator $x_{i,t}^j$, where $h = (1,\dots,8)$, $i = (1,\dots,386)$ and $j = (1,\dots,12)$, the following equation is estimated using OLS:

$$y_t = \beta_0 + \beta_1 x_{i,t-h}^j + e_{i,t} \tag{7}$$

The R-squareds (the coefficients of determination) from these bivariate regressions are then used to sort the indicators from most to least informative. We allow only the transformation j of the untransformed series i that yields the highest R-squared to enter into the final flexible data set.

The flexible data set thus contains the transformations of the original 386 series that maximise past predictive performance according to R-

[4] Our focus is on forecasting, we thus prefer to use a one-sided HP filter – which is not subject to trend revisions like its two-sided analogue.

squared, at a lag equal to the horizon *h* being forecast. The flexible data set thus depends on both the horizon and the forecast variable (there is actually a multiplicity of flexible data sets), whereas the fixed data set is the same across horizons and variables.

3.3 Varying the size of the data set based on past predictive performance

So how does the number of series in the data set influence the factor model's forecasting performance? This remains an open question in the empirical literature. Thus far, the empirical work tends to favour using as much data as possible to estimate factors. And for good reason – the theory of factor model estimation was developed for large N and T. Boivin and Ng (2003), however, show that extracting factors from larger data sets does not always yield better forecasting performance, especially when the added data increases cross-section correlation in the idiosyncratic errors. Indeed, conceptually, it seems reasonable to exclude those series that are in some sense idiosyncratic – those series whose inclusion deteriorates the overall quality of the data set.

Boivin and Ng (2003) reduce the size of their empirical data set using rules based on removing (or down-weighting) series with highly cross-correlated errors in the factor model, and rules based on categorising the data into sub-groups with an economic interpretation (real and nominal variables, for example) before factors are extracted. We propose a similar approach, which has the added feature of linking the data to the particular variable and the particular horizon being forecast.

For both the fixed and flexible data sets, we reduce the size of our data set by categorising our data based on past predictive performance. In particular, we compute (7) using both the fixed and flexible data sets and rank the resulting R-squareds (as above). Now, the size of both data sets is allowed to vary, based on the past predictive performance of the indicators entering into each data set. Specifically, we choose to 'cut off' the top proportion θ of the ranked indicators and only allow these indicators to enter into each data set, with $\theta =$(5%, 10%, 50%, 100%). The smallest data set contains the top 5% of the ranked indicators, and the largest data set contains all 386 indicators. We then extract factors from these different-sized data sets.

Effectively, by allowing all of the indicators, $\theta = 100\%$, into a data set, we assume that all of the data have some information useful for forecasting the particular variable at the particular horizon we are interested in. Conversely, by trimming the size of the data sets based on R-squared, we impose a zero weight on those indicators that share lower common variance with the variable and horizon being forecast. In this way we hope to better estimate the factors driving each variable on a case-by-case basis – we hope to tailor each data set to the particular forecasting problem at hand.

Notice that when $\theta = 100\%$ all of the indicators are included into both data sets, but the fixed data set has deterministic transformations and will be the same over forecast horizons.

4 Forecasts

This section outlines the forecasts we compare in our analysis, beginning with a general description of our forecasting model.

4.1 The *h*-step-ahead forecast

Aside from the vector autoregressive and the Reserve Bank of New Zealand forecasts, all of the forecasts that we analyse are based on *h*-step-ahead linear projections. Specifically, the *h*-step-ahead variable y_{t+h}^h is forecast using the following regression model:

$$y_{t+h}^h = \phi + \beta(L) f_t + \gamma(L) y_t + e_{t+h}^h \qquad (8)$$

where e_{t+h}^h is an error term, ϕ is a constant, $\beta(L)$ and $\gamma(L)$ are lag polynomials, and f_t is a vector of predictor variables; the interpretation of f_t depends on the particular model being used. The construction of y_{t+h}^h depends on whether the series of interest z_{t+h}^h is modelled as being I(0) or I(1). If z_{t+h}^h is modelled as I(0):

$$y_{t+h}^h = z_{t+h}^h \text{ and } y_t = z_t \qquad (9)$$

And, if z^h_{t+h} is modelled as I(1):

$$y^h_{t+h} = \ln\left(\frac{z^h_{t+h}}{z^h_t}\right) \text{ and } y_t = \ln\left(\frac{z_t}{z_{t-1}}\right) \tag{10}$$

or

$$y^h_{t+h} = \ln(z^h_{t+h}) - \ln(z^h_t) \text{ and } y_t = \ln(z_t) - \ln(z_{t-1}) \tag{11}$$

We model CPI, GDP and the exchange rate using (10), and the interest rate using (11).[5]

4.2 Forecasting models

The range of different forecast models that we estimate over both the fixed and flexible data sets is discussed below.

4.2.1 Autoregressive forecasts

The autoregressive forecast *far* is based on (8), excluding f_t. As is commonplace in the literature, we choose the lag length according to a Schwartz-Bayesian Information Criterion (BIC), with lags varying from 0 to 4: the largest autoregressive model possible includes 4 lags and a constant and the smallest includes only a constant.

4.2.2 Bivariate forecasts

We construct bivariate forecasts for each indicator. In the bivariate regressions f_t in (8) becomes a single indicator $x_{i,t}$. For each bivariate forecast, we allow 1 to 4 lags of $x_{i,t}$ and 0 to 4 lags of the dependent variable y_t, with all the lags selected using the BIC. The BICs for all bivariate indicator equations are then ranked. The best bivariate indicator *fbiv_best* is found, along with the mean *fbiv_mean* and

5 Modelling the 90 day interest rate in differences is supported by evidence of a falling neutral real interest rate in New Zealand over our sample period (Basdevant et al (2004)).

median *fbiv_med* forecasts from the top 5% and 10% of the ranked bivariate indicators.[6] These 5% and 10% cut-off points correspond to the first two θ cut-offs that we use to vary the size of the two data sets when we extract factors.

4.2.3 Factor model forecasts

We analyse three different variants of factor model, similar to Stock and Watson (2002). The first variant excludes lagged dependent variables and explores forecasts when different numbers of contemporaneous factors *k* are included. In this group of forecasts equation (8) is estimated with *k* contemporaneous factors, with *k* ranging from 1 to 4 *fdi_k*. In (8) $\beta(L)f_t$ becomes βf_t, where f_t is a $k \times 1$ vector of factors. We then define *fdi_bic* to be the forecast where *k* is chosen by the BIC.

The second set of factor forecasts is similar to the first, but allows the BIC to select between 0 and 4 lags of the dependent variables. These forecasts are denoted *fdiar_k* for fixed *k*, and *fdiar_bic* where *k* is chosen by the BIC.

The third factor forecast, *fdiarlag_bic*, is the most general. Here, we allow the BIC to determine the number of factors (1 to 4), the number of lagged factors (0 to 2), and the number of lagged dependent variables (0 to 4). Together, we estimate 44 different factor models for each horizon (and for each data set): the 11 models outlined above over the 4 different data set cut-offs (θ).

4.2.4 Vector Autoregressive (VAR) forecast

The VAR forecasts, *fvar*, are computed from a system containing each of our four forecast variables. The VAR is estimated in levels, and the number of lags of the endogenous variables is set at 2. VAR forecasts are made by iterating forecasts forward, unlike in the *h*-step-ahead method we use for our other forecasting models.

6 In a cross-country forecasting exercise, Stock and Watson (2004) found that the simple average of indicator forecasts out-performed a wide range of different methods of combining forecasts, when forecasting output growth.

4.2.5 Reserve Bank forecasts

The Reserve Bank forecasts, denoted *rbnz*, are the real-time forecasts published in the Reserve Bank's quarterly *Monetary Policy Statement*. The forecasts are a combination of model-based forecasts and judgement. There is a distinction between how the Reserve Bank forecasts over the near-term (1 to 2 quarters ahead) and how it forecasts over longer horizons. The Reserve Bank's near-term forecasts can be characterised as being more judgement- and indicator-based. The longer-term forecasts, on the other hand, are made with the help of a large-scale macroeconomic model, the Reserve Bank's Forecasting and Policy System (FPS).[7]

5 Out-of-sample forecast comparisons

Our forecasts are compared using a fully recursive simulated out-of-sample methodology. For these simulations, we transform all data and estimate all equations for each quarter from 1999:4 to 2004:3. These forecasts are then tested against the ex-post data from 2000:1 to 2004:4. The real-time exercise is more 'pure' than is common in the literature since the raw data are seasonally adjusted each quarter, thereby mimicking the real-time problems associated with estimating seasonal factors. Also, we use real-time vintages of our forecast series in estimation – the data that were available when such forecasts would have been made.

For each of our forecasts, we compute the implied levels of the forecast variables; the CPI growth forecasts, for example, are transformed into CPI level forecasts, ie $z_{t+h}^{h} = z_t(1+y_{t+h}^{h})$. We then construct annual percentage changes for the CPI, GDP and the exchange rate, leaving the interest rate in levels. These are the forecasts that we compare in our real-time simulations: y_{t+h}^{h} for the CPI becomes the annual percentage change of the CPI in period $t+h$, likewise for the other variables, except interest rates, which are left as levels.

7 See Drew and Hunt (1998) for a detailed description of FPS.

The forecasting performance of a candidate forecast is evaluated by comparing its out-of-sample MSFE to a Reserve Bank of New Zealand benchmark. For an *h*-step ahead forecast, the MSFE of a candidate model *i* relative to the benchmark Reserve Bank forecast *0* is:

$$MSFE\_relative = \frac{\sum_{t=T_1}^{T_2-h}(\hat{y}_{i,t+h}^{h} - y_{t+h})^2}{\sum_{t=T_1}^{T_2-h}(\hat{y}_{0,t+h}^{h} - y_{t+h})^2} \tag{12}$$

where T_1 and $T_2 - h$ are the first and last dates over which the out-of-sample forecasts are compared, respectively. Due to a small out-of-sample period, we test whether the MSFEs of the candidate forecast are significantly smaller than those of the Reserve Bank using the Wilcoxon ranked sign test. The serial dependence in the errors for *h*>1 is handled via the use of Bonferroni bounds, as suggested by Diebold and Mariano (1995).[8] Specifically, we assume that the loss differentials (the differences in MSFEs) are symmetrically distributed about zero and test:

Null Hypothesis: $E[\varepsilon_t] = 0$ (13)

against:

Alternative Hypothesis: $E[\varepsilon_t] < 0$ (14)

where:

$$\varepsilon_t = (\hat{y}_{i,t+h}^{h} - y_{t+h})^2 - (\hat{y}_{0,t+h}^{h} - y_{t+h})^2 \tag{15}$$

As above, the subscript *i* refers to a candidate model and the subscript *0* refers to forecasts from the Reserve Bank of New Zealand.

8 We have just 20 forecast errors to analyse when *h*=1, hence we decide to use a finite-sample non-parametric test.

It is well known that even optimal *h*-step-ahead forecast errors will follow a moving average process of order *h-1*. As the Wilcoxon ranked sign test requires independence in the errors, it needs an adjustment when *h*>1. Under the assumption that the loss differentials (ε_t) are *h*-1-dependent, following *h* sub-samples will contain uncorrelated elements:

$$\{\varepsilon_1, \varepsilon_{1+h}, \varepsilon_{1+2h}, \ldots\}, \{\varepsilon_2, \varepsilon_{2+h}, \varepsilon_{2+2h}, \ldots\}, \ldots, \{\varepsilon_h, \varepsilon_{2h}, \varepsilon_{3h}, \ldots\} \quad (16)$$

Now, *h* tests can be performed on these samples, each of size α/h. If the null hypothesis is rejected for any of the *h* samples, the overall null is rejected, with Bonferroni's inequality ensuring that the overall size of the test is bounded by α (Diebold and Mariano, 1995).[9] It should be noted that this procedure is conservative, even asymptotically. As an alternative, an exact test could be performed on just one of the *k* error series at a level α, but this test comes at a cost of reduced power due to the discarded observations.

6 Empirical results

In this section, we report the forecast comparisons for each of the macroeconomic variables. Our statistical tests yield disappointingly few significant results, even though we use quite liberal levels of significance. We thus prefer to discuss the results in a descriptive manner. We leave a more rigorous statistical analysis of the competing models (and data sets) for the future, when more time series data is available.

6.1 CPI inflation

The MSFEs of our forecast models relative to the Reserve Bank benchmark are displayed in table B1. In general, the Reserve Bank forecasts have lower MSFEs at shorter horizons, *h*<4. At longer horizons, however, some of our forecasting models begin to outperform the benchmark. As noted by Stock and Watson (2002) for the United States, models that incorporate one or two factors (with or without autoregressive terms) generally perform better than models that allow for more factors. Models that allow for multi-factors and lags of the

9 The critical values are taken from Hollander and Wolf (1973).

factors, *fdiarlag_bic*, perform the worst out of the competing models. Similarly, forecasting using the best bivariate indicator at each horizon *fbiv_best* yields poor results, and the VAR forecast *fvar* is worse than the best factor model forecast at all horizons except when *h*=6 and 7.

The mean and median bivariate forecasts, *fbiv_mean* and *fbiv_med*, compare favourably to both the Reserve Bank and the factor model forecasts, especially at longer horizons. It also seems that small gains can be made by averaging or taking the median of a larger number of bivariate indicators, ie when $\theta = 10\%$, rather than $\theta = 5\%$. At longer horizons, the simple autoregressive model *far* also performs well relative to most models – including the Reserve Bank benchmark.

Making the transformations of the regressors data-dependent (ie the flexible data set, the right hand panel in the tables) seems to worsen forecasting performance relative to the case where transformations are applied in a pre-determined fashion (the fixed data set), though this result is not as clear-cut when varying the size of the data set. At shorter horizons, extracting factors from the entire data set, $\theta = 100\%$, leads to better forecasts than when the factor model is restricted to a smaller data set of 'better' indicators. At some longer horizons, however, such as *h*=4 and *h*=8, the factor models seem to perform better with fewer indicators. Thus, there does not seem to be any clear relationship between the size of the data set, as represented by θ, and forecast performance.

6.2 GDP growth

The MSFEs of our GDP forecasts models relative to the Reserve Bank benchmark are displayed in table B2. Similar to CPI inflation, the Reserve Bank forecasts outperform the competing models at shorter horizons (*h*<4), and at longer horizons the competing models begin to outperform the Reserve Bank benchmark forecasts. Also, it appears that including only one or two factors (with or without autoregressive terms) generally leads to better forecasts. Again, VAR models *fvar*, models that allow for multi-factors and lags of the factors *fdiarlag_bic*, and the best bivariate model at each horizon *fbiv_best* yield poor forecasts.

As with the results for CPI inflation, the mean, median, and autoregressive forecasts, *fbiv_mean*, *fbiv_med*, and *far,* compare favourably to both the Reserve Bank and the factor model forecasts, especially at longer horizons. And it appears that small gains can be made when averages or medians are taken over a larger number of bivariate forecasts.

Likewise, it seems that allowing the data to determine the transformations that are performed on the raw indicators (the flexible data set) deteriorates most of the factor model forecasts, particularly at longer horizons. The ideal size of the data set from which factors are extracted is also not clear-cut. At shorter horizons, it appears that including all of the indicators, $\theta = 100\%$, improves the forecasting performance of models with one or two factors. Yet, at longer horizons, some of the better factor models perform better with fewer indicators. For example, when h=4 or 6, the model with one factor and no autoregressive terms *fdi_1* applied to the fixed data set outperforms the benchmark by more when the factor model is applied to fewer indicators (according to MSFE).

6.3 Interest rate

The MSFEs of our interest rate models relative to the Reserve Bank benchmark are displayed in table B3. The results for the interest rate are broadly the same as for CPI inflation. That is: the competing models are out-performed by the Reserve Bank benchmark at shorter horizons, h<5, and are comparable or better to the benchmark forecasts at longer horizons. The optimal number of factors to incorporate in the interest rate models (with or without autoregressive terms) is difficult to determine. The mean and median bivariate forecasts *fbiv_mean* and *fbiv_med* compare favourably to both the Reserve Bank and the factor model forecasts at longer horizons; the best bivariate model, *fbiv_best*, allowing for lags of the factors *fdiarlag_bic*, and the VAR *fvar* all performed poorly. Lastly, the fixed data set outperforms the flexible data set.

Although not entirely clear cut, it seems that the better factor model forecasts tend to use the entire data set, $\theta = 100\%$, at most horizons. It is also worth noting that the univariate autoregressive model *far* performs particularly well at longer horizons, h<4, and generally yields the lowest MSFE of the competing models.

6.4 Exchange rate

The MSFEs of our exchange rate models relative to the Reserve Bank benchmark are displayed in table B4. Our results for forecasting the exchange rate are disappointing; our models are outperformed by the Reserve Bank benchmark over most horizons.

Comparing our forecasts, the same themes emerge. The models with one or two factors (drawn from the fixed data set) and the average and median forecasts seem to perform best. The VAR *fvar*, the best bivariate forecasts *fbiv_best*, and the models that allow lagged factors *fdiarlag_bic* perform worst. Similar to CPI and GDP, it is not clear-cut whether allowing for a larger data set improves factor model forecasts at longer horizons.

7 Summary and conclusions

Several conclusions emerge from our empirical results. First, across most of the variables we forecast, with the exception of the exchange rate, the forecasting models that use a large number of predictors (either factor models with one or two factors, or the mean/median of a range of bivariate forecasts) seem to out-perform the Reserve Bank benchmark at longer horizons – one year ahead and beyond. Likewise, at longer horizons, a simple autoregressive forecast generally performs well relative to Reserve Bank benchmark. Thus, these models appear to be tough benchmarks for future forecasting model comparisons in New Zealand.

Second, it seems that at short horizons it is better to allow the factor model to use all of the indicators than to impose a zero weight to the indicators with relatively poor predictive performance in the past. At longer horizons, the evidence is less clear-cut. This may have implications for the degree of ‘data-mining’ that can take place before factors are extracted from the data and, as a consequence, for the size of the data set from which factors are extracted. While our data-reduction rule was ad hoc, it still yielded superior forecasts at some horizons.

This rule, together with the rules outlined in Boivin and Ng (2003), may help guide future researchers in determining how to choose data for factor model forecasts.

Our third conclusion is that allowing data transforms to be dictated by past predictive performance generally leads to poorer forecasting performance. This reminds us that transforming data to improve within-sample fit may come at the cost of over-fitting the data, evidenced by degraded out-of-sample forecasting performance. Our data-dependent transformation-selection algorithm generally chooses transforms that are heavily dependent on the past for longer horizons (seasonal differences and one-sided gaps). This means that the transformed data will be slow to adjust at turning points. A longer out-of-sample period would help gauge whether sufficient gains can be made over the cycle to outweigh the costs incurred when using this type of algorithm around turning points.

Overall, we find merits in using a large number of predictors to forecast in New Zealand, especially at longer horizons. It should be noted, however, that our out-of-sample forecasting exercises were conducted with a quite short sample of data. Our results will thus need to be revisited in future.

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Appendix A Data

#	Source and Series
	Statistics New Zealand
	National accounts
1	Real GDP – Total Expenditure
2	Real GDP - Total Production
3	Real GDP - Exports Total
4	Real GDP - Imports Total
5	Real GDP – Agriculture
6	Real GDP - Forestry, Fishing, Mining
7	Real GDP - Fishing & Hunting
8	Real GDP - Forestry & Logging
9	Real GDP - Mining & Quarrying
10	Real GDP - Primary Industries
11	Real GDP - Manufacturing - Primary Food
12	Real GDP - Manufacturing - Other Food
13	Real GDP - Manufacturing - Primary Food, beverage, tobacco
14	Real GDP - Manufacturing - Textiles & Apparel
15	Real GDP - Manufacturing - Wood & Paper products
16	Real GDP - Manufacturing - Printing & Publishing & Recorded Media
17	Real GDP - Manufacturing - Chemicals, Plastics, Petroleum, Rubber
18	Real GDP - Manufacturing - Non-metallic Mineral products
19	Real GDP - Manufacturing - Basic Metal products
20	Real GDP - Manufacturing - Machinery and Equipment
21	Real GDP - Manufacturing - Furniture & other manufacturing
22	Real GDP - Manufacturing - Total
23	Real GDP - Electricity ,Gas &Water
24	Real GDP - Construction
25	Real GDP - Goods producing industries
26	Real GDP - Wholesale and Retail , Accommodation Cafes and Restaurants
27	Real GDP - Wholesale trade
28	Real GDP - Retail Trade, including motor vehicle repairs
29	Real GDP - Retail Trade, accommodation, cafes, restaurants
30	Real GDP - Accommodation, restaurants, cafes
31	Real GDP - Transport, Communications, Business and Personal Services
32	Real GDP - Transport, Storage
33	Real GDP - Communications
34	Real GDP - Transport, Storage & Communications
35	Real GDP - Finance and Insurance
36	Real GDP - Real Estate and Business services
37	Real GDP - Finance, Insurance, Property and Business services
38	Real GDP - Education, health, cultural, recreation, personal & other
39	Real GDP - Owner Occupied Dwellings
40	Real GDP - General Govt Services - Govt Administration and Defence
41	Real GDP - General Govt Services - Local Govt Services
42	Real GDP - General Government Services
43	Real GDP - Service Industries
44	Real GDP - Unallocated
45	Consumption deflator
46	GDP deflator
47	GDP deflator (excluding exports)

Retail Trade Survey

48 Real Retail Sales - Subtotal (ex auto)
49 Real Retail Sales - Grand total
50 Nominal Retail Sales - Subtotal (ex auto)
51 Nominal Retail Sales - Grand total
52 Retail trade deflator (ex auto)
53 Retail trade deflator

Household Labour Force Survey

54 Official employed
55 Official hours worked
56 Official labour force
57 Official not in labour force
58 Official participation rate
59 Official unemployed
60 Official unemployment rate
61 Labour productivity
62 Total Paid Hours - Total All Industries
63 Labour productivity

64 Total Paid Hours - Forestry & Mining
65 Total Paid Hours – Manufacturing
66 Total Paid Hours - Electricity, Gas & Water Supply
67 Total Paid Hours – Construction
68 Total Paid Hours - Wholesale Trade
69 Total Paid Hours - Retail Trade
70 Total Paid Hours - Accommodation, Cafes & Restaurants
71 Total Paid Hours - Transport, Storage & Communication Services
72 Total Paid Hours - Finance & Insurance
73 Total Paid Hours - Property & Business Services
74 Total Paid Hours - Government Administration & Defence
75 Total Paid Hours – Education
76 Total Paid Hours - Health & Community Services
77 Total Paid Hours - Cultural & Recreational Services
78 Total Paid Hours - Personal & Other Services

79 Average hourly earnings (ord + o/time) - Acc, cafes, & Restaurants
80 Average hourly earnings (ord + o/time) – Construction
81 Average hourly earnings (ord + o/time) - Cultural & recreational services
82 Average hourly earnings (ord + o/time) - Education
83 Average hourly earnings (ord + o/time) - Electricity, gas & water
84 Average hourly earnings (ord + o/time) - Finance & insurance
85 Average hourly earnings (ord + o/time) - Forestry & mining
86 Average hourly earnings (ord + o/time) - Govt admin and defence
87 Average hourly earnings (ord + o/time) - Health & community services
88 Average hourly earnings (ord + o/time) - Manufacturing
89 Average hourly earnings (ord + o/time) - Personal & other services
90 Average hourly earnings (ord + o/time) - Property & business services
91 Average hourly earnings (ord + o/time) - Retail trade
92 Average hourly earnings (ord + o/time) - Total
93 Average hourly earnings (ord + o/time) - Transport, storage & communication
94 Average hourly earnings (ord + o/time) - Wholesale trade
95 Average hourly earnings (ordinary time) - Private sector
96 Average hourly earnings (ordinary time) - Public sector
97 Average hourly earnings (ordinary time) - All sectors

Building consents

98 Houses and flats – Number
99 Total additions and alterations - Number
100 Total new/altered – Number
101 New residential buildings – Total
102 Apartment Buildings – number
103 New Dwellings Average Price per square metre

Building work put in place

104 Real building work put in place - Residential
105 Real building work put in place - Non-residential

Car registrations

106 New vehicles - including cars previously registered overseas

Producers' Price Indexes

107 PPI Inputs - All Industries
108 PPI Outputs - All Industries

Merchandise Trade Indexes

109 Terms of Trade Index
110 Export volume index -All Merchandise
111 Export Price Index -All Merchandise
112 Volume of Total Merchandise Imports
113 Import Price Index Total Merchandise Imports

External Migration

114 Net short-term migration
115 Net permanent & long-term migration
116 Short-term visitor arrivals

Energy production data

117 Electricity generation - Sale to consumers (Hydro)
118 Electricity generation - Sale to consumers (Thermal)
119 Gas Production
120 Electricity generation

Slaughter numbers

121 Livestock slaughter, by weight, millions kg
122 Cattle slaughter, by total number
123 Sheep slaughter, by total number
124 Lamb slaughter, by total number

Reserve Bank of New Zealand

Money and credit aggregates

125 Official series of M1
126 Official series of M2
127 Official series of M3
128 Official series of PSCR
129 Official series of DC
130 Household claims

Interest and exchange rates

131 Monetary conditions index
132 Trade weighted index
133 NZD/AUD exchange rate (average 11am)

134 NZD/GBP exchange rate (average 11am)
135 NZD/JPY exchange rate (average 11am)
136 NZD/USD exchange rate (average 11am)
137 Real exchange rate
138 Real exchange rate (deviation from equilibrium)

139 Real 90 day interest rate (deviation from equilibrium)
140 Nominal 90 day interest rate (deviation from equilibrium)
141 Yield spread (90day rate - 10 year bond yield)
142 Australia 10 year bond
143 Australia 90 day bank bill
144 Australia yield spread (90day rate - 10 year bond yield)
145 US 10 year bond
146 US 90 day bank bill
147 US yield spread (90day rate - 10 year bond yield)
148 World long interest rates
149 World short interest rates
150 World yield spread (90day rate - 10 year bond yield)

Output and prices

151 World real GDP - Trade weighted
152 Growth difference between NZ and ROW (APC)
153 World CPI trade weighted

Marketscope Survey

154 Expected current inflation – Mean
155 Net % Exp Higher Inflation (12 Months)
156 Expected Inflation (12 Months) - Mean

Survey of Expectations

157 Exp quarterly CPI - next quarter
158 Exp annual CPI - 1 year from now
159 Exp annual CPI - 2 years from now
160 Exp HLFS Unemployment Rate - 1 year ahead

Datastream

Prices

161 Consumers Price Index - Australia
162 Consumers Price Index - Euro
163 Consumers Price Index - Japan
164 Consumers Price Index - UK
165 Consumers Price Index - US

Output

166 GDP (constant prices) - Australia
167 GDP (constant prices) - Europe
168 GDP (constant prices) - Japan
169 GDP (constant prices) - US

Oil prices

170 Brent oil prices ($US/barrel)

Real Estate Institute of New Zealand

Housing-related data

171 Median dwelling price
172 Median list price

173 No of Dwelling Sales
174 No of Dwelling Sales – Auckland
175 Median days to sell

Quotable Value New Zealand

House prices

176 Quarterly House Price Index

New Zealand Institute of Economic Research

Quarterly Survey of Business Opinion

177 ECONOMY-WIDE - PAST 3 MONTHS - Average Costs
178 ECONOMY-WIDE - NEXT 3 MONTHS - Average Costs
179 ECONOMY-WIDE - PAST 3 MONTHS - Average selling price
180 ECONOMY-WIDE - NEXT 3 MONTHS - Average selling price
181 ECONOMY-WIDE - Capacity Utilisation
182 ECONOMY-WIDE - PAST 3 MONTHS - Domestic Trading Activity
183 ECONOMY-WIDE - NEXT 3 MONTHS - Domestic Trading Activity
184 ECONOMY-WIDE - Find. labour: skilled
185 ECONOMY-WIDE - Find labour: unskilled
186 ECONOMY-WIDE - General bus situation
187 ECONOMY-WIDE - New investment: buildings
188 ECONOMY-WIDE - New investment: Plant and Machinery
189 ECONOMY-WIDE - Limiting factor – Capital
190 ECONOMY-WIDE - Limiting factor – Finished orders
191 ECONOMY-WIDE - Limiting factor – Labour
192 ECONOMY-WIDE - Limiting factor - Materials
193 ECONOMY-WIDE - Limiting factor - New orders
194 ECONOMY-WIDE - Limiting factor – Other
195 ECONOMY-WIDE - PAST 3 MONTHS - No. employed
196 ECONOMY-WIDE - NEXT 3 MONTHS - No. employed
197 ECONOMY-WIDE - PAST 3 MONTHS - Profitability
198 ECONOMY-WIDE - NEXT 3 MONTHS - Profitability
199 ECONOMY-WIDE - PAST 3 MONTHS - Overtime Wkd
200 ECONOMY-WIDE - NEXT 3 MONTHS - Overtime Wkd

201 BUILDERS - PAST 3 MONTHS - Average Costs
202 BUILDERS - NEXT 3 MONTHS - Average Costs
203 BUILDERS - PAST 3 MONTHS - Average selling price.
204 BUILDERS - NEXT 3 MONTHS - Average selling price.
205 BUILDERS - Capacity Utilisation
206 BUILDERS - Find. labour: skilled
207 BUILDERS - Find. labour: unskilled
208 BUILDERS - General bus situation
209 BUILDERS - New investment: Buildings
210 BUILDERS - New investment: Plant and Machinery
211 BUILDERS - Limiting factor – Capital
212 BUILDERS - Limiting factor - Finished orders
213 BUILDERS - Limiting factor – Labour
214 BUILDERS - Limiting factor – Materials
215 BUILDERS - Limiting factor - New orders
216 BUILDERS - Limiting factor – Other
217 BUILDERS - PAST 3 MONTHS - No. employed
218 BUILDERS - NEXT 3 MONTHS - No. employed
219 BUILDERS - PAST 3 MONTHS - New Orders
220 BUILDERS - NEXT 3 MONTHS - New Orders
221 BUILDERS - PAST 3 MONTHS – Output

222 BUILDERS - NEXT 3 MONTHS – Output
223 BUILDERS - PAST 3 MONTHS – Profitability
224 BUILDERS - NEXT 3 MONTHS – Profitability
225 BUILDERS - PAST 3 MONTHS - Overtime Wkd
226 BUILDERS - NEXT 3 MONTHS - Overtime Wkd

227 BUILDING & CONSTRUCTION - PAST 3 MONTHS - Deliveries in NZ
228 BUILDING & CONSTRUCTION - NEXT 3 MONTHS - Deliveries in NZ
229 BUILDING & CONSTRUCTION - Find. labour: skilled
230 BUILDING & CONSTRUCTION - Find. labour: unskilled
231 BUILDING & CONSTRUCTION - General bus situation
232 BUILDING & CONSTRUCTION - New investment: buildings
233 BUILDING & CONSTRUCTION - New investment: plant and machinery
234 BUILDING & CONSTRUCTION - PAST 3 MONTHS - No. employed
235 BUILDING & CONSTRUCTION - NEXT 3 MONTHS - No. employed
236 BUILDING & CONSTRUCTION - PAST 3 MONTHS - New Orders
237 BUILDING & CONSTRUCTION - NEXT 3 MONTHS - New Orders
238 BUILDING & CONSTRUCTION - PAST 3 MONTHS - Output
239 BUILDING & CONSTRUCTION - NEXT 3 MONTHS - Output
240 BUILDING & CONSTRUCTION - PAST 3 MONTHS - Profitability
241 BUILDING & CONSTRUCTION - NEXT 3 MONTHS - Profitability

242 BUILDING MATERIALS - General bus situation
243 BUILDING MATERIALS - PAST 3 MONTHS - No. employed
244 BUILDING MATERIALS - NEXT 3 MONTHS - No. employed
245 BUILDING MATERIALS - PAST 3 MONTHS - New Orders
246 BUILDING MATERIALS - NEXT 3 MONTHS - New Orders
247 BUILDING MATERIALS - PAST 3 MONTHS - Profitability
248 BUILDING MATERIALS - NEXT 3 MONTHS - Profitability

249 MANUFACTURERS - PAST 3 MONTHS - Average Costs
250 MANUFACTURERS - NEXT 3 MONTHS - Average Costs
251 MANUFACTURERS - PAST 3 MONTHS - Average selling price.
252 MANUFACTURERS - NEXT 3 MONTHS - Average selling price.
253 MANUFACTURERS - Capacity utilisation
254 MANUFACTURERS - PAST 3 MONTHS - Deliveries in NZ
255 MANUFACTURERS - NEXT 3 MONTHS - Deliveries in NZ
256 MANUFACTURERS - Find. labour: skilled
257 MANUFACTURERS - Find. labour: unskilled
258 MANUFACTURERS - General bus situation
259 MANUFACTURERS - New investment: buildings
260 MANUFACTURERS - New invest: plant and machinery
261 MANUFACTURERS - Limiting factor - Capital
262 MANUFACTURERS - Limiting factor - Finished orders
263 MANUFACTURERS - Limiting factor - Labour
264 MANUFACTURERS - Limiting factor - Materials
265 MANUFACTURERS - Limiting factor - New Orders
266 MANUFACTURERS - Limiting factor – Other
267 MANUFACTURERS - PAST 3 MONTHS – No. employed
268 MANUFACTURERS - NEXT 3 MONTHS - No. employed
269 MANUFACTURERS - PAST 3 MONTHS - New Orders
270 MANUFACTURERS - NEXT 3 MONTHS - New Orders
271 MANUFACTURERS - PAST 3 MONTHS - Output
272 MANUFACTURERS - NEXT 3 MONTHS - Output
273 MANUFACTURERS - PAST 3 MONTHS - Profitability
274 MANUFACTURERS - NEXT 3 MONTHS - Profitability

275 MANUFACTURERS - PAST 3 MONTHS - Overtime Wkd
276 MANUFACTURERS - NEXT 3 MONTHS - Overtime Wkd
277 MANUFACTURERS & BUILDERS - PAST 3 MONTHS - Profitability
278 MANUFACTURERS & BUILDERS - NEXT 3 MONTHS - Profitability
279 MANUFACTURERS & BUILDERS - PAST 3 MONTHS - Overtime Wkd
280 MANUFACTURERS & BUILDERS - NEXT 3 MONTHS - Overtime Wkd

281 MERCHANTS - PAST 3 MONTHS - Average costs
282 MERCHANTS - NEXT 3 MONTHS – Average costs
283 MERCHANTS - PAST 3 MONTHS - Average selling price.
284 MERCHANTS - NEXT 3 MONTHS – Average selling price.
285 MERCHANTS - Find. labour: skilled
286 MERCHANTS - Find. labour: unskilled
287 MERCHANTS - General business situation
288 MERCHANTS - New investment: buildings
289 MERCHANTS -New invest Fix. F
290 MERCHANTS - Limiting factor – Capital
291 MERCHANTS - Limiting factor - Finished orders
292 MERCHANTS - Limiting factor – Labour
293 MERCHANTS - Limiting factor – Material
294 MERCHANTS - Limiting factor - New Orders
295 MERCHANTS - Limiting factor – Other
296 MERCHANTS - PAST 3 MONTHS - No. employed
297 MERCHANTS - NEXT 3 MONTHS - No. employed
298 MERCHANTS - PAST 3 MONTHS - New forward orders
299 MERCHANTS - NEXT 3 MONTHS - New forward orders
300 MERCHANTS - PAST 3 MONTHS - Sales in NZ
301 MERCHANTS - NEXT 3 MONTHS - Sales in NZ
302 MERCHANTS - Volume of Sales next 6 months
303 MERCHANTS - PAST 3 MONTHS - Profitability
304 MERCHANTS - NEXT 3 MONTHS - Profitability
305 MERCHANTS - PAST 3 MONTHS – Overtime Wkd
306 MERCHANTS - NEXT 3 MONTHS - Overtime Wkd

307 SERVICES - PAST 3 MONTHS - Average cost per service
308 SERVICES - NEXT 3 MONTHS - Average cost per service
309 SERVICES - Find. labour: skilled
310 SERVICES - Find. labour: unskilled
311 SERVICES - General bus situation
312 SERVICES - New investment: buildings
313 SERVICES - New investment: Plant and machinery
314 SERVICES - Limiting factor – Capital
315 SERVICES - Limiting factor – Demand
316 SERVICES - Limiting factor - Finished orders
317 SERVICES - Limiting factor – Labour
318 SERVICES - Limiting factor – Other
319 SERVICES - Limiting factor – supply
320 SERVICES - PAST 3 MONTHS - No. employed
321 SERVICES - NEXT 3 MONTHS - No. employed
322 SERVICES - PAST 3 MONTHS - Volume of services
323 SERVICES - NEXT 3 MONTHS - Volume of services
324 SERVICES - PAST 3 MONTHS – Profitability
325 SERVICES - NEXT 3 MONTHS – Profitability
326 SERVICES - PAST 3 MONTHS - Overtime Wkd
327 SERVICES - NEXT 3 MONTHS - Overtime Wkd

328 FINANCIAL SERVICES - PAST 3 MONTHS - Average cost per service
329 FINANCIAL SERVICES - NEXT 3 MONTHS - Average cost per service
330 FINANCIAL SERVICES - Find. labour: skilled
331 FINANCIAL SERVICES - Find. labour: unskilled
332 FINANCIAL SERVICES - General business situation
333 FINANCIAL SERVICES - New investment: buildings
334 FINANCIAL SERVICES - New invest: Plant and machinery
335 FINANCIAL SERVICES - Limiting factor - Capital
336 FINANCIAL SERVICES - Limiting factor - Demand
337 FINANCIAL SERVICES - Limiting factor - Finished orders
338 FINANCIAL SERVICES - Limiting factor - Labour
339 FINANCIAL SERVICES - Limiting factor - Other
340 FINANCIAL SERVICES - Limiting factor - Supply
341 FINANCIAL SERVICES - PAST 3 MONTHS - No. employed
342 FINANCIAL SERVICES - NEXT 3 MONTHS - No. employed
343 FINANCIAL SERVICES - PAST 3 MONTHS - Volume of services
344 FINANCIAL SERVICES - NEXT 3 MONTHS - Volume of services
345 FINANCIAL SERVICES - PAST 3 MONTHS - Profitability
346 FINANCIAL SERVICES - NEXT 3 MONTHS - Profitability
347 FINANCIAL SERVICES - PAST 3 MONTHS - Overtime Wkd
348 FINANCIAL SERVICES - NEXT 3 MONTHS - Overtime Wkd

National Bank of New Zealand
Business Outlook Survey

349 INFLATION EXPECTATIONS - Next 12 Months - Retail
350 INFLATION EXPECTATIONS - Next 12 Months - Manufacturing
351 INFLATION EXPECTATIONS - Next 12 Months - Agriculture
352 INFLATION EXPECTATIONS - Next 12 Months - Construction
353 INFLATION EXPECTATIONS - Next 12 Months - Services
354 INFLATION EXPECTATIONS - Next 12 Months - Total (All Sectors)

355 BUSINESS CONFIDENCE - Next 12 Months - Retail
356 BUSINESS CONFIDENCE - Next 12 Months - Manufacturing
357 BUSINESS CONFIDENCE - Next 12 Months - Agriculture
358 BUSINESS CONFIDENCE - Next 12 Months - Construction
359 BUSINESS CONFIDENCE - Next 12 Months - Services
360 BUSINESS CONFIDENCE - Next 12 Months - Total (All Sectors)

361 ACTIVITY OUTLOOK - Next 12 Months - Retail
362 ACTIVITY OUTLOOK - Next 12 Months - Manufacturing
363 ACTIVITY OUTLOOK - Next 12 Months - Agriculture
364 ACTIVITY OUTLOOK - Next 12 Months - Construction
365 ACTIVITY OUTLOOK - Next 12 Months - Services
366 ACTIVITY OUTLOOK - Next 12 Months - Total (All Sectors)

367 PRICING INTENTIONS - Next 3 Months - Total (all sectors)
368 PRICING INTENTIONS - Next 3 Months - Retail
369 PRICING INTENTIONS - Next 3 Months - Manufacturing

ANZ Banking Group Ltd
Commodity Price Indexes

370 COMMODITY PRICE INDEX - NZ$
371 COMMODITY PRICE INDEX - NZ$ - Meat, Skins & Wool
372 COMMODITY PRICE INDEX - NZ$ - Dairy Products
373 COMMODITY PRICE INDEX - NZ$ - Horticultural Products
374 COMMODITY PRICE INDEX - NZ$ - Forestry Products

375 COMMODITY PRICE INDEX - NZ$ - Seafood
376 COMMODITY PRICE INDEX - NZ$ - Aluminium

Westpac Banking Corporation
Westpac-McDermott-Millar

377 Consumer Confidence Index

Television New Zealand

378 *One News Colmar Brunton poll*
Consumer Confidence

AON Consulting Ltd

379 ***Economist Survey***
CPI Inflation – In 1 years time
380 CPI Inflation - In 4 years time
381 CPI Inflation - In 7 years time
382 Increase Avg. Weekly Wage - In 1 years time
383 Increase Avg. Weekly Wage - In 4 years time
384 Increase Avg. Weekly Wage - In 7 years time

Cement and Concrete Assoc (NZ)

385 Cement sales

National Institute of Water and Atmospheric Research

386 Southern Oscillation Index

Appendix B Relative Mean Squared Forecast Errors

Notes for appendix B

For each model, the mean squared forecast error relative to the Reserve Bank's mean squared forecast error is reported. As discussed in the text, $\theta = 5, 10, ..., 100$ is the proportion of series used to derive the factors. The forecasts in the rows of the tables are:

rbnz Reserve Bank of New Zealand benchmark

far Autoregressive model, with BIC selection of 0 to 4 lags

fvar VAR model, with lags set at 2

fbiv_best The best bivariate indicator, allowing 1 to 4 lags of the indicator and 0 to 4 lags of the dependent variable (BIC selection of both)

fbiv_mean Mean of the top 5% and 10% of BIC-ranked bivariate indicators

fbiv_med Median of the top 5% and 10% of BIC-ranked bivariate indicators

fdi_*k* Factor model with (suffix) k=1,2,3,4 factors

fdi_bic Factor model using BIC selection of factors (1 to 4)

fdiar_*k* Factor model with (suffix) k=1, 2, 3, 4 factors and 0 to 4 lags of the dependent variable (BIC selection of lag numbers)

fdiar_bic Factor model with 1 to 4 factors and 0 to 4 lags of the dependent variable (BIC selection of factors and lags)

fdiarlag_bic Factor model with 1 to 4 factors, 1 to 3 lags of the factors, and 1 to 4 lags of the dependent variable (BIC selection of all three)

RMSFE Root mean squared forecast errors

Significance tests

Asterisks denote that the mean squared errors of the given test are significantly better than those of the Reserve Bank of New Zealand. The test used is a *one-tailed* Wilcoxon test. The test is performed for horizons h=1, 2, 3 quarters. The lack of data makes it effectively impossible to test longer horizon forecasts.

*** shows significance at the 5% level
** shows significance at the 10% level
* shows significance at the 20% level

The use of the non-parametric signed-rank tests means it is possible to obtain significance for a given hypothesis even when the statistic appearing in the tables seems to contradict that hypothesis. For example, with relative mean squared errors above one, it is still possible to accept an alternative hypothesis that a given forecast is better than the Reserve Bank benchmark forecast. This is because the ranking procedure ignores the magnitude of individual errors (weighting them by rank depends on relative size and removes absolute magnitude). If the mean squared error of a given model has been affected by a small number of very large errors it may have a large MSFE, but the signed-rank test may still indicate the model's overall superiority because more of the ranked forecasts are better than those of the Reserve Bank.

Table B.1
CPI Inflation (year on year)

***h*=1**	**Fixed data set**					**Flexible data set**				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	3.28									
fvar	3.76									
fbiv_best	4.19					3.41				
fbiv_mean		3.71	3.67				3.60	3.50		
fbiv_med		3.67	3.59				3.50	3.54		
fdi_1		3.51	3.41	3.10	2.88		3.92	4.01	3.41	3.18
fdi_2		3.62	3.54	3.11	2.83		4.21	3.80	3.34	3.21
fdi_3		4.15	4.13	3.67	3.33		4.25	3.48	3.52	3.42
fdi_4		3.88	4.31	4.19	4.00		4.28	3.40	3.71	3.92
fdi_bic		4.22	3.76	3.25	3.22		4.54	4.28	3.36	3.49
fdiar_1		4.53	4.34	3.10	3.34		4.22	4.22	3.42	3.60
fdiar_2		4.41	4.19	3.93	3.48		4.86	3.98	3.42	3.70
fdiar_3		5.52	4.88	4.30	4.26		4.72	3.71	3.47	4.26
fdiar_4		5.19	5.73	4.42	4.94		5.01	3.50	3.77	4.32
fdiar_bic		5.61	4.76	3.90	3.80		4.82	4.27	3.39	3.53
fdiarlag_bic		5.70	5.92	5.72	3.75		4.67	4.22	3.28	4.46
RMSFE rbnz	0.23									

***h*=2**	**Fixed data set**					**Flexible data set**				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.55									
fvar	2.02									
fbiv_best	1.96					3.08				
fbiv_mean		1.70	1.70				2.17	2.05		
fbiv_med		1.62	1.63				2.09	2.00		
fdi_1		2.05	1.84	1.68	1.60		1.98	2.06	1.95	1.97
fdi_2		2.04	2.11	1.64	1.56		2.28	2.13	2.17	2.24
fdi_3		2.19	2.47	2.43	2.11		2.21	2.42	2.11	2.10
fdi_4		2.09	2.58	2.72	2.52		2.46	2.74	2.73	2.46
fdi_bic		2.25	2.33	2.21	2.16		2.08	2.06	2.20	2.64
fdiar_1		2.24	2.01	1.68	1.60		2.19	2.08	2.07	2.16
fdiar_2		1.99	2.01	1.57	1.52		2.45	2.17	2.34	2.20
fdiar_3		2.13	2.24	1.79	2.29		2.33	2.47	1.83	1.89
fdiar_4		2.17	2.48	2.01	2.48		3.09	2.96	2.39	2.55
fdiar_bic		2.12	2.27	1.92	1.80		2.63	2.44	2.30	2.51
fdiarlag_bic		2.31	2.27	1.92	1.91		3.14	2.53	2.34	2.80
RMSFE rbnz	0.48									

***h*=3**	**Fixed data set**					**Flexible data set**				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.37									
fvar	1.46									
fbiv_best	2.29					2.43				
fbiv_mean		1.58	1.54				2.06	1.91		
fbiv_med		1.56	1.48				2.11	1.93		
fdi_1		1.41	1.48	1.53	1.42		1.59	1.65	1.73	1.69
fdi_2		1.56	1.70	1.50	1.37		1.72	2.07	1.86	2.03
fdi_3		1.50	1.83	2.43	2.26		1.47	2.00	1.81	2.08
fdi_4		1.73	1.74	2.43	2.59		1.66	2.38	2.56	2.79
fdi_bic		1.49	1.49	2.32	2.13		1.59	1.83	2.49	2.79
fdiar_1		1.73	1.72	1.69	1.57		1.75	1.83	1.93	1.84
fdiar_2		1.70	1.58	1.48	1.69		1.73	2.28	2.39	2.01
fdiar_3		1.99	1.96	1.96	2.40		1.69	2.03	2.21	2.50
fdiar_4		2.00	2.05	2.16	2.57		1.90	2.45	2.89	3.05
fdiar_bic		1.97	1.97	2.07	2.33		1.78	2.39	2.82	3.04
fdiarlag_bic		2.14	2.25	2.12	2.83		1.82	2.33	2.77	3.23
RMSFE rbnz	0.66									

***h*=4**	**Fixed data set**					**Flexible data set**				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.65									
fvar	1.24									
fbiv_best	3.43					6.06				
fbiv_mean		0.86	0.68				2.03	1.60		
fbiv_med		0.78	0.56				2.23	1.67		
fdi_1		0.71	0.75	0.77	0.78		1.12	1.08	1.11	1.06
fdi_2		0.71	0.77	1.19	1.23		1.06	1.10	0.66	1.10
fdi_3		1.76	1.98	1.13	0.85		3.29	1.81	1.19	1.30
fdi_4		2.37	1.55	3.53	1.79		4.27	4.40	4.54	6.30
fdi_bic		2.26	1.25	3.42	2.12		1.95	2.83	2.43	2.87
fdiar_1		0.59	0.72	0.80	0.92		1.04	0.93	1.27	1.20
fdiar_2		1.24	1.56	1.24	1.20		1.12	1.09	0.76	1.12
fdiar_3		1.96	1.95	1.47	0.94		3.17	1.93	2.92	2.48
fdiar_4		2.39	2.09	2.81	1.50		3.99	4.34	4.99	4.09
fdiar_bic		1.86	1.22	1.79	1.59		2.40	3.25	2.96	3.47
fdiarlag_bic		3.77	3.55	5.86	6.30		14.36	25.38	24.96	15.03
RMSFE rbnz	0.78									

h=5	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.84									
fvar	0.86									
fbiv_best	1.50					2.83				
fbiv_mean		0.98	1.00				1.48	1.48		
fbiv_med		0.99	0.98				1.53	1.50		
fdi_1		1.14	1.05	0.94	0.89		1.32	1.36	1.16	1.10
fdi_2		1.13	1.12	1.15	1.11		1.18	0.82	1.10	1.07
fdi_3		1.20	1.36	1.49	1.39		1.07	1.42	1.06	1.31
fdi_4		1.51	1.56	1.52	1.44		1.13	1.40	1.57	2.19
fdi_bic		1.06	1.00	1.36	1.20		1.42	1.50	1.31	1.79
fdiar_1		1.31	1.18	1.18	1.21		1.40	1.52	1.30	1.28
fdiar_2		1.24	1.21	1.70	1.56		1.05	0.77	0.98	1.30
fdiar_3		1.26	1.27	2.16	2.43		1.01	1.23	0.99	1.07
fdiar_4		1.81	1.51	2.37	2.12		1.21	1.28	1.52	2.01
fdiar_bic		1.71	1.32	1.51	1.63		1.02	1.30	1.16	1.90
fdiarlag_bic		2.67	2.12	1.64	1.71		1.11	1.54	1.69	4.77
RMSFE rbnz	0.82									

h=6	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.64									
fvar	0.50									
fbiv_best	1.69					2.13				
fbiv_mean		0.88	0.88				1.42	1.47		
fbiv_med		0.89	0.85				1.40	1.55		
fdi_1		1.07	0.97	0.73	0.69		1.45	1.20	1.07	1.05
fdi_2		1.24	1.38	1.25	1.24		0.91	0.83	1.04	1.14
fdi_3		1.38	1.90	1.34	1.37		0.93	1.07	1.17	1.19
fdi_4		1.73	1.84	1.40	1.14		1.21	1.41	1.30	1.23
fdi_bic		1.71	2.06	1.10	0.99		1.45	1.47	1.25	1.50
fdiar_1		1.18	1.04	1.18	1.10		1.63	1.18	1.24	1.30
fdiar_2		1.30	1.45	1.57	1.50		0.90	0.74	0.76	1.12
fdiar_3		1.55	1.86	1.39	1.47		0.92	1.41	0.88	1.01
fdiar_4		1.79	1.86	1.64	1.33		1.42	1.77	1.34	1.02
fdiar_bic		1.77	1.86	1.56	1.63		1.39	1.40	1.29	1.70
fdiarlag_bic		2.64	2.12	1.96	2.90		2.03	1.24	1.37	3.35
RMSFE rbnz	0.88									

h=7	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.57									
fvar	0.67									
fbiv_best	2.73					2.30				
fbiv_mean		0.61	0.53				1.34	1.43		
fbiv_med		0.54	0.56				1.32	1.41		
fdi_1		0.89	0.77	0.65	0.62		1.32	1.07	0.96	1.01
fdi_2		1.16	1.21	1.31	1.34		0.89	0.83	0.80	0.95
fdi_3		1.65	2.01	1.54	1.91		1.03	0.85	0.95	1.06
fdi_4		1.72	1.60	2.91	2.08		1.48	1.51	0.93	1.36
fdi_bic		1.74	1.65	2.50	2.00		1.05	1.01	1.05	1.60
fdiar_1		0.80	0.81	0.88	0.82		1.30	0.99	1.05	1.04
fdiar_2		1.04	1.12	1.19	0.95		0.98	0.88	0.90	1.04
fdiar_3		1.44	1.79	0.84	0.96		1.21	1.00	1.13	1.86
fdiar_4		1.42	1.13	2.46	1.28		1.66	1.48	1.16	2.02
fdiar_bic		1.58	1.23	2.38	1.31		1.25	1.13	1.26	1.98
fdiarlag_bic		3.05	3.47	5.83	6.23		1.33	5.90	2.25	6.98
RMSFE rbnz	0.85									

h=8	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.61									
fvar	1.14									
fbiv_best	3.25					5.74				
fbiv_mean		0.81	0.65				1.93	1.52		
fbiv_med		0.74	0.53				2.12	1.58		
fdi_1		0.67	0.71	0.73	0.74		1.06	1.03	1.06	1.00
fdi_2		0.68	0.73	1.13	1.17		1.01	1.04	0.62	1.04
fdi_3		1.66	1.88	1.07	0.81		3.12	1.71	1.13	1.24
fdi_4		2.25	1.47	3.34	1.70		4.05	4.17	4.31	5.97
fdi_bic		2.14	1.18	3.24	2.01		1.85	2.69	2.31	2.72
fdiar_1		0.56	0.69	0.76	0.87		0.98	0.88	1.21	1.14
fdiar_2		1.17	1.48	1.18	1.13		1.06	1.03	0.72	1.06
fdiar_3		1.86	1.85	1.40	0.89		3.01	1.83	2.77	2.35
fdiar_4		2.26	1.98	2.67	1.43		3.79	4.11	4.73	3.88
fdiar_bic		1.77	1.16	1.70	1.51		2.28	3.09	2.81	3.29
fdiarlag_bic		3.58	3.37	5.56	5.97		13.62	24.07	23.66	14.25
RMSFE rbnz	0.80									

Table B.2
GDP growth (year on year)

***h*=1**	Fixed data set					Flexible data set				
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	2.12									
fvar	1.75									
fbiv_best	2.53					2.87				
fbiv_mean		2.07	2.02				2.12	2.09		
fbiv_med		2.02	1.98				2.01	2.00		
fdi_1		2.02	2.00	1.83	1.73		2.13	2.08	2.03	2.14
fdi_2		2.43	2.00	1.88	1.74		2.22	2.16	2.13	2.14
fdi_3		2.57	2.52	2.23	1.87		2.31	2.56	2.10	2.09
fdi_4		2.61	2.61	2.77	1.97		2.59	2.78	2.37	2.22
fdi_bic		2.18	2.42	2.28	1.79		2.13	2.33	2.03	2.14
fdiar_1		2.18	2.15	1.97	1.87		2.25	2.27	2.21	2.36
fdiar_2		2.43	2.33	1.95	1.83		2.38	2.45	2.29	2.31
fdiar_3		2.51	2.74	2.22	2.02		2.48	2.67	2.28	2.28
fdiar_4		2.52	2.66	2.76	2.07		2.85	2.89	2.44	2.36
fdiar_bic		2.27	2.50	2.46	1.94		2.27	2.40	2.21	2.36
fdiarlag_bic		2.31	2.44	2.53	1.97		2.40	2.53	2.49	2.65
RMSFE rbnz	0.67									

***h*=2**	Fixed data set					Flexible data set				
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.54									
fvar	1.78									
fbiv_best	2.15					2.84				
fbiv_mean		1.33	1.28				1.54	1.61		
fbiv_med		1.53	1.49				1.58	1.60		
fdi_1		1.67	1.63	1.36	1.35		2.04	1.95	1.69	1.73
fdi_2		1.61	1.66	1.41	1.32		2.19	2.36	2.14	2.12
fdi_3		1.59	1.71	1.65	1.61		2.19	2.35	2.15	2.04
fdi_4		1.64	1.89	1.64	1.46		2.23	2.13	2.23	2.06
fdi_bic		1.67	1.63	1.47	1.43		2.04	1.95	1.69	1.73
fdiar_1		1.31	1.28	0.97	1.27		1.71	1.90	1.58	1.65
fdiar_2		1.24	1.26	1.09	1.27		2.05	2.07	1.82	2.17
fdiar_3		1.14	1.13	0.99	1.18		2.01	1.94	1.25	1.14
fdiar_4		1.12	1.71	1.01	1.44		1.79	1.65	1.88	1.71
fdiar_bic		1.28	1.28	1.08	1.21		1.54	1.46	1.58	2.04
fdiarlag_bic		1.30	1.10	1.10	1.15		1.61	1.47	1.58	2.36
RMSFE rbnz	1.03									

***h*=3**	Fixed data set					Flexible data set				
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.23									
fvar	1.84									
fbiv_best	1.95					2.19				
fbiv_mean		1.11	1.07				1.15	1.03*		
fbiv_med		1.22	1.08				1.08***	1.01		
fdi_1		1.28	1.21	0.93**	0.97**		1.42	1.35	1.19	1.32
fdi_2		1.25	1.22	1.13	1.06		2.29	1.54	1.49	1.51
fdi_3		1.32	1.67	1.11	1.09		1.97	1.56	1.38	1.35
fdi_4		1.36	1.65	1.15	1.18		1.84	1.77	1.44	1.30
fdi_bic		1.28	1.21	1.22	1.19		2.09	1.61	1.19	1.56
fdiar_1		1.21	1.24	1.21	1.25		1.30	1.31	1.14**	1.35
fdiar_2		1.26	1.33	1.37	1.37		1.92	1.46	1.43	1.53
fdiar_3		1.18	1.58	1.16	1.34		1.70	1.38	1.27	1.05
fdiar_4		1.39	1.45	1.35	1.33		1.49	1.83	1.52	1.40
fdiar_bic		1.25	1.18	1.46	1.39		1.50	1.89	1.14**	1.77
fdiarlag_bic		2.58	1.78	1.13	2.48		1.77	1.14	1.15**	1.44**
RMSFE rbnz	1.39									

***h*=4**	Fixed data set					Flexible data set				
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.16									
fvar	1.96									
fbiv_best	6.82					16.44				
fbiv_mean		1.83	1.43				2.54	2.22		
fbiv_med		1.31	1.32				1.85	1.55		
fdi_1		0.83	0.89	1.39	1.38		2.73	2.93	2.27	1.74
fdi_2		2.69	1.30	1.49	1.41		8.43	6.42	2.91	2.78
fdi_3		3.63	4.51	3.16	2.03		12.33	13.32	11.31	8.04
fdi_4		3.42	7.67	3.22	1.86		13.52	7.93	9.22	31.46
fdi_bic		2.62	4.71	3.07	2.04		9.26	6.71	10.02	34.05
fdiar_1		0.81	0.68	1.17	1.58		3.35	3.96	3.81	1.75
fdiar_2		2.67	1.62	2.12	1.57		6.26	4.02	1.71	1.97
fdiar_3		2.99	4.31	3.43	2.56		10.18	13.15	5.60	6.06
fdiar_4		3.02	3.83	2.49	1.56		11.19	8.76	8.02	15.19
fdiar_bic		2.43	4.02	4.41	2.81		8.60	9.37	7.10	12.24
fdiarlag_bic		6.47	5.33	14.15	14.85		40.14	60.68	8.91	43.13
RMSFE rbnz	1.65									

***h*=5**		**Fixed data set**					**Flexible data set**			
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.57									
fvar	0.93									
fbiv_best	0.87					3.47				
fbiv_mean		0.72	0.54				0.60	0.52		
fbiv_med		0.75	0.59				0.60	0.62		
fdi_1		0.57	0.56	0.48	0.46		1.34	0.77	0.59	0.78
fdi_2		0.71	0.80	1.02	1.08		1.63	1.52	1.01	0.79
fdi_3		1.12	1.72	0.66	0.78		2.13	1.39	1.96	0.63
fdi_4		1.18	1.53	1.54	1.09		1.75	1.88	1.86	1.39
fdi_bic		1.11	1.22	1.84	1.32		1.59	1.82	0.59	1.25
fdiar_1		0.62	0.67	1.25	0.83		1.44	0.83	0.87	1.40
fdiar_2		0.82	0.53	0.88	1.27		1.66	1.45	1.43	2.69
fdiar_3		0.59	0.96	0.92	0.83		2.38	1.54	2.05	2.45
fdiar_4		1.21	2.19	1.68	1.17		2.07	3.65	2.24	2.11
fdiar_bic		1.10	2.30	2.01	1.75		1.79	2.31	1.61	2.36
fdiarlag_bic		3.41	4.66	3.61	5.31		3.07	9.67	4.12	9.49
RMSFE rbnz	1.90									

***h*=6**		**Fixed data set**					**Flexible data set**			
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.59									
fvar	1.26									
fbiv_best	1.14					20.20				
fbiv_mean		0.63	0.65				3.54	3.45		
fbiv_med		0.65	0.71				2.40	2.57		
fdi_1		0.55	0.61	0.74	0.65		2.14	1.81	1.01	1.16
fdi_2		1.24	0.58	1.58	1.74		4.10	3.83	1.73	0.94
fdi_3		2.26	5.30	3.01	2.40		4.48	4.63	6.80	1.63
fdi_4		1.83	4.13	4.01	3.40		4.01	8.01	5.99	9.48
fdi_bic		1.49	3.05	5.41	4.22		3.44	3.08	5.51	6.63
fdiar_1		0.65	0.79	1.50	0.48		2.82	2.43	1.61	2.23
fdiar_2		0.73	0.76	1.40	1.39		4.15	3.42	3.73	5.68
fdiar_3		1.22	3.81	3.32	2.55		5.19	5.19	5.89	9.50
fdiar_4		2.26	3.83	4.15	3.39		4.89	8.15	6.09	7.86
fdiar_bic		1.67	3.87	5.31	4.22		4.13	5.50	5.72	7.51
fdiarlag_bic		4.68	4.31	5.22	10.81		5.27	14.32	10.46	28.38
RMSFE rbnz	1.63									

***h*=7**		**Fixed data set**					**Flexible data set**			
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.87									
fvar	1.01									
fbiv_best	7.56					15.77				
fbiv_mean		1.59	1.45				4.23	4.21		
fbiv_med		1.23	1.05				2.89	3.15		
fdi_1		0.67	0.71	1.05	0.99		2.68	2.49	1.56	1.42
fdi_2		1.84	0.53	1.43	1.68		8.47	8.00	2.06	1.34
fdi_3		5.90	5.75	5.71	2.95		9.24	8.31	10.70	4.39
fdi_4		5.47	5.63	6.35	3.64		10.14	15.92	9.08	23.40
fdi_bic		4.37	5.14	9.37	4.62		5.63	10.41	8.39	24.18
fdiar_1		1.02	0.98	1.07	1.28		3.58	3.66	2.99	2.98
fdiar_2		1.56	0.86	1.81	1.30		7.61	4.98	3.53	7.06
fdiar_3		3.04	4.43	5.62	3.01		9.35	5.56	6.43	10.13
fdiar_4		5.28	5.21	6.62	3.53		11.72	9.00	6.24	14.87
fdiar_bic		4.76	4.51	7.56	4.71		7.57	6.22	7.12	18.07
fdiarlag_bic		10.52	6.99	8.25	11.20		8.87	9.87	23.97	18.62
RMSFE rbnz	1.62									

***h*=8**		**Fixed data set**					**Flexible data set**			
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.07									
fvar	1.18									
fbiv_best	6.29					15.16				
fbiv_mean		1.69	1.32				2.35	2.04		
fbiv_med		1.21	1.22				1.70	1.43		
fdi_1		0.77	0.82	1.28	1.28		2.52	2.70	2.09	1.61
fdi_2		2.48	1.20	1.37	1.30		7.77	5.92	2.69	2.56
fdi_3		3.35	4.16	2.92	1.87		11.37	12.28	10.43	7.42
fdi_4		3.15	7.07	2.97	1.71		12.46	7.31	8.50	29.01
fdi_bic		2.41	4.34	2.83	1.88		8.53	6.18	9.24	31.40
fdiar_1		0.75	0.63	1.08	1.46		3.09	3.66	3.51	1.61
fdiar_2		2.46	1.49	1.95	1.45		5.78	3.71	1.58	1.82
fdiar_3		2.76	3.97	3.16	2.36		9.39	12.13	5.16	5.59
fdiar_4		2.78	3.53	2.30	1.44		10.32	8.08	7.40	14.01
fdiar_bic		2.24	3.70	4.07	2.59		7.93	8.64	6.55	11.28
fdiarlag_bic		5.96	4.91	13.05	13.69		37.01	55.95	8.22	39.77
RMSFE rbnz	1.72									

Table B.3
Interest rate (90 day bank bill)

h=1	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	16.19									
fvar	29.18									
fbiv_best	50.45						49.38			
fbiv_mean		23.55	18.61				20.78	18.02		
fbiv_med		22.49	19.56				19.67	16.97		
fdi_1		25.10	23.64	21.39	20.52		33.66	23.11	15.11	16.50
fdi_2		31.83	27.18	24.46	21.71		38.80	40.54	22.16	17.26
fdi_3		34.98	26.13	19.95	24.87		29.51	41.91	41.01	20.23
fdi_4		31.47	24.04	58.38	57.12		25.07	19.73	31.88	35.59
fdi_bic		32.91	25.23	48.55	20.52		30.41	24.08	36.81	34.42
fdiar_1		24.94	22.74	19.33	19.00		33.66	21.89	15.31	16.04
fdiar_2		31.50	32.25	37.30	39.02		39.50	41.98	34.06	28.28
fdiar_3		36.39	26.60	34.35	33.42		30.51	50.12	42.58	25.87
fdiar_4		38.58	25.15	62.34	60.28		25.18	31.38	33.45	36.99
fdiar_bic		32.82	31.93	49.83	26.89		29.11	32.67	39.63	35.46
fdiarlag_bic		27.91	31.72	92.41	29.90		26.31	27.49	37.48	36.28
RMSFE rbnz	0.09									

h=2	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	4.18									
fvar	8.16									
fbiv_best	20.25					16.38				
fbiv_mean		7.94	5.91				8.60	6.50		
fbiv_med		7.20	5.47				8.36	6.41		
fdi_1		7.53	6.97	5.55	5.28		7.48	5.89	3.84	3.93
fdi_2		8.98	9.59	5.89	6.36		10.73	9.30	4.46	3.30
fdi_3		8.63	14.25	16.76	10.93		11.02	9.76	9.90	4.19
fdi_4		9.00	14.85	15.22	15.52		9.59	10.39	8.51	10.51
fdi_bic		9.77	15.32	13.43	5.28		8.57	10.97	7.19	8.42
fdiar_1		7.53	6.97	6.63	6.55		7.48	5.89	3.84	4.82
fdiar_2		9.22	10.54	13.54	14.45		12.85	11.42	8.25	10.70
fdiar_3		8.63	14.66	13.94	11.25		12.36	11.69	7.43	13.60
fdiar_4		9.00	14.85	19.38	11.41		10.98	11.11	4.62	7.87
fdiar_bic		9.77	15.32	14.49	11.54		10.96	12.29	5.03	7.30
fdiarlag_bic		10.07	31.37	13.09	11.13		10.32	12.67	5.06	7.41
RMSFE rbnz	0.35									

h=3	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	2.07									
fvar	5.72									
fbiv_best	11.19					32.22				
fbiv_mean		3.41	2.89				3.00	2.15		
fbiv_med		3.65	2.97				3.19	2.12		
fdi_1		4.53	4.11	3.18	2.92		4.28	1.95	1.27	2.35
fdi_2		4.84	5.32	4.98	5.15		6.90	3.08	1.48	1.45
fdi_3		7.11	8.69	14.27	12.63		8.79	3.23	3.28	9.96
fdi_4		10.84	10.89	12.08	13.63		11.22	3.44	2.82	8.84
fdi_bic		9.22	6.33	12.08	11.93		10.57	3.63	2.38	7.86
fdiar_1		4.53	4.43	4.03	3.76		4.28	1.95	1.27	3.03
fdiar_2		7.97	7.23	6.36	6.14		7.86	3.78	2.73	5.65
fdiar_3		8.98	10.37	13.46	5.32		9.53	3.87	2.46	14.49
fdiar_4		12.24	13.23	12.52	6.29		11.81	3.68	1.53	5.62
fdiar_bic		10.76	10.40	15.20	5.99		10.79	4.07	1.66	2.55
fdiarlag_bic		10.38	19.34	8.38	7.05		22.69	4.20	1.68	6.83
RMSFE rbnz	0.61									

h=4	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.47									
fvar	4.86									
fbiv_best	5.75					23.51				
fbiv_mean		1.67	1.37				2.91	2.91		
fbiv_med		1.38	1.46				2.81	2.33		
fdi_1		1.71	1.46	1.00	0.88		4.41	3.23	2.72	2.19
fdi_2		1.80	1.81	5.33	6.19		3.08	2.54	7.06	5.61
fdi_3		2.19	5.45	4.87	3.33		4.56	3.52	5.91	2.08
fdi_4		2.28	6.25	9.83	4.39		16.21	4.42	4.64	13.51
fdi_bic		1.71	3.10	6.86	4.04		4.44	3.10	8.75	10.65
fdiar_1		1.71	1.48	1.06	1.09		4.34	3.34	3.00	2.40
fdiar_2		2.70	1.82	5.45	6.82		3.95	2.52	5.36	4.77
fdiar_3		3.11	8.16	3.32	3.01		4.76	3.32	9.78	4.85
fdiar_4		3.23	10.15	21.46	3.73		15.29	2.90	16.18	16.35
fdiar_bic		2.81	8.86	4.66	4.04		4.50	3.45	8.00	9.42
fdiarlag_bic		3.32	24.17	17.10	38.42		695.63	334.76	1368.23	28.51
RMSFE rbnz	0.84									

h=5	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.76									
fvar	3.23									
fbiv_best	1.70					1.78				
fbiv_mean		0.72	0.56				1.06	0.70		
fbiv_med		0.93	0.75				0.75	0.59		
fdi_1		1.45	1.14	1.12	1.24		1.25	1.29	1.32	1.07
fdi_2		1.37	1.34	2.36	2.46		3.87	3.94	1.87	1.23
fdi_3		1.73	1.56	3.75	4.53		4.41	5.13	2.65	3.93
fdi_4		1.93	1.70	2.67	4.09		4.88	5.98	1.68	6.23
fdi_bic		1.45	1.18	2.58	3.00		3.82	4.96	1.92	5.56
fdiar_1		1.46	1.14	1.39	1.55		1.19	1.30	1.52	1.33
fdiar_2		1.99	1.80	1.38	1.62		2.52	2.79	1.35	1.73
fdiar_3		2.11	2.36	0.75	1.62		2.70	2.48	2.29	2.43
fdiar_4		2.28	3.23	0.47	1.32		3.56	1.88	2.73	8.48
fdiar_bic		2.02	2.75	1.46	1.80		2.92	2.05	1.70	6.91
fdiarlag_bic		4.85	1.49	7.67	2.96		3.36	3.07	18.96	19.92
RMSFE rbnz	1.08									

h=6	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.39									
fvar	3.24									
fbiv_best	2.36					4.00				
fbiv_mean		0.59	0.51				0.68	0.73		
fbiv_med		0.70	0.56				0.74	0.64		
fdi_1		1.11	0.75	0.67	0.77		1.92	1.87	1.02	0.81
fdi_2		1.09	0.94	1.70	2.02		2.08	1.16	1.16	1.29
fdi_3		1.05	1.40	1.41	1.98		3.63	2.02	0.95	2.52
fdi_4		0.96	2.11	2.01	1.78		4.25	3.40	1.04	2.11
fdi_bic		1.11	0.75	2.03	2.18		4.14	1.67	1.69	1.24
fdiar_1		1.10	0.77	0.74	0.89		1.96	1.95	1.15	0.94
fdiar_2		1.09	0.94	0.99	1.31		2.40	1.35	0.87	1.05
fdiar_3		1.03	1.21	0.69	0.82		3.66	2.89	1.01	0.91
fdiar_4		1.06	1.55	1.28	0.87		4.01	4.42	1.24	1.09
fdiar_bic		1.02	1.03	1.34	0.98		3.83	4.62	1.11	1.17
fdiarlag_bic		2.73	0.98	2.28	3.74		13.77	9.54	1.21	15.34
RMSFE rbnz	1.25									

h=7	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.25									
fvar	4.43									
fbiv_best	2.06					9.27				
fbiv_mean		0.76	0.57				1.11	0.89		
fbiv_med		0.71	0.61				1.33	0.69		
fdi_1		1.13	0.73	0.50	0.54		2.21	2.29	0.96	0.81
fdi_2		1.20	0.96	2.10	2.18		2.07	1.55	1.94	1.64
fdi_3		1.26	1.42	1.69	1.71		2.49	1.39	1.77	1.86
fdi_4		1.93	1.23	3.41	2.23		1.66	2.03	1.52	2.72
fdi_bic		1.13	0.73	3.52	2.37		2.61	2.35	2.06	1.77
fdiar_1		1.16	0.75	0.53	0.62		2.21	2.28	0.95	0.85
fdiar_2		0.82	0.69	1.75	2.18		2.17	1.83	1.82	1.65
fdiar_3		0.82	1.11	1.59	1.41		2.47	1.63	1.77	2.33
fdiar_4		1.27	0.96	2.95	1.91		1.68	2.78	1.87	2.35
fdiar_bic		1.16	0.75	3.00	2.12		2.55	2.23	2.19	2.02
fdiarlag_bic		5.30	3.53	4.43	22.78		7.21	14.17	9.31	40.29
RMSFE rbnz	1.26									

h=8	Fixed data set					Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	0.21									
fvar	5.15									
fbiv_best	2.58					10.57				
fbiv_mean		0.75	0.62				1.31	1.31		
fbiv_med		0.62	0.66				1.26	1.05		
fdi_1		0.77	0.66	0.45	0.40		1.98	1.45	1.22	0.98
fdi_2		0.81	0.81	2.40	2.78		1.38	1.14	3.17	2.52
fdi_3		0.99	2.45	2.19	1.49		2.05	1.58	2.66	0.94
fdi_4		1.02	2.81	4.42	1.97		7.29	1.99	2.08	6.07
fdi_bic		0.77	1.40	3.09	1.82		2.00	1.40	3.93	4.79
fdiar_1		0.77	0.66	0.48	0.49		1.95	1.50	1.35	1.08
fdiar_2		1.21	0.82	2.45	3.07		1.78	1.13	2.41	2.14
fdiar_3		1.40	3.67	1.49	1.35		2.14	1.49	4.40	2.18
fdiar_4		1.45	4.56	9.64	1.68		6.87	1.30	7.27	7.35
fdiar_bic		1.26	3.98	2.09	1.82		2.02	1.55	3.60	4.23
fdiarlag_bic		1.49	10.86	7.69	17.27		312.7	150.5	615.0	12.81
RMSFE rbnz	1.25									

Table B.4
Nominal trade weighted exchange rate

h=1		Fixed data set				Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	8.34									
fvar	10.01									
fbiv_best	12.18					8.41				
fbiv_mean		7.06	6.97				7.30	6.90		
fbiv_med		7.65	7.33				7.09	7.07		
fdi_1		7.45	6.62	5.71	5.71		7.71	7.01	6.09	6.09
fdi_2		7.60	7.29	6.39	5.81		6.91	6.69	6.29	6.81
fdi_3		8.06	7.57	8.19	6.82		7.44	7.04	6.74	6.57
fdi_4		8.55	9.01	8.48	6.34		7.14	6.77	8.13	7.28
fdi_bic		8.17	8.76	8.40	6.07		7.74	7.15	7.95	7.34
fdiar_1		7.45	6.62	6.19	6.01		7.71	7.01	6.09	6.09
fdiar_2		7.66	7.02	6.72	6.26		6.38	6.95	6.42	6.96
fdiar_3		8.03	6.98	7.95	6.82		7.44	7.04	6.55	6.61
fdiar_4		8.55	9.01	9.97	6.34		7.10	6.14	7.99	6.97
fdiar_bic		7.84	7.87	9.22	6.01		6.82	6.80	7.74	7.47
fdiarlag_bic		6.89	7.93	11.97	7.43		6.59	6.34	8.21	6.53
RMSFE rbnz	1.43									

h=2		Fixed data set				Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.69									
fvar	2.18									
fbiv_best	2.24					3.84				
fbiv_mean		1.20	1.21				1.37	1.34		
fbiv_med		1.22	1.28				1.53	1.41		
fdi_1		1.35	1.20	1.08	1.09		1.54	1.36	1.36	1.31
fdi_2		1.35	1.48	1.24	1.19		1.34	1.24	1.28	1.49
fdi_3		1.29	1.33	1.73	1.50		1.19	1.21	1.24	1.48
fdi_4		1.54	1.45	1.55	1.38		1.27	1.58	1.17	1.01
fdi_bic		1.45	1.51	2.02	1.27		1.54	1.38	1.36	1.21
Fdiar_1		1.30	1.20	1.08	1.09		1.72	1.37	1.36	1.31
Fdiar_2		1.25	1.53	1.24	1.19		1.43	1.20	1.30	1.49
Fdiar_3		1.22	1.40	2.05	1.63		1.16	1.16	1.35	1.59
Fdiar_4		1.41	1.28	1.40	1.42		1.07	1.68	1.07***	0.95
fdiar_bic		1.16**	1.43	1.86	1.27		1.21	1.57	1.32	1.13
fdiarlag_bic		2.23**	1.61	1.80	1.34		1.45	3.04	0.81*	2.12
RMSFE rbnz	5.02									

h=3		Fixed data set				Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.28									
fvar	2.16									
fbiv_best	2.15					3.68				
fbiv_mean		1.00	1.03				1.63	1.36		
fbiv_med		1.02	1.07				1.72	1.51		
fdi_1		1.05	0.99	0.93	0.95		1.58	1.55	1.45	1.27
fdi_2		1.35	1.52	0.94	1.04		1.34	1.04	1.46	1.19
fdi_3		1.54	1.35	1.27	1.24		1.31	1.13	1.44	1.59
fdi_4		1.37	1.15	0.99	1.18		1.30	0.82	1.43	0.78
fdi_bic		1.27	1.05	1.11	1.29		1.26	1.41	1.71	0.87
fdiar_1		1.05	0.99	0.93	0.95		1.92	1.96	1.45	1.27
fdiar_2		1.40	1.52	0.94	1.04		1.53	1.27	1.43	1.19
fdiar_3		1.72	1.43	1.25	1.23		1.69	1.60	2.13	2.49
fdiar_4		1.70	1.12	0.91	1.18		1.72	1.23	1.17	1.21
fdiar_bic		1.43	1.05	0.95	1.29		1.77	1.49	1.29	1.35
fdiarlag_bic		3.67	1.06	0.81	1.40		1.71	2.94	1.44	2.97
RMSFE rbnz	6.96									

h=4		Fixed data set				Flexible data set				
θ=		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.99									
fvar	2.11									
fbiv_best	5.40					9.31				
fbiv_mean		1.99	2.19				1.80	2.29		
fbiv_med		2.24	2.27				1.59	1.72		
fdi_1		2.03	2.17	1.87	1.91		5.07	5.08	4.55	3.64
fdi_2		1.75	1.74	1.92	1.89		1.45	2.53	2.88	2.15
fdi_3		1.78	1.56	1.02	0.78		1.37	2.26	5.05	2.59
fdi_4		2.56	2.53	4.10	1.45		3.49	2.49	10.24	15.59
fdi_bic		2.21	1.86	1.56	1.09		1.63	2.53	9.51	14.33
fdiar_1		1.90	2.17	1.68	1.72		5.44	5.64	5.09	3.85
fdiar_2		1.83	1.81	1.15	1.37		1.72	3.23	3.44	2.89
fdiar_3		1.87	2.75	1.43	0.86		3.41	2.93	5.33	4.77
fdiar_4		2.44	3.46	5.14	1.89		1.79	2.43	7.99	10.36
fdiar_bic		2.52	2.20	2.13	1.46		3.32	2.55	7.17	11.43
fdiarlag_bic		7.06	7.14	6.06	4.99		21.77	34.40	41.76	147.4
RMSFE rbnz	8.35									

***h*=5**	**Fixed data set**					**Flexible data set**				
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.13									
fvar	1.91									
fbiv_best	2.49					4.45				
fbiv_mean		1.54	1.22				2.26	2.26		
fbiv_med		1.46	1.31				2.13	2.25		
fdi_1		0.91	0.87	0.95	1.01		2.51	2.84	2.10	1.65
fdi_2		1.77	1.36	0.63	0.90		4.14	2.14	2.42	1.57
fdi_3		2.24	1.85	1.68	0.88		3.77	2.86	2.61	2.33
fdi_4		1.98	1.89	1.37	0.82		4.04	4.20	3.79	1.38
fdi_bic		1.92	2.23	1.37	1.10		4.15	4.25	4.09	1.70
fdiar_1		1.04	1.01	0.95	1.01		3.31	3.65	2.56	1.61
fdiar_2		2.06	1.75	1.15	1.12		4.85	3.73	3.77	2.84
fdiar_3		2.51	2.64	1.89	0.70		4.01	3.90	3.74	3.96
fdiar_4		1.97	1.59	1.64	0.70		4.00	4.30	4.73	1.32
fdiar_bic		1.83	1.49	1.58	1.11		4.41	4.77	4.62	1.15
fdiarlag_bic		2.83	2.30	1.31	1.86		7.74	8.26	6.45	3.67
RMSFE rbnz	9.40									

***h*=6**	**Fixed data set**					**Flexible data set**				
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	1.39									
fvar	2.49									
fbiv_best	1.92					4.65				
fbiv_mean		1.82	1.68				2.81	3.28		
fbiv_med		1.69	1.68				3.18	3.52		
fdi_1		1.16	1.06	1.14	1.22		3.15	4.04	2.80	2.12
fdi_2		2.36	1.64	0.58	0.88		3.17	3.19	3.22	2.08
fdi_3		2.23	2.31	2.74	1.07		4.92	3.45	4.80	2.96
fdi_4		2.26	2.14	3.40	1.21		4.88	6.56	10.29	6.58
fdi_bic		1.82	1.57	2.71	1.01		5.24	5.92	8.08	5.07
fdiar_1		1.51	1.14	1.05	1.09		3.98	5.51	4.01	2.94
fdiar_2		2.96	2.49	1.40	1.13		4.43	6.43	6.09	5.11
fdiar_3		2.90	4.62	3.07	1.13		6.55	5.48	8.73	5.69
fdiar_4		2.91	2.76	4.19	1.58		10.71	9.14	8.74	2.74
fdiar_bic		2.84	2.69	3.29	1.10		10.01	8.19	6.51	2.58
fdiarlag_bic		3.43	3.83	2.62	1.14		14.02	18.97	5.38	20.78
RMSFE rbnz	8.96									

***h*=7**	**Fixed data set**					**Flexible data set**				
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	2.23									
fvar	3.42									
fbiv_best	5.21					8.60				
fbiv_mean		2.28	2.00				2.87	3.12		
fbiv_med		2.25	2.11				3.10	3.33		
fdi_1		1.59	1.56	1.59	1.64		5.08	4.85	4.02	3.03
fdi_2		3.19	1.79	0.95	1.24		1.71	3.00	4.01	2.90
fdi_3		1.85	2.60	2.44	1.54		1.97	4.55	6.17	3.48
fdi_4		2.00	2.49	4.93	1.23		2.56	7.10	13.79	12.82
fdi_bic		2.29	2.08	3.41	1.70		2.78	2.98	13.91	12.76
fdiar_1		2.00	1.98	1.83	1.88		5.89	5.61	5.59	4.30
fdiar_2		4.33	3.06	1.07	1.43		2.94	4.77	6.62	5.28
fdiar_3		1.95	5.08	2.74	1.85		3.79	5.70	10.38	6.82
fdiar_4		1.79	5.23	5.69	1.83		3.88	6.76	14.91	6.56
fdiar_bic		1.99	5.05	3.67	1.94		2.89	5.68	17.47	8.30
fdiarlag_bic		5.78	6.87	8.23	2.65		13.65	259.4	78.51	59.36
RMSFE rbnz	8.25									

***h*=8**	**Fixed data set**					**Flexible data set**				
***θ*=**		**5**	**10**	**50**	**100**		**5**	**10**	**50**	**100**
rbnz	1.00									
far	2.13									
fvar	4.37									
fbiv_best	5.77					9.95				
fbiv_mean		2.12	2.34				1.92	2.44		
fbiv_med		2.39	2.43				1.70	1.84		
fdi_1		2.17	2.32	2.00	2.04		5.41	5.43	4.86	3.89
fdi_2		1.87	1.86	2.05	2.02		1.55	2.71	3.08	2.30
fdi_3		1.90	1.67	1.09	0.83		1.47	2.42	5.40	2.76
fdi_4		2.74	2.71	4.38	1.55		3.73	2.67	10.94	16.66
fdi_bic		2.36	1.98	1.67	1.17		1.74	2.71	10.17	15.31
fdiar_1		2.03	2.32	1.79	1.84		5.81	6.03	5.44	4.11
fdiar_2		1.96	1.93	1.23	1.47		1.84	3.46	3.67	3.09
fdiar_3		2.00	2.94	1.53	0.91		3.64	3.13	5.70	5.10
fdiar_4		2.61	3.70	5.49	2.02		1.91	2.60	8.54	11.07
fdiar_bic		2.69	2.36	2.28	1.56		3.55	2.73	7.66	12.21
fdiarlag_bic		7.54	7.64	6.48	5.33		23.26	36.77	44.63	157.6
RMSFE rbnz	8.07									