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13. April 2006

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MPRA Paper No. 807, posted 07. November 2007 / 01:17

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.

*I have benefited from discussions with various members of the Economics Department of the Reserve Bank of New Zealand. I would especially like to thank Anne Guan and Madeline Penny for their excellent research assistance, and Shaun Vahey and Christie Smith for useful comments on earlier drafts. Any errors and omissions are entirely my own, and the views expressed in the paper are not necessarily those of the Reserve Bank of New Zealand. Author contact: E-mail: troy.matheson@rbnz.govt.nz; Tel: 64 4 471 3859.

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

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

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:

$$X_t = \Lambda F_t + e_t. \quad (2)$$

In the above equation, $X_t = (X_{1t}, X_{2t}, \dots, X_{Nt})'$, $\Lambda = (\lambda_1, \lambda_2, \dots, \lambda_N)'$, $F_t = (f'_t, \dots, f'_{t-q})'$, and $e_t = (e_{1t}, e_{2t}, \dots, e_{Nt})'$ (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, $h = (1, \dots, 8)$.

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.

¹Stock 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 $h = (1, \dots, 8)$ and $i = (1, \dots, 384)$, the following equation is estimated using OLS:

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

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

²Thanks 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.

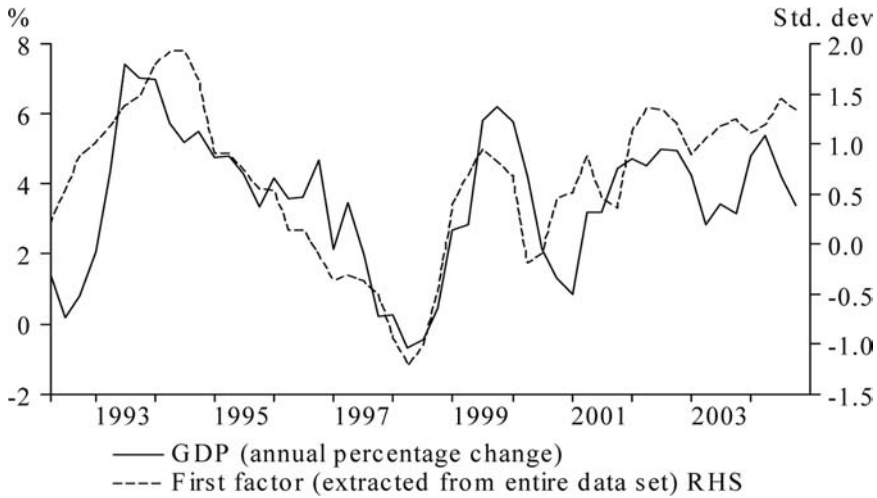
4. Forecasts

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_{t+h}^h is forecast using the following regression model:

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

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 modeled as being I(0) or I(1). If z_{t+h}^h is modeled as I(0),

$$y_{t+h}^h = z_{t+h}^h \text{ and } y_t = z_t. \tag{5}$$

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

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

or

$$y_{t+h}^h = z_{t+h}^h - z_t^h \text{ and } y_t = z_t - z_{t-1}. \tag{7}$$

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

³Modeling 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, Björkstén, and Karagedikli 2004).

⁴In 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

⁵See 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.

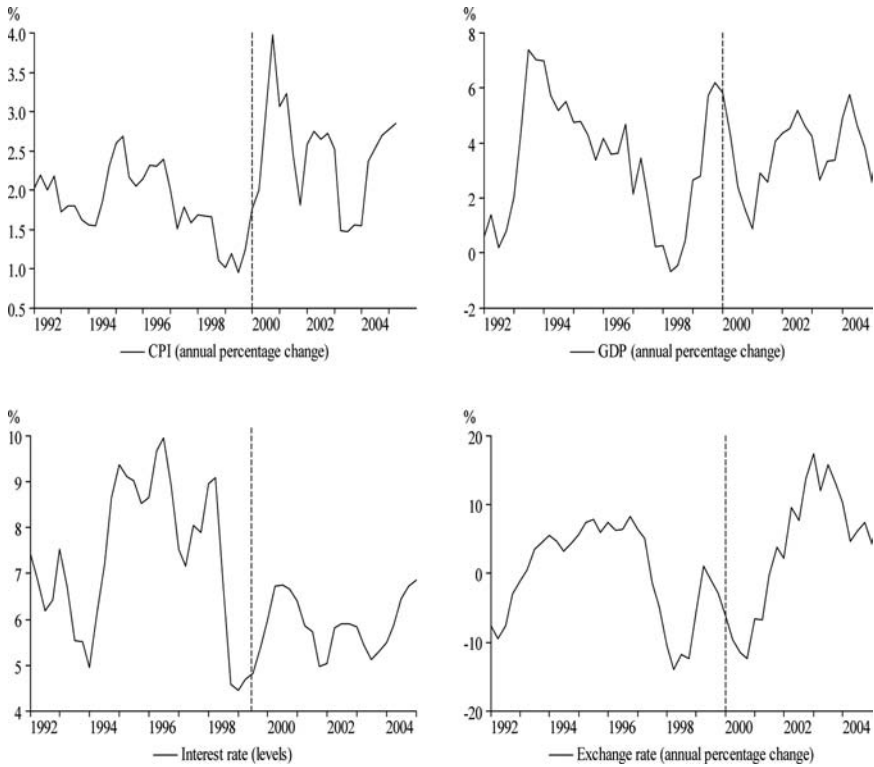
The forecasting performance of a candidate forecast is evaluated by comparing its out-of-sample MSFE to a Reserve Bank of New Zealand benchmark. For an h -step-ahead forecast, the MSFE of a candidate model i relative to the benchmark Reserve Bank forecast 0 is

$$MSFE_relative = \frac{\sum_{t=T_1}^{T_2-h} (\hat{y}_{i,t+h}^h - y_{t+h})^2}{\sum_{t=T_1}^{T_2-h} (\hat{y}_{0,t+h}^h - y_{t+h})^2}, \quad (8)$$

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.,

$$\text{Null Hypothesis: } E[\varepsilon_t] = 0 \quad (9)$$

Figure 2. The Ex Post Data



against

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

where

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

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

⁶The 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

	far	fvar	fbiv_best	$\theta = 5\%$		$\theta = 10\%$	
				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

	far	fvar	fbiv_best	$\theta = 5\%$		$\theta = 10\%$	
				fbiv_mean	fbiv_med	fbiv_mean	fbiv_med
Exchange Rate							
<i>h</i> = 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
	5	10	50	5	10	50	100
CPI							
<i>h</i> = 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, $\theta = 5, 10, \dots, 100$ 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)

<i>h</i> = 1 Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 2 Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 3	Factor Model Forecasts						
	One-Step			Two-Step			None
	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)

<i>h</i> = 4	Factor Model Forecasts						
	One-Step			Two-Step			None
	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)

<i>h</i> = 5	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%)=	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)

<i>h</i> = 6	Factor Model Forecasts						
	One-Step			Two-Step			None
	θ (%) =	5	10	50	5	10	50
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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 7 Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

$h = 8$ Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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)

<i>h</i> = 1 Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 2	Factor Model Forecasts						
	One-Step			Two-Step			None
	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)

<i>h</i> = 3 Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 4	Factor Model Forecasts						
	One-Step			Two-Step			None
	θ (%) =	5	10	50	5	10	50
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)

<i>h</i> = 5 Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 6 Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 7 Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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						
	One-Step			Two-Step			None
	θ (%) =	5	10	50	5	10	50
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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 1	Factor Model Forecasts						
	One-Step			Two-Step			None
	θ (%) =	5	10	50	5	10	50
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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 2	Factor Model Forecasts						
	One-Step			Two-Step			None
	θ (%) =	5	10	50	5	10	50
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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 3 Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 4	Factor Model Forecasts						
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 5	Factor Model Forecasts						
	One-Step			Two-Step			None
	θ (%) =	5	10	50	5	10	50
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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 6	Factor Model Forecasts						
	One-Step			Two-Step			None
	θ (%) =	5	10	50	5	10	50
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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 7	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 8	Factor Model Forecasts						
	One-Step			Two-Step			None
	θ (%) =	5	10	50	5	10	50
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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 1 Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

$h = 2$ Cut-Off Criterion θ (%) =	Factor Model Forecasts						
	One-Step			Two-Step			None
	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)

<i>h</i> = 3	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 4	Factor Model Forecasts						
	One-Step			Two-Step			None
	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)

<i>h</i> = 5	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						
<i>Cut-off</i> (%) =	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)

<i>h</i> = 6	Factor Model Forecasts						
	One-Step			Two-Step			None
	θ (%) =	5	10	50	5	10	50
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)

<i>h</i> = 7	Factor Model Forecasts						
	One-Step			Two-Step			None
	5	10	50	5	10	50	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						
<i>Cut-off</i> (%) =	5	10					
fbiv_mean	2.28	2.00					
fbiv_med	2.25	2.11					
RMSFE rbz	8.25						

(continued)

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

<i>h</i> = 8	Factor Model Forecasts						
	One-Step			Two-Step			None
	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						

References

- Artis, M., A. Banerjee, and M. Marcellino. 2002. "Factor Forecasts for the UK." CEPR Discussion Paper No. 3119.
- Bai, J., and S. Ng. 2002. "Determining the Number of Factors in Approximate Factor Models." *Econometrica* 70 (1): 191–221.
- Basdevant, O., N. Björkstén, and Ö. Karagedikli. 2004. "Estimating a Time Varying Neutral Real Interest Rate for New Zealand." Reserve Bank of New Zealand Discussion Paper DP2004/01.
- Boivin, J., and S. Ng. 2003. "Are More Data Always Better for Factor Analysis?" NBER Working Paper No. 9829.
- Diebold, F., and R. Mariano. 1995. "Comparing Predictive Accuracy." *Journal of Economic and Business Statistics* 13 (3): 253–63.
- Drew, A., and B. Hunt. 1998. "The Forecasting and Policy System: Preparing Economic Projections." Reserve Bank of New Zealand Discussion Paper G98/7.
- Forni, M., M. Hallin, M. Lippi, and L. Reichlin. 2000. "The Generalized Dynamic-Factor Model: Identification and Estimation." *The Review of Economics and Statistics* 82 (4): 540–54.
- . 2001. "Coincident and Leading Indicators for the Euro Area." *The Economic Journal* 111 (471): 62–85.
- . 2004. "The Generalized Dynamic-Factor Model Consistency and Rates." *Journal of Econometrics* 119 (2): 231–55.
- Geweke, J. 1977. "The Dynamic Factor Analysis of Economic Time Series." In *Latent Variables in Socio-Economic Models*, ed. D. J. Aigner and A. S. Goldberger. Amsterdam: North Holland.
- Marcellino, M., J. M. Stock, and M. W. Watson. 2003. "Macroeconomic Forecasting in the Euro Area: Country Specific versus Area-Wide Information." *European Economic Review* 47 (1): 1–18.
- Newey, W. K., and K. West. 1987. "A Simple, Positive Semidefinite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55 (3): 703–8.
- Sargent, T. J., and C. A. Sims. 1977. "Business Cycle Modelling without Pretending to Have Too Much A Priori Economic Theory." In *New Methods in Business Cycle Research*, ed. C. A. Sims. Minneapolis, MN: Federal Reserve Bank of Minneapolis.

- Stock, J. H., and M. W. Watson. 1989. "New Indexes of Coincident and Leading Economic Indicators." In *National Bureau of Economic Research Macroeconomics Annual*, ed. O. Blanchard and S. Fischer, 351–94. Cambridge, MA: MIT Press.
- . 1998. "Diffusion Indexes." NBER Working Paper No. 6702.
- . 1999. "Forecasting Inflation." *Journal of Monetary Economics* 44 (2): 293–334.
- . 2002. "Macroeconomic Forecasting Using Diffusion Indexes." *Journal of Business and Economic Statistics* 20 (2): 147–62.
- . 2004. "Combination Forecasts of Output Growth in a Seven-Country Data Set." *Journal of Forecasting* 23 (6): 405–30.