Factor Model Forecasts for New Zealand*

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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 (including the Reserve Bank of New Zealand's published forecasts), and we gauge the sensitivity of our results to alternative variable-selection algorithms. We find that the factor model performs particularly well at longer horizons.

JEL Codes: C32, E47.

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 6,000 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 that were not so useful in the past may prove to be the most useful in the 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.

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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 distill 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 United States, then use the estimated factors to forecast future realizations 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 favorably to a large number of other univariate, bivariate, and multivariate benchmarks (according to comparisons of mean-squared forecast errors, or MSFEs). Stock and Watson's (1999) results are particularly striking when forecasting inflation.

With similarly impressive results, Forni et al. (2001) and Marcellino, Stock, and Watson (2003) use factor models to analyze large panels of euro-area data, while Artis, Banerjee, and Marcellino (2002) 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 analyze 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 ninety-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 data set is important in determining the quality of factor model forecasts. Boivin and Ng (2003) show that extracting factors from larger data sets does not always yield better forecasting performance, and they propose some rules to reduce the size of their data set before factors are extracted. They show that forecasting performance can be improved by removing (or down-weighting) series with highly cross-correlated errors in the factor model and by categorizing the data into subgroups with an economic interpretation (real and nominal variables, for example). Conceptually, it seems reasonable to exclude series that deteriorate the overall quality of the data set. Boivin and Ng also note that the choice of data is not innocuous. The factors are defined with respect to a specific data set and depend on the exercise at hand: two researchers can end up with different factor estimates by choosing different data sets at the outset of the estimation exercise.

Stock and Watson (1999), for example, show that a single factor extracted from a broad-based data set produces very good forecasts of inflation one year ahead. But the factors extracted from Stock and Watson's data set are by no means guaranteed to be good at forecasting other macroeconomic variables or even inflation at a horizon other than one year ahead.

This paper aims to forecast a variety of variables at different horizons. Since it is not at all clear how to go about finding the appropriate data to use when constructing factor model forecasts in these circumstances, we propose two simple rules that link the dimension of the data set to the particular variable and the particular horizon being forecast. Effectively, our rules group series together based on their past predictive performance, thereby aiming to tailor each data set 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 our data-reduction rules yield 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 data. 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 generalized 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 $i = 1, \ldots, N$ and $t = 1, \ldots, T$. 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 component, and $\lambda_i(L)$ are polynomials of nonnegative 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, $X_t = (X_{1t}, X_{2t}, \ldots, X_{Nt})'$, $\Lambda = (\lambda_1, \lambda_2, \ldots, \lambda_N)'$, $F_t = (f_t', \ldots, f_{t-q}')'$, and $e_t = (e_{1t}, e_{2t}, \ldots, e_{Nt})'$ (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_{it} are allowed to be correlated across i, 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 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. We use asymptotic principal components to estimate our factors.

An estimated factor can be thought of as a weighted average of the variables in a data set, where the weights (the loadings) can be either positive or negative and reflect how correlated each variable is with each factor. Factors are extracted in a sequential fashion, with the first factor explaining the most variation in the data set, the second factor explaining the next most variation (not explained by the first factor), and so on. Factor models thus aim to summarize the information contained in a data set in a parsimonious fashion. The idea is to reduce the size of the data set to a few variables that can be considered representative of the key features of the data set as a whole.

Bai and Ng (2002) propose several information criteria for estimating the number of factors that should be extracted. 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 minimizes the MSFEs, as in Stock and Watson (1998, 2002).

3. Data

This section describes the macroeconomic variables that we forecast. It also describes how we vary the size of the data set, based on the past predictive ability of the indicators (explained below).

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 ninety-day bank-bill interest rates; and the growth rate of the nominal trade-weighted exchange rate index. All data are analyzed at a quarterly frequency. Our sample period ranges from 1992:2 to 2004:3. We forecast at horizons between one and eight quarters ahead, $h = (1, \ldots, 8)$.

The raw indicator set contains 384 series drawn from a variety of sources (appendix 1). 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.[1] Some of the series were included at the finest level of disaggregation 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 disaggregation, and the backward-looking variables are included only as aggregates. Series considered to display excessive volatility in disaggregate form were only included as aggregates.

All series in the raw data set are seasonally adjusted using X12 (additive). The series are then transformed to account for stochastic and deterministic trends; the I(1) series are logged and then differenced, and the I(0) series are left as levels.

3.1 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 favor 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.

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

Boivin and Ng (2003) reduce the size of their empirical data set using rules based on removing (or downweighting) series with highly cross-correlated errors in the factor model and rules based on categorizing the data into subgroups with an economic interpretation (real and nominal variables, for example). They show that both of these methods can produce more efficient estimates of the factors and better forecasts.

Nevertheless, estimated factors are data dependent and not guaranteed to be good at forecasting, certainly not over a variety of variables at different horizons. We thus propose a simple approach that aims to tailor the data to the particular variable and the particular horizon being forecast.

Explicitly, for each forecast horizon h, each stationary forecast variable y_t, and each potential indicator $x_{i,t}$, where $h = (1, \ldots, 8)$ and $i = (1, \ldots, 384)$, the following equation is estimated using OLS:

$$y_t = \beta_0 + \beta_1 x_{i,t-h} + e_{i,t}. \tag{3}$$

The R-squareds (the coefficients of determination) from these bivariate regressions are then used to sort the indicators from most to least informative.

We then reduce the size of our data set by categorizing our data based on past predictive performance. Specifically, we choose to "cut off" the top proportion θ of the ranked indicators and only allow these indicators to enter into our data set, with $\theta = (5\%, 10\%, 50\%, 100\%)$. The smallest data set contains the top 5 percent of the ranked indicators, and the largest data set contains all 386 indicators. We then extract factors from these different-sized data sets.

We also report a variation on this procedure that combines Boivin and Ng's (2003) idea of estimating the factor model first (before reducing the size of the data set) with the rule suggested above. In this second rule, the factor model is estimated over the entire data set, and then the common component of each indicator (the projection of each indicator on the factors) is used in (3), instead of the indicator itself.[2] The ranked indicators resulting from

[2]Thanks to an anonymous referee for suggesting this hybrid criterion. Eight factors are extracted in the initial step.

this rule are ensured to have large common components from the entire data set relative to the previous rule. However, if there is some useful information for forecasting purposes outside the common components, it may be that this rule does not perform as well.

We call the first selection criterion the *one-step* rule (estimate (3) using each indicator) and the second selection criterion the *two-step* rule (estimate the factor model, then estimate (3) using the common component from each indicator). Note that the rules are identical when $\theta = 100\%$.

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.

Analysis of the first two factors extracted from the entire data set, $\theta = 100\%$, shows that the first factor loads highly on indicators of real economic activity. The time profile of the first factor also looks similar to real GDP growth over our sample period, suggesting that it can be broadly interpreted as a measure of real economic activity, consistent with Stock and Watson's (2002) findings for the United States (figure 1). The second factor, on the other hand, loads highly on more direct measures of pricing pressure—price and inflation expectations, etc.

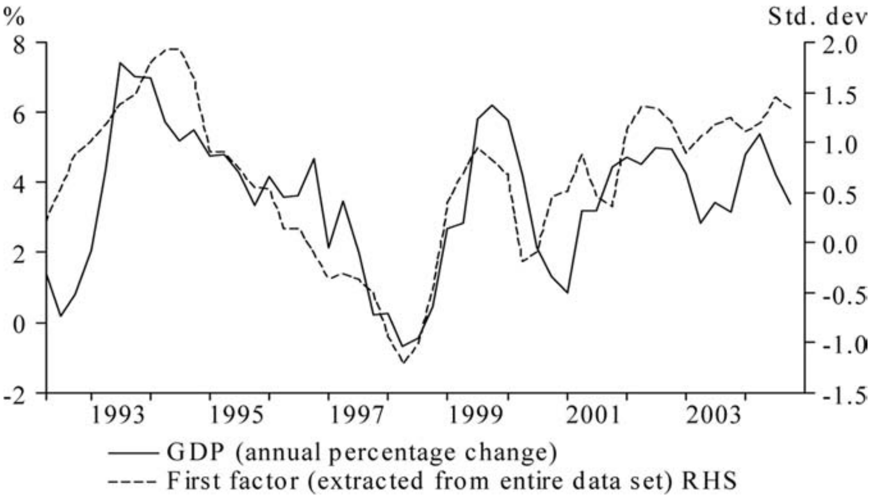
4. Forecasts

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 analyze are based

Figure 1. The First Factor from the Entire Data Set and GDP Growth



on h-step-ahead linear projections. Specifically, the h-step-ahead variable y^h_{t+h} is forecast using the following regression model:

$$y^h_{t+h} = \phi + \beta(L)f_t + \gamma(L)y_t + e^h_{t+h}, \tag{4}$$

where e^h_{t+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^h_{t+h} depends on whether the series of interest z^h_{t+h} is modeled as being I(0) or I(1). If z^h_{t+h} is modeled as I(0),

$$y^h_{t+h} = z^h_{t+h} \text{ and } y_t = z_t. \tag{5}$$

If z^h_{t+h} is modeled as I(1),

$$y^h_{t+h} = \ln\left(\frac{z^h_{t+h}}{z^h_t}\right) \text{ and } y_t = \ln\left(\frac{z_t}{z_{t-1}}\right) \tag{6}$$

or

$$y^h_{t+h} = z^h_{t+h} - z^h_t \text{ and } y_t = z_t - z_{t-1}. \tag{7}$$

We model the CPI, the GDP, and the exchange rate using (6), and we model the interest rate using (7).[3]

4.2 Forecasting Models

The range of different forecast models that we estimate is discussed below.

4.2.1 Autoregressive Forecasts

The autoregressive forecast *far* is based on (4), 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 zero to four: the largest autoregressive model possible includes four 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 (4) becomes a single indicator $x_{i,t}$. For each bivariate forecast, we allow one to four lags of $x_{i,t}$ and zero to four 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 median *fbiv_med* forecasts from the top 5 percent and 10 percent of the ranked bivariate indicators.[4] These 5 percent and 10 percent cut-off points correspond to the first two θ cut-offs that we use to vary the size of our data set when we extract factors.

4.2.3 Factor Model Forecasts

We analyze three different variants of factor model forecasts, similar to Stock and Watson (2002). The first variant excludes lagged dependent variables and explores forecasts when different numbers of

[3] Modeling the ninety-day interest rate in differences is supported by evidence of a falling neutral real interest rate in New Zealand over our sample period (Basdevant, Björksten, and Karagedikli 2004).

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

contemporaneous factors k are included. In this group of forecasts, equation (4) is estimated with k contemporaneous factors, with k ranging from one to four *fdi_k*. In (4) $\beta(L)f_t$ 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 zero and four 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 (one to four), the number of lagged factors (zero to two), and the number of lags of the dependent variable (zero to four). Together, we estimate forty-four different factor models for each horizon (and for each data-reduction rule): the eleven models outlined above over the four different data set cut-offs (θ).

4.2.4 Vector Autoregressive (VAR) Forecasts

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 two. VAR forecasts are made by iterating forecasts forward, unlike in the h-step-ahead method we use for our other forecasting models.

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 judgment. There is a distinction between how the Reserve Bank forecasts over the near term (one to two quarters ahead) and how it forecasts over longer horizons. The Reserve Bank's near-term forecasts can be characterized as being more judgment 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).[5]

[5]See Drew and Hunt (1998) for a detailed description of FPS.

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, i.e., $z_{t+h}^h = z_t(1 + y_{t+h}^h)$. We then construct annual percentage changes for the CPI, the 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. The data against which we compare our real-time forecasts are displayed in figure 2.

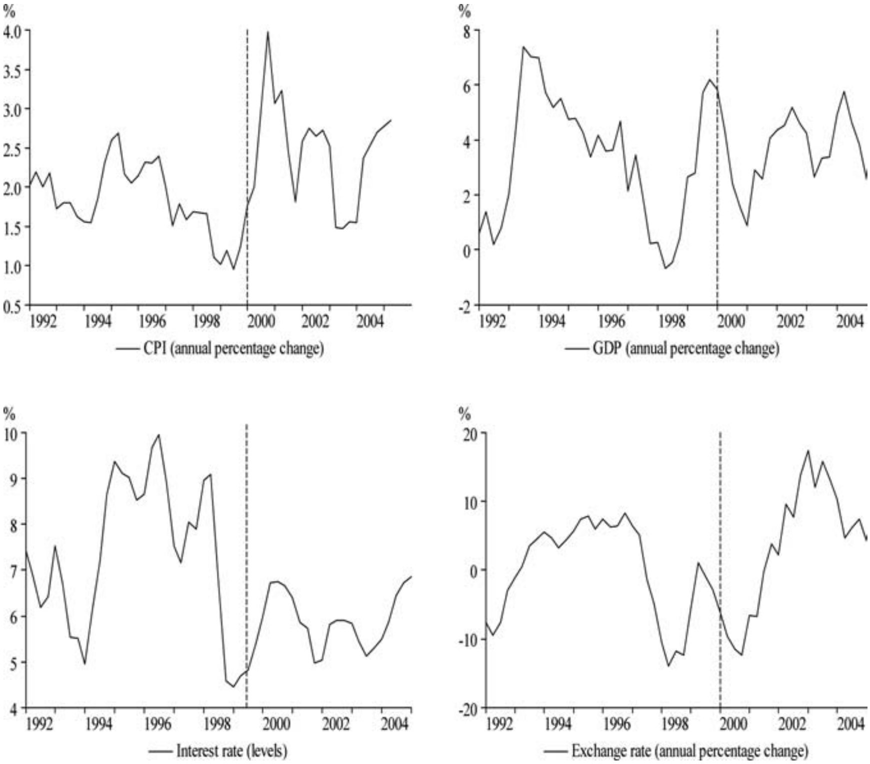
The forecasting performance of a candidate forecast is evaluated by comparing its out-of-sample MSFE to a Reserve Bank of New Zealand benchmark. For an h-step-ahead forecast, the MSFE of a candidate model i relative to the benchmark Reserve Bank forecast 0 is

$$MSFE\_relative = \frac{\sum_{t=T_1}^{T_2-h}\left(\hat{y}_{i,t+h}^h - y_{t+h}\right)^2}{\sum_{t=T_1}^{T_2-h}\left(\hat{y}_{0,t+h}^h - y_{t+h}\right)^2}, \tag{8}$$

where T_1 and $T_2 - h$ are the first and last dates over which the out-of-sample forecasts are compared, respectively. We test whether the MSFE of the candidate model is significantly smaller than that of the Reserve Bank using methods described in Diebold and Mariano (1995). Specifically, we test whether the difference in MSFEs between the benchmark and the candidate model is negative, i.e.,

$$\text{Null Hypothesis: } E[\varepsilon_t] = 0 \tag{9}$$

Figure 2. The Ex Post Data



against

$$\text{Alternative Hypothesis: } E[\varepsilon_t] < 0, \tag{10}$$

where

$$\varepsilon_t = \left(\hat{y}^h_{i,t+h} - y_{t+h}\right)^2 - \left(\hat{y}^h_{0,t+h} - y_{t+h}\right)^2. \tag{11}$$

As above, the subscript i refers to a candidate model and the subscript 0 refers to forecasts from the Reserve Bank of New Zealand.[6]

[6]The variance of the mean difference in MSFEs is estimated using the Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) estimator, with a truncation lag of $(h-1)$. The test statistic is compared to a Student-t distribution with $(T-1)$ degrees of freedom.

6. Empirical Results

In this section, we include a table displaying the results for the models other than the factor model (*far*, *fvar*, *fbiv_best*, *fbiv_mean*, and *fbiv_med*) (table 1) and a table displaying the results for the simplest factor model forecast (*fdi_1*) (table 2). All other results can be found in appendix 2. 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 are available.

6.1 CPI Inflation

In general, the Reserve Bank forecasts have lower MSFEs at shorter horizons, $h < 5$. At longer horizons, however, some of the forecasting models begin to outperform the benchmark. As noted by Stock and Watson (2002) for the United States, we find that 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 multifactors and lags of the 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.

The mean and median bivariate forecasts, *fbiv_mean* and *fbiv_med*, and the VAR forecast, *fvar,* compare favorably 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, i.e., 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.

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. When $h = 8$, however, the factor models seem to perform better with fewer indicators. Thus, there does not seem to be any clear relationship

Table 1. MSFEs Relative to Reserve Bank

				$\theta = 5\%$		$\theta = 10\%$	
	far	**fvar**	**fbiv_best**	**fbiv_mean**	**fbiv_med**	**fbiv_mean**	**fbiv_med**
CPI							
$h = 1$	3.28	3.42	4.18	3.71	3.66	3.66	3.60
2	1.55	1.83	1.96	1.70	1.62	1.70	1.63
3	1.38	1.30	2.29	1.58	1.56	1.54	1.48
4	1.29	1.14	2.80	1.53	1.46	1.54	1.47
5	**0.84**	**0.76**	1.51	**0.98**	**0.99**	1.00	**0.98**
6	**0.64****	**0.45**	1.69	**0.88**	**0.89**	**0.88**	**0.85**
7	**0.57***	**0.58**	2.73	**0.61**	**0.54**	**0.53***	**0.56***
8	**0.61**	**0.98**	3.25	**0.81**	**0.74**	**0.65**	**0.53**
GDP							
$h = 1$	2.12	1.69	2.53	2.07	2.02	2.02	1.98
2	1.54	1.75	2.15	1.33	1.53	1.28	1.49
3	1.23	1.81	1.95	1.11	1.22	1.07	1.08
4	**0.96**	2.08	1.00	**0.60***	**0.66**	**0.64***	**0.71**
5	**0.57***	**0.90**	**0.87**	**0.72**	**0.75**	**0.54***	**0.59**
6	**0.59****	1.29	1.14	**0.63**	**0.65**	**0.65**	**0.71**
7	**0.87**	1.25	7.56	1.59	1.23	1.45	1.05
8	1.07	1.59	6.29	1.69	1.21	1.32	1.22
Interest Rate							
$h = 1$	16.19	27.50	50.45	23.55	22.49	18.67	19.32
2	4.18	7.30	20.25	7.94	7.20	5.92	5.45
3	2.07	4.96	11.19	3.41	3.65	2.98	3.09
4	1.25	3.94	1.99	1.29	1.65	1.30	1.49
5	**0.76**	2.72	1.70	**0.72**	**0.93**	**0.56**	**0.75**
6	**0.40****	2.62	2.36	**0.59**	**0.70**	**0.49**	**0.55**
7	**0.25****	3.52	2.06	**0.76**	**0.71**	**0.58**	**0.60**
8	**0.21**	4.20	2.58	**0.75**	**0.62**	**0.72**	**0.66**

(continued)

Table 1 (continued). MSFEs Relative to Reserve Bank

				θ = 5%		θ = 10%	
	far	**fvar**	**fbiv_best**	**fbiv_mean**	**fbiv_med**	**fbiv_mean**	**fbiv_med**
Exchange Rate							
$h = 1$	8.34	9.03	12.18	7.06	7.65	6.97	7.33
2	1.69	2.04	2.24	1.20	1.22	1.21	1.28
3	1.28	1.94	2.15	1.00	1.02	1.03	1.07
4	1.32	1.88	2.17	1.46	1.50	1.30	1.36
5	1.13	1.79	2.49	1.54	1.46	1.22	1.31
6	1.39	2.32	1.92	1.82	1.69	1.68	1.68
7	2.23	3.52	5.22	2.28	2.25	2.00	2.11
8	2.13	3.88	5.77	2.12	2.39	2.34	2.43

Note: ** denotes significance at the 5 percent level. * denotes significance at the 10 percent level.

Table 2. MSFEs Relative to Reserve Bank—*fdi_1*

Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
CPI							
$h = 1$	3.50	3.41	3.05	3.60	3.80	3.03	2.87
2	2.05	1.84	1.68	2.09	1.99	1.71	1.60
3	1.41	1.48	1.53	1.79	1.66	1.55	1.42
4	1.45	1.47	1.45	1.91	1.70	1.48	1.38
5	1.14	1.05	**0.94**	1.33	1.25	**0.96**	**0.89**
6	1.07	**0.97**	**0.73**	1.10	1.06	**0.76**	**0.69**
7	**0.89**	**0.77**	**0.65**	**0.87**	**0.82**	**0.66**	**0.62***
8	**0.67**	**0.71**	**0.73**	**0.68**	**0.72**	**0.72**	**0.74**

(continued)

Table 2 (continued). MSFEs Relative to Reserve Bank—*fdi_1*

Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
GDP							
$h = 1$	2.02	2.00	1.83	1.92	2.04	1.80	1.73
2	1.67	1.63	1.36	1.67	1.62	1.31	1.35
3	1.28	1.21	**0.93**	1.22	1.21	**0.93**	**0.97**
4	**0.97**	**0.84**	**0.66**	**0.94**	**0.81**	**0.64**	**0.66**
5	**0.57****	**0.56****	**0.48****	**0.67***	**0.60****	**0.48****	**0.46****
6	**0.55****	**0.61***	**0.74**	1.02	**0.88**	**0.74**	**0.65***
7	**0.67****	**0.71**	1.05	1.20	**0.88**	1.04	**0.99**
8	**0.77****	**0.82**	1.28	1.63	**0.95**	1.27	1.28
Interest Rate							
$h = 1$	25.10	24.58	21.25	25.72	24.63	21.83	20.52
2	7.53	7.06	5.55	7.19	6.86	5.86	5.28
3	4.53	4.08	3.19	5.79	4.70	3.29	2.92
4	2.62	2.16	2.05	3.20	2.71	2.01	2.03
5	1.45	1.14	1.11	1.38	1.40	1.10	1.25
6	1.11	**0.75**	**0.67**	1.08	**0.85**	**0.67**	**0.77**
7	1.13	**0.73**	**0.50**	1.30	**0.90**	**0.52**	**0.54**
8	**0.77**	**0.65**	**0.45**	1.33	**0.83**	**0.47**	**0.40**
Exchange Rate							
$h = 1$	7.45	6.62	5.71	6.71	6.10	5.77	5.71
2	1.35	1.20	1.08	1.27	1.22	1.06	1.09
3	1.05	**0.99**	**0.93**	1.08	**0.93**	**0.89**	**0.95**
4	1.20	1.09	1.05	1.14	1.07	1.02	1.11
5	**0.91**	**0.87**	**0.95**	**0.86**	**0.77**	**0.90**	1.01
6	1.16	1.06	1.14	**0.95**	**0.93**	1.12	1.22
7	1.59	1.56	1.59	1.36	1.45	1.60	1.64
8	2.17	2.32	2.00	2.24	2.03	2.03	2.04

Note: ** denotes significance at the 5 percent level. * denotes significance at the 10 percent level.

between the size of the data set, as represented by θ, and forecast performance. Likewise, it is not clear which data-reduction rule (the one-step rule or the two-step rule) produces the best factor model forecasts; for some models and some horizons the one-step rule seems to be preferable, and for other models and other horizons the two-step rule appears to be better.

6.2 GDP Growth

Similar to CPI inflation, the Reserve Bank forecasts outperform the competing models at shorter horizons ($h < 3$), 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. The VAR model *fvar*, models that allow for multifactors 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 favorably to both the Reserve Bank and the factor model forecasts, especially at longer horizons. It also appears that small gains can be made when averages or medians are taken over a larger number of bivariate forecasts.

Again, the ideal size of the data set from which factors are extracted is 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 $h = 6$ the model with one factor extracted from the data set reduced using the one-step rule *fdi_1* outperforms the benchmark by more when the factor model is applied to fewer indicators. Generally speaking, the one-step and two-step rules have comparable forecasting performance across most factor models and forecast horizons.

6.3 Interest Rate

The results for the interest rate are broadly the same as for CPI inflation. That is, the competing models are outperformed 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 favorably 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.

Although it is not entirely clear cut, it seems that the better factor model forecasts tend to use the entire data set, $\theta = 100\%$, at shorter horizons. At longer horizons, the better factor model forecasts generally use only half of the indicators, $\theta = 50\%$: the two-step rule and the one-step rule produce comparable forecasts in these cases. It is also worth noting that the univariate autoregressive model *far* performs particularly well at longer horizons, $h > 5$, and generally yields the lowest MSFE of the competing models.

6.4 Exchange Rate Growth

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 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 the results for interest rates, the better factor model forecasts tend to use only half of the indicators, $\theta = 50\%$: the two-step rule seems to perform slightly better than the one-step rule in these cases.

7. Summary and Conclusions

Two 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 outperform 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 the 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 rules were ad hoc, they still yielded superior forecasts at some horizons. These rules, 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.

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 very short sample of data. Our results will thus need to be revisited in the future.

Appendix 1. 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 & 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 & Retail, Accommodation, Cafes, 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 & Personal Services
32	Real GDP – Transport, Storage
33	Real GDP – Communications
34	Real GDP – Transport, Storage & Communications
35	Real GDP – Finance & Insurance
36	Real GDP – Real Estate & Business Services
37	Real GDP – Finance, Insurance, Property & 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)

Consumers Price Index

48 Headline CPI
49 Non-tradable CPI
50 Tradable CPI
51 Non-tradable – Weighted Median
52 Non-tradable – Trimmed Mean
53 Tradable – Weighted Median
54 Tradable – Trimmed Mean

Retail Trade Survey

55 Retail Trade Deflator (excluding auto)
56 Retail Trade Deflator

Quarterly Employment Survey

57 Total Paid Hours – Total All Industries
58 Labour Productivity
59 Total Paid Hours – Forestry & Mining
60 Total Paid Hours – Manufacturing
61 Total Paid Hours – Electricity, Gas & Water Supply
62 Total Paid Hours – Construction
63 Total Paid Hours – Wholesale Trade
64 Total Paid Hours – Retail Trade
65 Total Paid Hours – Accommodation, Cafes & Restaurants
66 Total Paid Hours – Transport, Storage and Communication Services
67 Total Paid Hours – Finance & Insurance
68 Total Paid Hours – Property & Business Services
69 Total Paid Hours – Government Administration & Defence
70 Total Paid Hours – Education
71 Total Paid Hours – Health & Community Services
72 Total Paid Hours – Cultural & Recreational Services
73 Total Paid Hours – Personal & Other Services

74 Average Hourly Earnings (ord + o/time) – Accom., Cafes & Restaurants
75 Average Hourly Earnings (ord + o/time) – Construction
76 Average Hourly Earnings (ord + o/time) – Cultural & Recreational Services
77 Average Hourly Earnings (ord + o/time) – Education
78 Average Hourly Earnings (ord + o/time) – Electricity, Gas & Water
79 Average Hourly Earnings (ord + o/time) – Finance & Insurance
80 Average Hourly Earnings (ord + o/time) – Forestry & Mining
81 Average Hourly Earnings (ord + o/time) – Govt Admin and Defence
82 Average Hourly Earnings (ord + o/time) – Health & Community Services
83 Average Hourly Earnings (ord + o/time) – Manufacturing
84 Average Hourly Earnings (ord + o/time) – Personal & Other Services
85 Average Hourly Earnings (ord + o/time) – Property & Business Services
86 Average Hourly Earnings (ord + o/time) – Retail Trade
87 Average Hourly Earnings (ord + o/time) – Total
88 Average Hourly Earnings (ord + o/time) – Transport, Storage, Communication
89 Average Hourly Earnings (ord + o/time) – Wholesale Trade
90 Average Hourly Earnings (ordinary time) – Private Sector
91 Average Hourly Earnings (ordinary time) – Public Sector
92 Average Hourly Earnings (ordinary time) – All Sectors

Building Consents

93 Houses and Flats – Number
94 Total Additions and Alterations – Number
95 Total New/Altered – Number
96 New Residential Buildings – Total
97 Apartment Buildings – Number

Building Work Put in Place

98 Real Building Work Put in Place – Residential
99 Real Building Work Put in Place – Non-residential

Car Registrations

100 New Vehicles – Including Cars Previously Registered Overseas

Producers' Price Indexes

101 PPI Inputs – All Industries
102 PPI Outputs – All Industries

Merchandise Trade Indexes

103 Terms of Trade Index
104 Export Volume Index – All Merchandise
105 Export Price Index – All Merchandise
106 Volume of Total Merchandise Imports
107 Import Price Index Total Merchandise Imports

External Migration

108 Net Short-Term Migration
109 Net Permanent & Long-Term Migration
110 Short-Term Visitor Arrivals

Energy Production Data

111 Electricity Generation – Sale to Consumers (Hydro)
112 Electricity Generation – Sale to Consumers (Thermal)
113 Gas Production
114 Electricity Generation

Slaughter Numbers

115 Livestock Slaughter, by Weight, Millions kg
116 Cattle Slaughter, by Total Number
117 Sheep Slaughter, by Total Number
118 Lamb Slaughter, by Total Number

Reserve Bank of New Zealand
Money and Credit Aggregates

119 Official Series of M1
120 Official Series of M2
121 Official Series of M3
122 Official Series of PSCR
123 Official Series of DC
124 Household Claims

Interest and Exchange Rates

125 Monetary Conditions Index
126 Trade Weighted Index
127 NZD/AUD Exchange Rate (average 11am)
128 NZD/GBP Exchange Rate (average 11am)
129 NZD/JPY Exchange Rate (average 11am)
130 NZD/USD Exchange Rate (average 11am)
131 Real Exchange Rate
132 Real Exchange Rate (deviation from equilibrium)
133 Real 90-Day Interest Rate (deviation from equilibrium)
134 Nominal 90-Day Interest Rate (deviation from equilibrium)
135 Yield Spread (90-day rate – 10-year bond yield)
136 Australia 10-Year Bond
137 Australia 90-Day Bank Bill
138 Australia Yield Spread (90-day rate – 10-year bond yield)
139 US 10-Year Bond
140 US 90-Day Bank Bill
141 US Yield Spread (90-day rate – 10-year bond yield)
142 World Long Interest Rates
143 World Short Interest Rates
144 World Yield Spread (90-day rate – 10-year bond yield)

Output and Prices

145 World Real GDP – Trade Weighted
146 Growth Difference between NZ and ROW (APC)
147 World CPI Trade Weighted

Marketscope Survey

148 Expected Current Inflation – Mean
149 Net % Exp Higher Inflation (12 Months)
150 Expected Inflation (12 Months) – Mean

Survey of Expectations

151 Exp Quarterly CPI – Next Quarter
152 Exp Annual CPI – 1 Year from Now
153 Exp Annual CPI – 2 Years from Now
154 Exp HLFS Unemployment Rate – 1 Year Ahead

Datastream
Prices

155 PPI (manufacturing) – Australia
156 PPI (manufacturing) – Japan
157 PPI (manufacturing) – UK
158 PPI (manufacturing) – US
159 PPI (total) – Japan
160 Consumers Price Index – Australia
161 Consumers Price Index – Euro
162 Consumers Price Index – Japan
163 Consumers Price Index – UK
164 Consumers Price Index – US

Output

165 GDP (constant prices) – Australia
166 GDP (constant prices) – Europe
167 GDP (constant prices) – Japan
168 GDP (constant prices) – US

Oil Prices

169 Brent oil prices ($US/barrel)

Real Estate Institute of New Zealand
Housing-Related Data

170 Median Dwelling Price
171 Median List Price
172 No. of Dwelling Sales
173 Median Days to Sell

Quotable Value New Zealand
House Prices

174 Quarterly House Price Index

New Zealand Institute of Economic Research
Quarterly Survey of Business Opinion

175 ECONOMY-WIDE – PAST 3 MONTHS – Average Costs
176 ECONOMY-WIDE – NEXT 3 MONTHS – Average Costs
177 ECONOMY-WIDE – PAST 3 MONTHS – Average Selling Price

178 ECONOMY-WIDE – NEXT 3 MONTHS – Average Selling Price
179 ECONOMY-WIDE – Capacity Utilisation
180 ECONOMY-WIDE – PAST 3 MONTHS – Domestic Trading Activity
181 ECONOMY-WIDE – NEXT 3 MONTHS – Domestic Trading Activity
182 ECONOMY-WIDE – Find. Labour: Skilled
183 ECONOMY-WIDE – Find. Labour: Unskilled
184 ECONOMY-WIDE – General Business Situation
185 ECONOMY-WIDE – New Investment: Buildings
186 ECONOMY-WIDE – New Investment: Plant & Machinery
187 ECONOMY-WIDE – Limiting Factor – Capital
188 ECONOMY-WIDE – Limiting Factor – Finished orders
189 ECONOMY-WIDE – Limiting Factor – Labour
190 ECONOMY-WIDE – Limiting Factor – Materials
191 ECONOMY-WIDE – Limiting Factor – New orders
192 ECONOMY-WIDE – Limiting Factor – Other
193 ECONOMY-WIDE – PAST 3 MONTHS – No. Employed
194 ECONOMY-WIDE – NEXT 3 MONTHS – No. Employed
195 ECONOMY-WIDE – PAST 3 MONTHS – Profitability
196 ECONOMY-WIDE – NEXT 3 MONTHS – Profitability
197 ECONOMY-WIDE – PAST 3 MONTHS – Overtime Wkd
198 ECONOMY-WIDE – NEXT 3 MONTHS – Overtime Wkd

199 BUILDERS – PAST 3 MONTHS – Average Costs
200 BUILDERS – NEXT 3 MONTHS – Average Costs
201 BUILDERS – PAST 3 MONTHS – Average Selling Price
202 BUILDERS – NEXT 3 MONTHS – Average Selling Price
203 BUILDERS – Capacity Utilisation
204 BUILDERS – Find. Labour: Skilled
205 BUILDERS – Find. Labour: Unskilled
206 BUILDERS – General Business Situation
207 BUILDERS – New Investment: Buildings
208 BUILDERS – New Investment: Plant & Machinery
209 BUILDERS – Limiting Factor – Capital
210 BUILDERS – Limiting Factor – Finished Orders
211 BUILDERS – Limiting Factor – Labour
212 BUILDERS – Limiting Factor – Materials

213 BUILDERS – Limiting Factor – New Orders
214 BUILDERS – Limiting Factor – Other
215 BUILDERS – PAST 3 MONTHS – No. Employed
216 BUILDERS – NEXT 3 MONTHS – No. Employed
217 BUILDERS – PAST 3 MONTHS – New Orders
218 BUILDERS – NEXT 3 MONTHS – New Orders
219 BUILDERS – PAST 3 MONTHS – Output
220 BUILDERS – NEXT 3 MONTHS – Output
221 BUILDERS – PAST 3 MONTHS – Profitability
222 BUILDERS – NEXT 3 MONTHS – Profitability
223 BUILDERS – PAST 3 MONTHS – Overtime Wkd
224 BUILDERS – NEXT 3 MONTHS – Overtime Wkd

225 BUILDING & CONSTRUCTION – PAST 3 MONTHS – Deliveries in NZ
226 BUILDING & CONSTRUCTION – NEXT 3 MONTHS – Deliveries in NZ
227 BUILDING & CONSTRUCTION – Find. Labour: Skilled
228 BUILDING & CONSTRUCTION – Find. Labour: Unskilled
229 BUILDING & CONSTRUCTION – General Business Situation
230 BUILDING & CONSTRUCTION – New Investment: Buildings
231 BUILDING & CONSTRUCTION – New Investment: Plant & Machinery
232 BUILDING & CONSTRUCTION – PAST 3 MONTHS – No. Employed
233 BUILDING & CONSTRUCTION – NEXT 3 MONTHS – No. Employed
234 BUILDING & CONSTRUCTION – PAST 3 MONTHS – New Orders
235 BUILDING & CONSTRUCTION – NEXT 3 MONTHS – New Orders
236 BUILDING & CONSTRUCTION – PAST 3 MONTHS – Output
237 BUILDING & CONSTRUCTION – NEXT 3 MONTHS – Output

238 BUILDING & CONSTRUCTION – PAST 3 MONTHS – Profitability
239 BUILDING & CONSTRUCTION – NEXT 3 MONTHS – Profitability

240 BUILDING MATERIALS – General Business Situation
241 BUILDING MATERIALS – PAST 3 MONTHS – No. Employed
242 BUILDING MATERIALS – NEXT 3 MONTHS – No. Employed
243 BUILDING MATERIALS – PAST 3 MONTHS – New Orders
244 BUILDING MATERIALS – NEXT 3 MONTHS – New Orders
245 BUILDING MATERIALS – PAST 3 MONTHS – Profitability
246 BUILDING MATERIALS – NEXT 3 MONTHS – Profitability

247 MANUFACTURERS – PAST 3 MONTHS – Average Costs
248 MANUFACTURERS – NEXT 3 MONTHS – Average Costs
249 MANUFACTURERS – PAST 3 MONTHS – Average Selling Price
250 MANUFACTURERS – NEXT 3 MONTHS – Average Selling Price
251 MANUFACTURERS – Capacity Utilisation
252 MANUFACTURERS – PAST 3 MONTHS – Deliveries in NZ
253 MANUFACTURERS – NEXT 3 MONTHS – Deliveries in NZ
254 MANUFACTURERS – Find. Labour: Skilled
255 MANUFACTURERS – Find. Labour: Unskilled
256 MANUFACTURERS – General Business Situation
257 MANUFACTURERS – New Investment: Buildings
258 MANUFACTURERS – New Investment: Plant & Machinery
259 MANUFACTURERS – Limiting Factor – Capital
260 MANUFACTURERS – Limiting Factor – Finished Orders

261 MANUFACTURERS – Limiting Factor – Labour
262 MANUFACTURERS – Limiting Factor – Materials
263 MANUFACTURERS – Limiting Factor – New Orders
264 MANUFACTURERS – Limiting Factor – Other
265 MANUFACTURERS – PAST 3 MONTHS – No. Employed
266 MANUFACTURERS – NEXT 3 MONTHS – No. Employed
267 MANUFACTURERS – PAST 3 MONTHS – New Orders
268 MANUFACTURERS – NEXT 3 MONTHS – New Orders
269 MANUFACTURERS – PAST 3 MONTHS – Output
270 MANUFACTURERS – NEXT 3 MONTHS – Output
271 MANUFACTURERS – PAST 3 MONTHS – Profitability
272 MANUFACTURERS – NEXT 3 MONTHS – Profitability
273 MANUFACTURERS – PAST 3 MONTHS – Overtime Wkd
274 MANUFACTURERS – NEXT 3 MONTHS – Overtime Wkd
275 MANUFACTURERS & BUILDERS – PAST 3 MONTHS – Profitability
276 MANUFACTURERS & BUILDERS – NEXT 3 MONTHS – Profitability
277 MANUFACTURERS & BUILDERS – PAST 3 MONTHS – Overtime Wkd
278 MANUFACTURERS & BUILDERS – NEXT 3 MONTHS – Overtime Wkd

279 MERCHANTS – PAST 3 MONTHS – Average Costs
280 MERCHANTS – NEXT 3 MONTHS – Average Costs
281 MERCHANTS – PAST 3 MONTHS – Average Selling Price
282 MERCHANTS – NEXT 3 MONTHS – Average Selling Price
283 MERCHANTS – Find. Labour: Skilled
284 MERCHANTS – Find. Labour: Unskilled
285 MERCHANTS – General Business Situation
286 MERCHANTS – New Investment: Buildings
287 MERCHANTS – New Investment: Fix. F
288 MERCHANTS – Limiting Factor – Capital
289 MERCHANTS – Limiting Factor – Finished Orders
290 MERCHANTS – Limiting Factor – Labour
291 MERCHANTS – Limiting Factor – Material
292 MERCHANTS – Limiting Factor – New Orders

293 MERCHANTS – Limiting Factor – Other
294 MERCHANTS – PAST 3 MONTHS – No. Employed
295 MERCHANTS – NEXT 3 MONTHS – No. Employed
296 MERCHANTS – PAST 3 MONTHS – New Forward Orders
297 MERCHANTS – NEXT 3 MONTHS – New Forward Orders
298 MERCHANTS – PAST 3 MONTHS – Sales in NZ
299 MERCHANTS – NEXT 3 MONTHS – Sales in NZ
300 MERCHANTS – Volume of Sales Next 6 Months
301 MERCHANTS – PAST 3 MONTHS – Profitability
302 MERCHANTS – NEXT 3 MONTHS – Profitability
303 MERCHANTS – PAST 3 MONTHS – Overtime Wkd
304 MERCHANTS – NEXT 3 MONTHS – Overtime Wkd

305 SERVICES – PAST 3 MONTHS – Average Cost per Service
306 SERVICES – NEXT 3 MONTHS – Average Cost per Service
307 SERVICES – Find. Labour: Skilled
308 SERVICES – Find. Labour: Unskilled
309 SERVICES – General Business Situation
310 SERVICES – New Investment: Buildings
311 SERVICES – New Investment: Plant & Machinery
312 SERVICES – Limiting Factor – Capital
313 SERVICES – Limiting Factor – Demand
314 SERVICES – Limiting Factor – Finished Orders
315 SERVICES – Limiting Factor – Labour
316 SERVICES – Limiting Factor – Other
317 SERVICES – Limiting Factor – Supply
318 SERVICES – PAST 3 MONTHS – No. Employed
319 SERVICES – NEXT 3 MONTHS – No. Employed
320 SERVICES – PAST 3 MONTHS – Volume of Services
321 SERVICES – NEXT 3 MONTHS – Volume of Services
322 SERVICES – PAST 3 MONTHS – Profitability
323 SERVICES – NEXT 3 MONTHS – Profitability
324 SERVICES – PAST 3 MONTHS – Overtime Wkd
325 SERVICES – NEXT 3 MONTHS – Overtime Wkd

326 FINANCIAL SERVICES – PAST 3 MONTHS – Average Cost per Service

327 FINANCIAL SERVICES – NEXT 3 MONTHS – Average Cost per Service
328 FINANCIAL SERVICES – Find. Labour: Skilled
329 FINANCIAL SERVICES – Find. Labour: Unskilled
330 FINANCIAL SERVICES – General Business Situation
331 FINANCIAL SERVICES – New Investment: Buildings
332 FINANCIAL SERVICES – New Investment: Plant & Machinery
333 FINANCIAL SERVICES – Limiting Factor – Capital
334 FINANCIAL SERVICES – Limiting Factor – Demand
335 FINANCIAL SERVICES – Limiting Factor – Finished Orders
336 FINANCIAL SERVICES – Limiting Factor – Labour
337 FINANCIAL SERVICES – Limiting Factor – Other
338 FINANCIAL SERVICES – Limiting Factor – Supply
339 FINANCIAL SERVICES – PAST 3 MONTHS – No. Employed
340 FINANCIAL SERVICES – NEXT 3 MONTHS – No. Employed
341 FINANCIAL SERVICES – PAST 3 MONTHS – Volume of Services
342 FINANCIAL SERVICES – NEXT 3 MONTHS – Volume of Services
343 FINANCIAL SERVICES – PAST 3 MONTHS – Profitability
344 FINANCIAL SERVICES – NEXT 3 MONTHS – Profitability
345 FINANCIAL SERVICES – PAST 3 MONTHS – Overtime Wkd
346 FINANCIAL SERVICES – NEXT 3 MONTHS – Overtime Wkd

National Bank of New Zealand
Business Outlook Survey

347 INFLATION EXPECTATIONS – Next 12 Months – Retail
348 INFLATION EXPECTATIONS – Next 12 Months – Manufacturing
349 INFLATION EXPECTATIONS – Next 12 Months – Agriculture

350 INFLATION EXPECTATIONS – Next 12 Months – Construction
351 INFLATION EXPECTATIONS – Next 12 Months – Services
352 INFLATION EXPECTATIONS – Next 12 Months – Total (All Sectors)

353 BUSINESS CONFIDENCE – Next 12 Months – Retail
354 BUSINESS CONFIDENCE – Next 12 Months – Manufacturing
355 BUSINESS CONFIDENCE – Next 12 Months – Agriculture
356 BUSINESS CONFIDENCE – Next 12 Months – Construction
357 BUSINESS CONFIDENCE – Next 12 Months – Services
358 BUSINESS CONFIDENCE – Next 12 Months – Total (All Sectors)

359 ACTIVITY OUTLOOK – Next 12 Months – Retail
360 ACTIVITY OUTLOOK – Next 12 Months – Manufacturing
361 ACTIVITY OUTLOOK – Next 12 Months – Agriculture
362 ACTIVITY OUTLOOK – Next 12 Months – Construction
363 ACTIVITY OUTLOOK – Next 12 Months – Services
364 ACTIVITY OUTLOOK – Next 12 Months – Total (All Sectors)

365 PRICING INTENTIONS – Next 3 Months – Total (All Sectors)
366 PRICING INTENTIONS – Next 3 Months – Retail
367 PRICING INTENTIONS – Next 3 Months – Manufacturing

ANZ Banking Group Ltd
Commodity Price Indexes

368 COMMODITY PRICE INDEX – NZ$
369 COMMODITY PRICE INDEX – NZ$ – Meat, Skins & Wool
370 COMMODITY PRICE INDEX – NZ$ – Dairy Products

371 COMMODITY PRICE INDEX – NZ$ – Horticultural Products
372 COMMODITY PRICE INDEX – NZ$ – Forestry Products
373 COMMODITY PRICE INDEX – NZ$ – Seafood
374 COMMODITY PRICE INDEX – NZ$ – Aluminium

Westpac Banking Corporation
Westpac-McDermott-Millar
375 Consumer Confidence Index

Television New Zealand
One News Colmar Brunton Poll
376 Consumer Confidence

AON Consulting Ltd
Economist Survey
377 CPI Inflation – In 1 Year's Time
378 CPI Inflation – In 4 Years' Time
379 CPI Inflation – In 7 Years' Time
380 Increase Avg. Weekly Wage – In 1 Year's Time
381 Increase Avg. Weekly Wage – In 4 Years' Time
382 Increase Avg. Weekly Wage – In 7 Years' Time

Cement and Concrete Assoc (NZ)
383 Cement Sales

National Institute of Water and Atmospheric Research
384 Southern Oscillation Index

Appendix 2. Relative Mean-Squared Forecast Errors (MSFEs)

Notes for Appendix B

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

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 one to four lags of the indicator and zero to four lags of the dependent variable (BIC selection of both)
fbiv_mean	Mean of the top 5 percent and 10 percent of BIC-ranked bivariate indicators
fbiv_med	Median of the top 5 percent and 10 percent 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 one to four lags of the dependent variable (BIC selection of lag numbers)
fdiar_bic	Factor model with one to four factors and zero to four lags of the dependent variable (BIC selection of factors and lags)
fdiarlag_bic	Factor model with one to four factors, one to three lags of the factors, and one to four lags of the dependent variable (BIC selection of all three)
RMSFEs	Root Mean-Squared Forecast Errors

Significance Tests

Asterisks denote that the mean-squared errors of the given test are significantly smaller than those of the Reserve Bank of New Zealand.

**	shows significance at the 5 percent level
*	shows significance at the 10 percent level

The variance of the mean difference in MSFEs is estimated using the Newey and West (1987) HAC estimator, with a truncation lag of $(h-1)$. The test statistic is compared to a Student-t distribution with $(T-1)$ degrees of freedom.

Table 3. CPI Inflation (Year on Year)

$h = 1$	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	3.50	3.41	3.05	3.60	3.80	3.03	2.87
fdi_2	3.61	3.55	3.10	3.53	3.45	3.10	2.83
fdi_3	4.14	4.13	3.68	3.47	3.55	3.81	3.32
fdi_4	3.88	4.30	4.20	3.55	3.53	4.64	3.99
fdi_bic	4.01	3.57	3.17	3.43	3.88	3.13	3.22
fdiar_1	4.53	4.34	3.05	3.99	4.64	3.03	3.34
fdiar_2	4.41	4.19	3.92	4.28	4.14	3.76	3.47
fdiar_3	5.51	4.87	4.30	4.17	3.99	4.43	4.25
fdiar_4	5.18	5.71	4.43	4.23	4.09	5.24	4.93
fdiar_bic	5.60	4.75	3.91	4.14	4.30	3.98	3.79
fdiarlag_bic	5.69	5.92	5.73	6.03	5.62	6.43	3.75
	Other Forecasts						
far	3.28						
fvar	3.42						
fbiv_best	4.18						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	3.71	3.66					
fbiv_med	3.66	3.60					
RMSFE rbnz	0.23						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

$h = 2$	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	2.05	1.84	1.68	2.09	1.99	1.71	1.60
fdi_2	2.04	2.12	1.64	2.03	2.07	1.68	1.56
fdi_3	2.19	2.47	2.44	2.21	2.03	2.01	2.11
fdi_4	2.09	2.58	2.72	2.15	1.98	2.53	2.52
fdi_bic	2.25	2.33	2.21	2.09	1.99	2.30	2.16
fdiar_1	2.24	2.01	1.68	2.02	2.09	1.71	1.60
fdiar_2	1.99	2.01	1.57	2.12	2.04	1.51	1.52
fdiar_3	2.13	2.24	1.97	2.36	2.59	1.62	2.35
fdiar_4	2.17	2.48	2.01	2.47	2.36	1.96	2.49
fdiar_bic	2.12	2.27	1.93	2.07	2.40	1.56	1.80
fdiarlag_bic	2.31	2.27	1.93	2.37	3.00	2.14	1.91
	Other Forecasts						
far	1.55						
fvar	1.83						
fbiv_best	1.96						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.70	1.70					
fbiv_med	1.62	1.63					
RMSFE rbnz	0.48						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

$h = 3$	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.41	1.48	1.53	1.79	1.66	1.55	1.42
fdi_2	1.56	1.70	1.50	1.65	1.68	1.55	1.37
fdi_3	1.50	1.83	2.43	1.28	1.52	2.39	2.26
fdi_4	1.74	1.74	2.43	1.17	1.66	2.50	2.59
fdi_bic	1.50	1.49	2.32	1.71	1.66	2.27	2.13
fdiar_1	1.73	1.72	1.69	2.13	1.92	1.71	1.57
fdiar_2	1.70	1.58	1.48	1.87	1.93	1.51	1.69
fdiar_3	1.99	1.96	2.07	1.68	1.79	2.10	2.47
fdiar_4	2.00	2.05	2.16	1.43	2.00	2.28	2.57
fdiar_bic	1.97	1.97	2.07	1.77	2.24	2.07	2.33
fdiarlag_bic	2.14	2.25	2.12	2.18	2.55	2.05	2.83
	Other Forecasts						
far	1.38						
fvar	1.30						
fbiv_best	2.29						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.58	1.54					
fbiv_med	1.56	1.48					
RMSFE rbnz	0.66						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

***h* = 4**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.45	1.47	1.45	1.91	1.70	1.48	1.38
fdi_2	1.50	1.50	1.48	1.85	1.72	1.49	1.46
fdi_3	1.53	1.84	2.13	1.80	1.68	2.17	2.10
fdi_4	1.72	2.02	2.26	1.79	1.34	2.15	2.12
fdi_bic	1.53	1.54	1.79	1.69	1.70	2.05	2.00
fdiar_1	1.55	1.55	1.47	1.91	1.84	1.49	1.41
fdiar_2	1.45	2.01	1.64	1.98	1.66	1.86	1.53
fdiar_3	1.56	1.93	2.10	2.08	2.02	1.93	2.41
fdiar_4	2.56	2.43	2.01	1.82	1.67	1.98	2.02
fdiar_bic	1.97	1.95	1.78	1.72	1.73	1.90	1.81
fdiarlag_bic	2.36	2.46	1.78	1.74	1.87	1.89	1.74
	Other Forecasts						
far	1.29						
fvar	1.14						
fbiv_best	2.80						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.53	1.54					
fbiv_med	1.46	1.47					
RMSFE rbnz	0.78						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

$h = 5$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.14	1.05	0.94	1.33	1.25	0.96	0.89
fdi_2	1.13	1.12	1.15	1.28	1.27	1.14	1.11
fdi_3	1.20	1.36	1.49	1.30	1.28	1.55	1.39
fdi_4	1.51	1.56	1.52	1.29	1.27	1.39	1.44
fdi_bic	1.06	1.00	1.36	1.34	1.21	1.06	1.20
fdiar_1	1.31	1.18	1.18	1.55	1.43	1.22	1.21
fdiar_2	1.24	1.21	1.70	1.67	1.45	1.87	1.56
fdiar_3	1.26	1.27	2.16	1.77	1.67	2.11	2.44
fdiar_4	1.81	1.51	2.37	1.60	1.46	2.27	2.12
fdiar_bic	1.72	1.32	1.51	1.57	1.74	1.53	1.63
fdiarlag_bic	2.67	2.12	1.64	1.72	1.37	1.46	1.71
	Other Forecasts						
far	0.84						
fvar	0.76						
fbiv_best	1.51						
Cut-off **(%)=**	**5**	**10**					
fbiv_mean	0.98	1.00					
fbiv_med	0.99	0.98					
RMSFE rbnz	0.82						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

***h* = 6**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
***θ* (%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.07	0.97	0.73	1.10	1.06	0.76	0.69
fdi_2	1.25	1.39	1.25	1.34	1.16	1.24	1.24
fdi_3	1.38	1.90	1.35	2.00	1.19	1.39	1.38
fdi_4	1.73	1.84	1.40	1.77	1.03	1.22	1.14
fdi_bic	1.71	2.06	1.10	2.05	1.06	1.04	0.99
fdiar_1	1.18	1.04	1.19	1.04	1.09	1.23	1.10
fdiar_2	1.30	1.45	1.57	1.43	1.26	1.65	1.50
fdiar_3	1.55	1.86	1.34	1.88	1.70	1.49	1.38
fdiar_4	1.79	1.86	1.61	1.80	1.51	1.46	1.22
fdiar_bic	1.77	1.87	1.51	2.06	1.32	1.40	1.53
fdiarlag_bic	2.64	2.12	2.01	4.06	2.18	1.47	2.87
	Other Forecasts						
far	0.64**						
fvar	0.45						
fbiv_best	1.69						
***Cut-off* (%)=**	**5**	**10**					
fbiv_mean	0.88	0.88					
fbiv_med	0.89	0.85					
RMSFE rbnz	0.88						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

***h* = 7**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.89	0.77	0.65	0.87	0.82	0.66	0.62*
fdi_2	1.16	1.21	1.31	1.45	1.27	1.23	1.34
fdi_3	1.65	2.01	1.54	2.20	1.82	1.56	1.91
fdi_4	1.72	1.60	2.91	2.59	2.24	2.28	2.08
fdi_bic	1.74	1.65	2.50	2.22	1.23	2.27	2.00
fdiar_1	0.80	0.81	0.88	0.67	0.64	0.82	0.82*
fdiar_2	1.04	1.12	1.19	1.21	1.08	1.22	0.95
fdiar_3	1.44	1.79	0.84	2.11	1.47	0.86	0.96
fdiar_4	1.42	1.13	2.46	2.34	1.17	1.64	1.28
fdiar_bic	1.58	1.23	2.38	1.66	0.83	1.53	1.32
fdiarlag_bic	3.05	3.48	5.83	5.70	3.67	8.07	6.23
	Other Forecasts						
far	0.57*						
fvar	0.58						
fbiv_best	2.73						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	0.61	0.53*					
fbiv_med	0.54	0.56*					
RMSFE rbnz	0.85						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

***h* = 8**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
***θ* (%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.67	0.71	0.73	0.68	0.72	0.72	0.74
fdi_2	0.68	0.73	1.13	0.94	0.88	0.90	1.17
fdi_3	1.66	1.88	1.07	0.99	0.80	1.03	0.81
fdi_4	2.25	1.47	3.34	1.14	1.19	2.91	1.70
fdi_bic	2.14	1.18	3.24	0.84	0.80	3.07	2.02
fdiar_1	0.56	0.69	0.76	0.75	0.78	0.75	0.87
fdiar_2	1.17	1.48	1.18	1.49	1.72	0.97	1.13
fdiar_3	1.86	1.85	1.39	1.80	1.40	1.03	0.98
fdiar_4	2.26	1.98	3.56	2.08	1.31	2.96	1.81
fdiar_bic	1.77	1.16	2.57	1.50	1.34	2.96	2.09
fdiarlag_bic	3.58	3.37	6.47	7.06	5.16	12.05	7.41
	Other Forecasts						
far	0.61						
fvar	0.98						
fbiv_best	3.25						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	0.81	0.65					
fbiv_med	0.74	0.53					
RMSFE rbnz	0.80						

Table 4. GDP Growth (Year on Year)

$h = 1$	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	2.02	2.00	1.83	1.92	2.04	1.80	1.73
fdi_2	2.44	2.00	1.88	2.14	2.02	1.91	1.74
fdi_3	2.57	2.52	2.23	2.20	2.28	2.03	1.87
fdi_4	2.61	2.61	2.77	2.32	2.57	2.22	1.97
fdi_bic	2.18	2.42	2.29	2.09	2.28	1.96	1.79
fdiar_1	2.18	2.15	1.97	1.90	2.22	1.94	1.87
fdiar_2	2.43	2.34	1.95	2.25	2.24	1.94	1.83
fdiar_3	2.51	2.74	2.22	2.18	2.29	2.03	2.02
fdiar_4	2.52	2.66	2.76	2.39	2.67	2.25	2.07
fdiar_bic	2.27	2.51	2.46	2.05	2.39	1.94	1.94
fdiarlag_bic	2.31	2.44	2.53	2.14	2.39	2.13	1.97
	Other Forecasts						
far	2.12						
fvar	1.69						
fbiv_best	2.53						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	2.07	2.02					
fbiv_med	2.02	1.98					
RMSFE rbnz	0.67						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

***h* = 2**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.67	1.63	1.36	1.67	1.62	1.31	1.35
fdi_2	1.61	1.66	1.41	1.68	1.84	1.40	1.32
fdi_3	1.59	1.71	1.65	1.80	1.99	1.77	1.61
fdi_4	1.64	1.89	1.64	1.61	1.96	1.61	1.46
fdi_bic	1.67	1.63	1.47	1.67	1.62	1.49	1.43
fdiar_1	1.32	1.28	0.97	1.67	1.33	0.94	1.27
fdiar_2	1.24	1.26	1.09	1.68	1.49	1.10	1.27
fdiar_3	1.14	1.13	1.01	1.63	1.88	1.11	1.49
fdiar_4	1.12	1.71	1.01	1.42	1.84	1.06	1.44
fdiar_bic	1.28	1.28	1.08	1.67	1.33	1.01	1.21
fdiarlag_bic	1.30	1.10	1.10	1.65	1.82	0.96	1.15
	Other Forecasts						
far	1.54						
fvar	1.75						
fbiv_best	2.15						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.33	1.28					
fbiv_med	1.53	1.49					
RMSFE rbnz	1.03						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

***h* = 3**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.28	1.21	0.93	1.22	1.21	0.93	0.97
fdi_2	1.25	1.22	1.13	1.33	1.21	1.09	1.06
fdi_3	1.32	1.67	1.11	1.24	1.51	1.11	1.09
fdi_4	1.36	1.65	1.15	1.58	1.74	1.07	1.18
fdi_bic	1.28	1.21	1.22	1.42	1.38	1.09	1.19
fdiar_1	1.21	1.24	1.21	1.22	1.25	1.28	1.25
fdiar_2	1.26	1.33	1.37	1.30	1.40	1.40	1.37
fdiar_3	1.18	1.58	1.20	1.20	1.45	1.30	1.34
fdiar_4	1.39	1.45	1.35	1.47	1.67	1.15	1.33
fdiar_bic	1.25	1.18	1.46	1.31	1.32	1.34	1.40
fdiarlag_bic	2.58	1.78	1.13	1.34	1.56	2.36	2.48
	Other Forecasts						
far	1.23						
fvar	1.81						
fbiv_best	1.95						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.11	1.07					
fbiv_med	1.22	1.08					
RMSFE rbnz	1.39						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

$h = 4$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.97	0.84	0.66	0.94	0.81	0.64	0.66
fdi_2	0.92	0.89	1.22	0.88	0.79	1.03	1.20
fdi_3	1.00	1.22	0.92	0.92	0.69	1.06	1.09
fdi_4	1.00	1.60	1.15	1.07	0.91	1.48	1.35
fdi_bic	0.97	0.84	1.11	0.94	0.81	1.44	1.47
fdiar_1	0.83	0.67*	0.75	0.94	0.77	0.79	0.79
fdiar_2	0.81	0.66	0.97	0.88	0.71	0.95	1.10
fdiar_3	0.77	0.88	0.99	0.92	0.64	1.07	1.14
fdiar_4	0.93	1.12	1.16	1.05	0.90	1.53	1.32
fdiar_bic	0.96	0.66*	0.78	1.03	0.76	1.02	1.66
fdiarlag_bic	1.21	1.12	1.33	1.04	2.16	0.97	1.99
	Other Forecasts						
far	0.96						
Fvar	2.08						
fbiv_best	1.00						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	0.60*	0.64*					
fbiv_med	0.66	0.71					
RMSFE rbnz	1.65						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

$h = 5$ Cut-Off Criterion	**Factor Model Forecasts**						
	One-Step			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.57**	0.56**	0.48**	0.67*	0.60**	0.48**	0.46**
fdi_2	0.71**	0.80	1.02	0.70**	0.68	0.80	1.08
fdi_3	1.12	1.72	0.66*	0.77*	1.31	0.72	0.78
fdi_4	1.18	1.53	1.54	0.84	1.72	1.60	1.09
fdi_bic	1.11	1.22	1.84	0.51**	0.60**	1.80	1.32
fdiar_1	0.62**	0.67	1.25	0.67*	0.61**	1.25	0.83
fdiar_2	0.82	0.53*	0.88	0.70**	0.68	0.88	1.27
fdiar_3	0.59	0.96	0.92	0.77*	1.58	0.87	0.83
fdiar_4	1.21	2.19	1.68	1.06	2.03	1.76	1.17
fdiar_bic	1.10	2.30	2.01	0.65**	0.90	1.67	1.75
fdiarlag_bic	3.41	4.66	3.61	1.74	1.96	1.79	5.31
	Other Forecasts						
far	0.57*						
fvar	0.90						
fbiv_best	0.87						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	0.72	0.54*					
fbiv_med	0.75	0.59					
RMSFE rbnz	1.90						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

$h = 6$ Cut-Off Criterion	Factor Model Forecasts						
	One-Step			Two-Step			None
θ (%) =	5	10	50	5	10	50	100
fdi_1	0.55**	0.61*	0.74	1.02	0.88	0.74	0.65*
fdi_2	1.24	0.58**	1.58	1.29	1.00	1.00	1.74
fdi_3	2.26	5.30	3.01	1.22	1.55	2.55	2.41
fdi_4	1.83	4.13	4.01	1.53	1.98	5.70	3.40
fdi_bic	1.49	3.05	5.41	1.07	1.62	5.92	4.22
fdiar_1	0.65*	0.79	1.50	1.22	1.11	1.49	0.48**
fdiar_2	0.73	0.76	1.40	1.17	1.04	1.40	1.39
fdiar_3	1.22	3.81	3.28	1.14	0.75	2.64	2.55
fdiar_4	2.26	3.83	4.16	1.35	1.05	6.02	3.52
fdiar_bic	1.67	3.87	5.35	1.10	0.82	6.13	4.38
fdiarlag_bic	4.68	4.31	5.26	5.52	13.27	8.74	10.97
	Other Forecasts						
far	0.59**						
fvar	1.29						
fbiv_best	1.14						
Cut-off (%) =	5	10					
fbiv_mean	0.63	0.65					
fbiv_med	0.65	0.71					
RMSFE rbnz	1.63						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

$h = 7$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.67**	0.71	1.05	1.20	0.88	1.04	0.99
fdi_2	1.84	0.53**	1.43	3.53	4.17	0.93	1.68
fdi_3	5.90	5.75	5.71	4.08	6.82	4.26	2.95
fdi_4	5.47	5.63	6.35	4.86	5.72	6.89	3.64
fdi_bic	4.37	5.14	9.37	3.17	6.81	9.39	4.62
fdiar_1	1.02	0.98	1.07	1.29	1.00	1.33	1.28
fdiar_2	1.56	0.86	1.81	3.74	4.99	1.41	1.30
fdiar_3	3.04	4.43	5.62	4.95	6.84	4.67	3.02
fdiar_4	5.28	5.21	6.62	6.71	5.70	7.66	3.53
fdiar_bic	4.76	4.51	7.56	4.85	4.37	9.62	4.71
fdiarlag_bic	10.52	6.99	8.26	19.92	10.07	17.42	11.20
	Other Forecasts						
far	0.87						
fvar	1.25						
fbiv_best	7.56						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	1.59	1.45					
fbiv_med	1.23	1.05					
RMSFE rbnz	1.62						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

$h = 8$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.77**	0.82	1.28	1.63	0.95	1.27	1.28
fdi_2	2.48	1.20	1.37	2.96	3.12	0.92	1.30
fdi_3	3.35	4.16	2.92	5.12	3.13	2.20	1.88
fdi_4	3.15	7.07	2.97	7.24	3.46	3.04	1.71
fdi_bic	2.41	4.35	2.83	3.92	3.39	4.08	1.88
fdiar_1	0.75	0.63**	1.08	2.15	1.02	0.85	1.46
fdiar_2	2.46	1.49	1.95	3.78	2.84	0.92	1.45
fdiar_3	2.76	3.97	3.22	5.64	2.83	2.66	2.39
fdiar_4	2.78	3.53	2.62	7.57	4.04	2.68	1.72
fdiar_bic	2.24	3.70	4.33	2.48	3.03	5.23	2.87
fdiarlag_bic	5.96	4.91	13.27	14.45	21.84	16.33	14.66
	Other Forecasts						
far	1.07						
fvar	1.59						
fbiv_best	6.29						
Cut-off (%) =	**5**	**10**					
fbiv_mean	1.69	1.32					
fbiv_med	1.21	1.22					
RMSFE rbnz	1.72						

Table 5. Interest Rate (90-Day Bank Bill)

$h = 1$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	25.10	24.58	21.25	25.72	24.63	21.83	20.52
fdi_2	31.83	28.76	23.92	24.72	25.11	25.72	21.71
fdi_3	34.98	26.41	20.69	20.45	29.27	32.90	24.87
fdi_4	31.47	24.09	59.19	23.74	31.88	49.57	57.12
fdi_bic	31.87	24.71	48.41	25.08	28.47	35.33	20.52
fdiar_1	24.94	23.45	19.26	22.67	21.95	19.33	19.00
fdiar_2	31.50	33.79	35.79	23.69	24.43	35.41	39.02
fdiar_3	36.39	26.87	34.50	19.74	28.50	45.67	33.42
fdiar_4	38.58	25.20	61.96	23.61	30.78	57.20	60.28
fdiar_bic	32.82	32.20	50.06	23.50	27.88	29.90	26.89
fdiarlag_bic	27.91	31.99	98.54	22.12	70.88	49.42	29.90
	Other Forecasts						
far	16.19						
fvar	27.50						
fbiv_best	50.45						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	23.55	18.67					
fbiv_med	22.49	19.32					
RMSFE rbnz	0.09						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

$h = 2$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	7.53	7.06	5.55	7.19	6.86	5.86	5.28
fdi_2	8.98	9.75	5.84	15.27	11.22	6.20	6.36
fdi_3	8.63	14.15	16.78	14.89	15.85	14.35	10.93
fdi_4	9.00	14.49	15.15	14.62	17.18	12.01	15.52
fdi_bic	9.77	15.21	13.43	13.89	12.56	5.86	5.28
fdiar_1	7.53	7.06	6.64	7.27	6.86	5.98	6.55
fdiar_2	9.22	10.92	14.13	15.27	15.63	13.14	14.45
fdiar_3	8.63	14.56	23.69	14.88	25.84	9.25	10.12
fdiar_4	9.00	14.49	19.87	14.61	23.66	11.16	11.41
fdiar_bic	9.77	15.21	15.59	11.50	16.98	12.28	11.54
fdiarlag_bic	10.07	31.26	14.19	19.73	19.34	14.31	11.13
	Other Forecasts						
far	4.18						
fvar	7.30						
fbiv_best	20.25						
Cut-off (%) =	**5**	**10**					
fbiv_mean	7.94	5.92					
fbiv_med	7.20	5.45					
RMSFE rbnz	0.35						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

***h* = 3**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
***θ* (%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	4.53	4.08	3.19	5.79	4.70	3.29	2.92
fdi_2	4.84	5.31	4.91	8.09	7.96	5.05	5.16
fdi_3	7.11	8.78	14.25	7.85	7.50	12.52	12.63
fdi_4	10.84	10.83	12.25	6.75	6.83	12.98	13.63
fdi_bic	9.22	6.27	11.88	7.47	6.63	11.87	11.93
fdiar_1	4.54	4.40	4.04	5.70	4.70	4.18	3.76
fdiar_2	7.97	6.98	6.79	7.45	7.29	7.13	6.14
fdiar_3	8.98	10.50	15.77	7.34	6.86	8.73	5.80
fdiar_4	12.24	13.16	13.25	6.24	7.23	8.68	6.30
fdiar_bic	10.76	10.33	15.63	7.29	6.47	7.84	5.99
fdiarlag_bic	10.38	19.23	8.78	9.95	7.78	14.33	7.05
	Other Forecasts						
far	2.07						
fvar	4.96						
fbiv_best	11.19						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	3.41	2.98					
fbiv_med	3.65	3.09					
RMSFE rbnz	0.61						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

$h=4$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	2.62	2.16	2.05	3.20	2.71	2.01	2.03
fdi_2	2.58	2.95	3.94	2.89	3.29	3.77	3.97
fdi_3	4.16	4.53	9.45	2.75	3.22	8.77	9.90
fdi_4	5.09	5.67	7.75	3.82	4.16	8.44	10.83
fdi_bic	4.36	4.98	8.01	2.72	2.69	6.41	9.37
fdiar_1	2.78	2.44	2.70	3.42	3.03	2.77	2.64
fdiar_2	4.41	2.78	3.22	3.19	4.62	3.98	3.58
fdiar_3	5.30	3.80	4.91	3.00	4.16	4.99	4.40
fdiar_4	6.84	4.64	4.60	3.90	5.14	5.07	3.80
fdiar_bic	6.07	3.68	3.62	3.69	3.22	4.02	3.81
fdiarlag_bic	2.96	2.33	3.20	4.64	5.57	9.09	5.08
	Other Forecasts						
far	1.25						
fvar	3.94						
fbiv_best	1.99						
Cut-off (%) =	**5**	**10**					
fbiv_mean	1.29	1.30					
fbiv_med	1.65	1.49					
RMSFE rbnz	0.84						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

***h* = 5** Cut-Off Criterion	Factor Model Forecasts						
	One-Step			**Two-Step**			**None**
***θ* (%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.45	1.14	1.11	1.38	1.40	1.10	1.25
fdi_2	1.37	1.34	2.42	1.25	1.11	2.01	2.46
fdi_3	1.73	1.62	3.82	1.34	1.49	3.17	4.53
fdi_4	1.93	1.78	2.80	1.24	1.53	3.76	4.09
fdi_bic	1.45	1.19	2.65	1.38	1.40	2.01	3.01
fdiar_1	1.46	1.15	1.38	1.43	1.49	1.46	1.55
fdiar_2	1.99	1.79	1.37	1.99	2.21	1.49	1.62
fdiar_3	2.11	2.40	0.66	1.87	2.22	1.37	1.62
fdiar_4	2.28	3.23	0.55	2.33	2.06	1.59	1.32
fdiar_bic	2.02	2.75	1.45	1.67	2.09	1.76	1.80
fdiarlag_bic	4.85	1.43	7.50	2.23	5.83	2.56	2.96
	Other Forecasts						
far	0.76						
Fvar	2.72						
fbiv_best	1.70						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	0.72	0.56					
fbiv_med	0.93	0.75					
RMSFE rbnz	1.08						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

***h* = 6** Cut-Off Criterion	**Factor Model Forecasts**						
	One-Step			**Two-Step**			**None**
***θ* (%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.11	0.75	0.67	1.08	0.85	0.67	0.77
fdi_2	1.09	0.94	1.74	1.37	0.88	1.50	2.02
fdi_3	1.05	1.51	1.47	1.84	1.60	1.16	1.98
fdi_4	0.96	2.43	2.04	2.05	1.54	1.40	1.78
fdi_bic	1.11	0.75	2.07	1.12	1.51	1.50	2.18
fdiar_1	1.10	0.77	0.74	1.06	0.90	0.74	0.89
fdiar_2	1.09	0.93	1.00	0.98	1.42	0.90	1.32
fdiar_3	1.03	1.25	0.64	1.26	2.20	0.55	0.82
fdiar_4	1.06	1.52	1.22	1.86	1.98	1.18	0.72
fdiar_bic	1.02	1.01	1.30	1.06	1.71	1.08	0.83
fdiarlag_bic	2.73	0.93	2.14	1.48	3.47	1.87	3.77
	Other Forecasts						
far	0.40**						
fvar	2.62						
fbiv_best	2.36						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	0.59	0.49					
fbiv_med	0.70	0.55					
RMSFE rbnz	1.25						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

$h = 7$ Cut-Off Criterion	Factor Model Forecasts						
	One-Step			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.13	0.73	0.50	1.30	0.90	0.52	0.54
fdi_2	1.20	0.97	2.17	1.63	1.16	1.79	2.18
fdi_3	1.26	1.49	1.60	1.58	1.01	1.20	1.71
fdi_4	1.93	1.22	3.62	1.65	2.20	3.93	2.24
fdi_bic	1.13	0.73	3.43	1.30	0.92	3.62	2.37
fdiar_1	1.16	0.75	0.52	1.29	0.88	0.54	0.62
fdiar_2	0.82	0.69	1.82	1.62	1.00	1.44	2.18
fdiar_3	0.82	1.13	1.54	1.59	0.92	0.84	1.41
fdiar_4	1.27	0.96	3.15	1.49	2.09	3.77	1.92
fdiar_bic	1.16	0.75	2.95	1.30	0.91	3.40	2.12
fdiarlag_bic	5.30	3.19	3.41	1.35	2.86	6.65	22.78
	Other Forecasts						
far	0.25**						
fvar	3.52						
fbiv_best	2.06						
Cut-off (%) =	**5**	**10**					
fbiv_mean	0.76	0.58					
fbiv_med	0.71	0.60					
RMSFE rbnz	1.26						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

$h=8$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.77	0.65	0.45	1.33	0.83	0.47	0.40
fdi_2	0.81	0.86	2.45	1.64	1.04	2.04	2.78
fdi_3	0.99	2.58	2.62	1.55	1.41	1.26	1.50
fdi_4	1.02	2.84	5.26	1.78	1.99	2.74	1.97
fdi_bic	0.77	1.61	3.51	1.36	0.83	2.41	1.82
fdiar_1	0.77	0.66	0.47	1.33	0.83	0.48	0.49
fdiar_2	1.22	0.86	2.51	1.64	1.04	2.04	3.07
fdiar_3	1.40	3.69	2.62	1.55	1.52	1.24	1.50
fdiar_4	1.45	4.61	11.50	1.78	2.31	3.02	1.97
fdiar_bic	1.26	4.00	3.54	1.36	1.10	2.69	1.82
fdiarlag_bic	1.49	11.71	6.05	4.05	4.56	14.30	21.36
	Other Forecasts						
far	0.21						
fvar	4.20						
fbiv_best	2.58						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	0.75	0.72					
fbiv_med	0.62	0.66					
RMSFE rbnz	1.25						

Table 6. Exchange Rate (Year-on-Year Growth)

$h = 1$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	7.45	6.62	5.71	6.71	6.10	5.77	5.71
fdi_2	7.60	7.29	6.39	7.50	6.79	6.63	5.81
fdi_3	8.06	7.57	8.19	8.02	7.24	7.45	6.82
fdi_4	8.55	9.01	8.48	9.35	8.44	7.58	6.34
fdi_bic	7.79	8.34	8.40	6.71	6.72	6.52	6.08
fdiar_1	7.45	6.62	6.19	6.71	6.10	6.23	6.01
fdiar_2	7.66	7.02	6.72	7.50	6.79	6.92	6.26
fdiar_3	8.03	6.99	7.95	8.72	7.24	7.45	6.82
fdiar_4	8.55	9.01	9.97	10.10	8.44	7.58	6.34
fdiar_bic	7.84	7.87	9.22	6.71	6.72	7.03	6.01
fdiarlag_bic	6.89	7.93	11.97	7.47	6.24	7.44	7.43
	Other Forecasts						
far	8.34						
fvar	9.03						
fbiv_best	12.18						
Cut-off (%) =	**5**	**10**					
fbiv_mean	7.06	6.97					
fbiv_med	7.65	7.33					
RMSFE rbnz	1.43						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

***h* = 2**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.35	1.20	1.08	1.27	1.22	1.06	1.09
fdi_2	1.35	1.48	1.24	1.35	1.25	1.29	1.19
fdi_3	1.29	1.33	1.73	1.42	1.52	1.23	1.50
fdi_4	1.54	1.45	1.55	1.55	1.73	1.57	1.38
fdi_bic	1.45	1.51	2.02	1.27	1.13	1.19	1.27
fdiar_1	1.30	1.20	1.08	1.27	1.22	1.06	1.09
fdiar_2	1.25	1.53	1.24	1.22	1.21	1.29	1.19
fdiar_3	1.22	1.40	1.85	1.17	1.63	1.36	1.50
fdiar_4	1.41	1.28	1.40	1.33	1.51	1.47	1.42
fdiar_bic	1.16	1.44	1.86	1.27	1.10	1.31	1.27
fdiarlag_bic	2.23	1.61	1.80	1.57	1.38	1.32	1.35
	Other Forecasts						
far	1.69						
fvar	2.04						
fbiv_best	2.24						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.20	1.21					
fbiv_med	1.22	1.28					
RMSFE rbnz	5.02						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

$h = 3$ Cut-Off Criterion	Factor Model Forecasts						
	One-Step			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.05	0.99	0.93	1.08	0.93	0.89	0.95
fdi_2	1.35	1.52	0.94	1.24	1.50	0.98	1.04
fdi_3	1.54	1.35	1.27	1.37	1.46	1.42	1.24
fdi_4	1.37	1.15	0.99	1.45	1.69	1.03	1.18
fdi_bic	1.27	1.05	1.11	1.16	1.57	0.85	1.29
fdiar_1	1.05	0.99	0.93	0.99	0.93	0.89	0.95
fdiar_2	1.40	1.52	0.94	1.23	1.76	0.98	1.04
fdiar_3	1.73	1.43	1.29	1.35	1.85	1.22	1.24
fdiar_4	1.70	1.12	0.91	1.42	1.87	1.65	1.18
fdiar_bic	1.43	1.05	0.95	1.07	1.52	0.89	1.29
fdiarlag_bic	3.67	1.06	0.81	1.73	1.50	0.91	1.40
	Other Forecasts						
far	1.28						
fvar	1.94						
fbiv_best	2.15						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.00	1.03					
fbiv_med	1.02	1.07					
RMSFE rbnz	6.96						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

***h* = 4**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.20	1.09	1.05	1.14	1.07	1.02	1.11
fdi_2	1.77	1.51	0.91	1.39	1.85	0.95	1.13
fdi_3	2.29	1.99	1.51	1.78	2.05	1.91	1.15
fdi_4	2.09	1.66	1.14	1.38	1.73	1.11	1.18
fdi_bic	2.12	1.68	1.46	1.44	1.91	1.69	1.28
fdiar_1	1.20	1.09	1.05	1.14	1.07	1.02	1.11
fdiar_2	1.77	1.51	0.83	1.39	1.85	0.86	1.13
fdiar_3	2.29	1.99	1.54	1.78	2.05	1.96	0.94
fdiar_4	2.09	1.66	1.22	1.38	1.73	1.64	0.94
fdiar_bic	2.12	1.68	1.62	1.44	1.91	1.83	1.28
fdiarlag_bic	2.76	2.28	1.97	1.07	1.50	1.96	1.96
	Other Forecasts						
far	1.32						
fvar	1.88						
fbiv_best	2.17						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.46	1.30					
fbiv_med	1.50	1.36					
RMSFE rbnz	8.35						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

$h = 5$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.91	0.87	0.95	0.86	0.77	0.90	1.01
fdi_2	1.77	1.36	0.63*	1.05	1.44	0.63	0.90
fdi_3	2.24	1.85	1.68	1.09	1.40	1.61	0.88
fdi_4	1.98	1.89	1.37	1.07	1.01	1.22	0.82
fdi_bic	1.92	2.23	1.37	0.94	0.91	1.05	1.10
fdiar_1	1.04	1.02	0.95	1.21	0.97	0.90	1.01
fdiar_2	2.06	1.75	1.15	1.16	1.94	1.13	1.12
fdiar_3	2.51	2.64	1.89	1.30	1.91	3.06	0.70
fdiar_4	1.97	1.59	1.64	1.15	1.25	1.84	0.70
fdiar_bic	1.83	1.49	1.58	1.17	1.21	1.82	1.11
fdiarlag_bic	2.83	2.30	1.31	2.10	0.83	2.29	1.86
	Other Forecasts						
far	1.13						
fvar	1.79						
fbiv_best	2.49						
Cut-off (%) =	**5**	**10**					
fbiv_mean	1.54	1.22					
fbiv_med	1.46	1.31					
RMSFE rbnz	9.40						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

$h = 6$	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.16	1.06	1.14	0.95	0.93	1.12	1.22
fdi_2	2.36	1.64	0.58**	1.42	1.32	0.56**	0.88
fdi_3	2.23	2.31	2.74	1.81	1.28	2.02	1.07
fdi_4	2.26	2.14	3.40	1.99	1.01	2.53	1.21
di_bic	1.82	1.57	2.71	1.85	0.95	1.71	1.01
fdiar_1	1.51	1.14	1.05	1.56	1.30	1.05	1.09
fdiar_2	2.97	2.49	1.40	2.42	1.76	1.55	1.13
fdiar_3	2.90	4.62	3.10	2.57	1.85	2.56	1.13
fdiar_4	2.91	2.76	4.39	2.26	1.31	3.00	1.58
fdiar_bic	2.84	2.69	3.33	2.18	1.76	2.46	1.10
fdiarlag_bic	3.43	3.83	3.50	6.66	2.44	2.45	1.12
	Other Forecasts						
far	1.39						
fvar	2.32						
fbiv_best	1.92						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.82	1.68					
fbiv_med	1.69	1.68					
RMSFE rbnz	8.96						

(continued)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

$h=7$ Cut-Off Criterion θ (%) =	Factor Model Forecasts One-Step 5	10	50	Two-Step 5	10	50	None 100
fdi_1	1.59	1.56	1.59	1.36	1.45	1.60	1.64
fdi_2	3.19	1.79	0.95	1.72	1.85	0.87	1.24
fdi_3	1.85	2.60	2.44	2.16	2.55	2.24	1.54
fdi_4	2.00	2.49	4.93	2.06	2.52	3.50	1.23
fdi_bic	2.29	2.08	3.41	2.13	2.24	2.18	1.70
fdiar_1	2.00	1.98	1.83	1.83	1.83	1.82	1.88
fdiar_2	4.33	3.06	1.07	2.70	2.65	1.07	1.43
fdiar_3	1.95	5.08	2.74	3.42	4.76	2.70	1.85
fdiar_4	1.79	5.23	5.69	4.01	4.85	3.47	1.84
fdiar_bic	1.99	5.05	3.67	4.42	4.55	3.09	1.94
fdiarlag_bic	5.78	6.87	8.23	5.96	6.82	5.21	2.65
	Other Forecasts						
far	2.23						
fvar	3.52						
fbiv_best	5.22						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	2.28	2.00					
fbiv_med	2.25	2.11					
RMSFE rbnz	8.25						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

$h = 8$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	2.17	2.32	2.00	2.24	2.03	2.03	2.04
fdi_2	1.87	1.86	2.05	2.84	1.28	1.84	2.02
fdi_3	1.90	1.67	1.09	2.88	1.92	1.65	0.83
fdi_4	2.74	2.71	4.38	2.94	2.56	3.52	1.55
fdi_bic	2.36	1.99	1.67	2.39	1.51	1.70	1.17
fdiar_1	2.03	2.32	1.79	2.15	1.93	1.83	1.84
fdiar_2	1.96	1.93	1.23	2.96	1.71	1.13	1.47
fdiar_3	2.00	2.94	1.59	3.10	2.90	2.27	0.85
fdiar_4	2.61	3.70	5.46	3.07	4.21	3.71	1.96
fdiar_bic	2.69	2.36	2.30	2.53	3.43	2.86	2.05
fdiarlag_bic	6.45	7.64	6.32	17.92	15.55	7.38	5.32
	Other Forecasts						
far	2.13						
fvar	3.88						
fbiv_best	5.77						
Cut-off (%) =	**5**	**10**					
fbiv_mean	2.12	2.34					
fbiv_med	2.39	2.43					
RMSFE rbnz	8.07						

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