RESERVE BANK OF NEW ZEALAND

# DP2009/04

# Forecasting national activity using lots of international predictors: an application to New Zealand

**Sandra Eickmeier and Tim Ng**

**May 2009**

**JEL classification: C53, F47, C33**

**www.rbnz.govt.nz/research/discusspapers**

**Discussion Paper Series**

**ISSN 1177-7567**

**DP2009/04**

# Forecasting national activity using lots of international predictors: an application to New Zealand[*]

**Sandra Eickmeier and Tim Ng[†]**

## Abstract

We apply "data-rich" factor and shrinkage methods to understand how large international datasets can be used to improve forecasts of New Zealand GDP. We find that exploiting a large number of international predictors can improve forecasts compared to more traditional models based on small datasets. This is in spite of New Zealand survey data capturing a substantial proportion of the predictive information in the international data. The largest forecasting accuracy gains from including international predictors are at longer forecast horizons. The forecasting performance achievable with the data-rich methods differs widely, with shrinkage methods and partial least squares performing best. We also assess the type of international data that contains the most predictive information for New Zealand growth over our sample.

[*] At the time this paper was written, Eickmeier was affiliated with the Deutsche Bundesbank. This paper was written while she visited the Reserve Bank of New Zealand. The views expressed in this paper are those of the author(s) and do not necessarily reflect the views of the Deutsche Bundesbank or the Reserve Bank of New Zealand. We are grateful to Jörg Breitung, Mardi Dungey, Heinz Herrmann, Massimiliano Marcellino, Troy Matheson and Christian Schumacher for helpful suggestions and discussions and to Troy Matheson for sharing his dataset with us. This paper benefited from discussions with participants at seminars at University of Otago, the RBNZ, the Deutsche Bundesbank and the Workshop on Modern Macroeconometric Methods and Applications at University of Tasmania, as well as from Victoria Zhang's very valuable research assistance. Any remaining errors are the authors' sole responsibility.
[†] The Reserve Bank of New Zealand, 2 The Terrace, Wellington, New Zealand; phone (04) 472-2029; fax (04) 473-1209; email tim.ng@rbnz.govt.nz.
ISSN 1177-7567 

# 1 Introduction

Exploiting information from large datasets has been shown to improve forecasts. Certain "data-rich" methods such as principal components (PC) are now widely used in economic forecasting and analysis by academics and practitioners. In this paper, we explore PC and other lesser-known data-rich methods using the case of New Zealand GDP growth forecasting. We focus in particular on whether data-rich methods are a useful way of handling effectively for forecasting purposes the large quantity (hundreds of series) and diversity (many countries and types) of available international data.

We use New Zealand as an example because it is an archetypal case of a small, open economy. New Zealand has many trading partners across the world, suggesting *a priori* that large international datasets and data-rich methods would be useful. Structural vector-autoregressive (SVAR) analyses of New Zealand macroeconomic fluctuations such as Buckle *et al*. (2007) and Dungey and Fry (2007) find that internationally sourced shocks contribute substantially to New Zealand GDP fluctuations. New Zealand's economic profile suggests many channels for international influences on the national economy. Exports account for around 30 percent of New Zealand GDP, with a large proportion of these accounted for by agricultural commodity products. New Zealand is thus (along with Australia and Canada) often viewed as a "commodity economy" (Chen and Rogoff 2003). New Zealand also has strong international links through financial markets, with a net foreign liability position of around 100 percent of GDP and a largely foreign-owned banking system dependent on offshore capital markets for a large proportion of its funding (Bedford 2008).

Most data-rich applications use datasets that include some international variables, but not very many compared to the number available. Surprisingly few explicitly assess the marginal predictive content of international data. None systematically examines how best to exploit international data for forecasting the domestic economy,[2] or what these methods can reveal about the predictive content of different types of international data for forecasting purposes.

We ask three main questions. (i) By how much can the use of international data improve forecasts of New Zealand GDP growth? (ii) Are data-rich

[2] An exception is Schumacher (2009) as we will note below.

techniques a feasible and useful means of handling the large quantity and diversity of available international data manageably, while retaining predictive power? (iii) How can data-rich methods shed light on the economic types of international data and regions of the world that have most predictive content for New Zealand growth forecasting?

For the first question, we look at the potential improvement in forecasting accuracy when a large number of international data are added to a predictor dataset containing national (in this case, New Zealand) data only. We also look at the forecasting performance of models based on international data only.

For the second question, we compare different data-rich approaches to capturing the predictive information in our international dataset. As noted, certain data-rich approaches have been shown to be useful in the context of essentially single-country datasets, but the dimensionality of the problem is an order of magnitude greater in the case of international datasets. The dataset we use here contains several hundred macroeconomic time series from 12 major trading partner economies of New Zealand, which together account for about three quarters of New Zealand's total trade in goods (exports and imports). These economies represent the three major world economic regions – North America and Europe (which each account for about 15 percent of goods trade) and Asia-Pacific (about half).[3]

Data-rich methods deal with large dimension datasets by one or both of two main approaches. The first is to shrink the variance of parameters in estimated equations. The second is to summarise the information contained in many data into a few common factors. These methods make forecasting using many predictors feasible. In addition to the familiar PC, we look at other data-rich methods that address some of the known limitations of PC when applied to forecasting in practice. Variants of PC are targeted predictors (TP) and weighted principal components (WPC). We also look at partial least squares (PLS), elastic net (EN) and ridge regression (RR; a special case of EN).

[3] North America is represented by the US and Canada, Europe by the euro area (measured as a single economy) and the UK, and Asia-Pacific by Australia, Japan, China, Singapore, Korea, Malaysia, Taiwan and Hong Kong.

We compare forecasting accuracy where these data-rich approaches are taken to the international data, with that where trade-weighted aggregates of international data are used instead. Trade-weighting is a much simpler approach to summarising international data, and is often used by practitioners because of its simplicity and intuitive appeal. Obvious advantages of the data-rich methods, though, are that they can easily cope with a much greater number and diversity of data; they are agnostic about which series among a large number have the greatest predictive content; they can (implicitly) capture international transmission channels beyond direct trade linkages, such as indirect trade, financial markets, commodity prices, and confidence; and they (generally) derive weights from an explicit statistical optimisation problem, which is not usually the case for trade-weights.

For the third question, we construct broad subsets of the international dataset across two alternative dimensions – macroeconomic type, and region of origin. The economic types are real activity, prices, monetary and financial and commodity price data. The regions are North America, Europe, Asia and Australia. We then assess the marginal predictive content of these subsets and their historical contributions to forecasts over our sample. The subset exercise provides a sense of the explanatory power of the different types of international data and different regions for the variance in New Zealand GDP growth over the sample. This exercise also addresses to some degree the criticism, sometimes levelled at large forecasting models with little imposed economic structure, that they are "black boxes" (Forni *et al.* 2008) and that their output is difficult to interpret and communicate.

The rest of the paper is organised as follows. In section 2 we review related literature. In section 3 we outline our approach to assessing relative forecasting accuracy, and introduce and discuss the data-rich methods. In section 4 we describe the data. In section 5 we present our results on forecasting accuracy. In section 6 we look at how the partitioning exercise and data-rich techniques can illuminate the drivers of the forecasts. We conclude in section 7.

## 2 Related literature

In a number of seminal papers, Stock and Watson (2002a, 2002b, 2004) show the benefits of factor-model approaches for economic forecasting.

Eickmeier and Ziegler (2008)'s recent meta-analysis overviews 52 studies (including one, Matheson (2006), for New Zealand) that predict output growth and inflation using factor models and compare the factor-based forecasts with forecasts based on alternative methods. Most of the studies are based on PC estimates of the factors. They find that, in general, factor models outperformed small-scale models (though gains were sometimes small or not robust across specifications), but that other data-rich methods tend to outperform factor models.

These other methods are much less widely applied. Most of them use US data. Boivin and Ng (2006) and Bai and Ng (2008) apply WPC and TP, respectively. TP is applied by Schumacher (2009) to German data. De Mol *et al*. (2008) produce their forecasts based on RR and LASSO, another special case of EN. Groen and Kapetanios (2008) and Lin and Tsay (2006) apply RR as well as PLS.

Although most papers using data-rich methods include a small set of foreign variables, very few explicitly investigate the information content of foreign data. Banerjee *et al.* (2006) investigate the importance of euro-area data for central and east European countries (CEECs). Gosselin and Tkacz (2001), Cheung and Demers (2007) and Brisson *et al.* (2003) assess the predictive content of US variables for Canadian real economic activity and inflation. Brisson *et al.* (2003) include other countries' data as well as US data. Finally, Schumacher (2009) uses G7-country data for German GDP forecasts.

All these studies compare forecasts based on factors extracted from national datasets with those based on factors estimated either from datasets containing both national and foreign variables, or containing foreign variables only. Banerjee *et al.* (2006), in addition, use in their forecasting equation distinct national and international factors, i.e. factors estimated separately from national and international datasets, as well as factors estimated from the entire dataset. The forecasting accuracy results are qualitatively similar. The Banerjee *et al.* (2006) study finds that euro-area information is of limited value in forecasting the CEECs, and attribute this result to the phase of low correlation between the CEECs and the euro area during convergence. In the studies for Canada, US variables generally appear to contain information beyond that in Canadian data. Brisson *et al.* (2003) find that data from countries outside North America provide useful information for forecasting Canadian inflation, but not Canadian GDP growth. Schumacher (2009) finds that international data is useful only when TP, but not simple PC, is applied to a joint national and international dataset.

There have been few data-rich approaches taken to New Zealand data in a forecasting context. Matheson (2006) estimates factors from a dataset of almost 400 variables to predict GDP and other variables. Most variables in this dataset are domestic variables, but there are a handful of international variables as well, including trade-weighted foreign aggregates. Bloor and Matheson (2008) use a large Bayesian VAR featuring almost one hundred variables to forecast GDP and other variables, finding its forecasting accuracy to be quite favourable, compared to smaller models such as small- or medium-sized VARs. The large Bayesian VAR includes similar international variables to Matheson (2006). However, the predictive content of the international variables for domestic forecasting is systematically examined in neither of these studies.

# 3 Methodology

## 3.1 Forecasting setup

Our benchmark forecasting model for our target variable $y_{t+h,t}$ is the univariate model:

$$y_{t+h,t} = \alpha' \mathrm{W}_t + e_{t+h,t}, \tag{1}$$

where $y_{t+h,t} = y_{t+h} - y_t$, the log difference of New Zealand GDP between period $t+h$ and $t$ and $\mathrm{W}_t$ is 1 or $\begin{bmatrix} 1 & y_{t,t-1} & \cdots & y_{t-p,t-p-1} \end{bmatrix}'$ with $y_{t,t-1} = y_t - y_{t-1}$, and $\alpha$ is the scalar or the $(p+1)\times 1$ vector of associated parameter(s).

Our target variable may also be influenced by other variables, summarised in the $N \times 1$ vector $\mathrm{X}_t$. Introducing $\mathrm{X}_t$ in equation (1) yields

$$y_{t+h,t} = \alpha' \mathrm{W}_t + \Gamma' \mathrm{X}_t + e_{t+h,t}, \tag{2}$$

where $\Gamma = [\Gamma_1 \quad \cdots \quad \Gamma_N]'$ has dimension $N \times 1$. If $N$ is large, the forecast is not efficient because the sampling variability increases with $N$. If $N > T$, forecasting with standard least squares (LS) methods is not even feasible. To deal with large $N$, data-rich techniques either shrink the $\Gamma$ parameters to or towards zero, or summarise $X_t$ in a few common factors, or both.

We consider forecasts based on $X_t$ where $X_t$ contains only national data, only international data, and both national and international data. To keep the number of results manageable, we do not estimate separate "national" and "international" factors from the respective datasets for inclusion in equation (2).

Our forecasting setup is as follows. We produce direct, recursive out-of-sample forecasts for horizons 1, 2, 4 and 8 quarters. We compute root mean squared errors (RMSE) between $y_{t+h,t}$ and its forecast $\hat{y}_{t+h,t} = \hat{a}' W_t + \hat{\Gamma}' X_t$, where '^' indicates an estimate, and compare them across models. To make RMSEs comparable across horizons, we divide them by $\sqrt{h}$. In the case where $W_t$ contains current and lagged GDP growth, we consider up to 4 lags, i.e. $p = 0,...,3$. For each horizon and each $p$, we compute the corresponding RMSE over the forecast evaluation period and choose the lag length which yields the minimal RMSE for each horizon.[4] We start the forecast evaluation period in 2000Q1.

## 3.2 Data-rich methods

As noted, data-rich methods either directly regress the target variable on the predictors where the parameters are shrunk towards or to zero (subsection 3.2.1), or summarise the information in a few common factors and regress the target variable on those factors (subsection 3.2.2). When presenting the

[4] Of course, this does not correspond to a real-time forecast situation. In real time, one would need to choose the lag length optimally for each recursion (which is usually done applying information criteria). This would, however, greatly lengthen the computation time, and is not the focus of our analysis. We adopt instead a performance-based approach where we pick the lag length that minimises the RMSE over the whole sample period. For a thorough discussion on performance-based criteria versus information criteria see Schumacher (2007).

data-rich methods here, we drop $W_t$ for clarity, but account for it at each recursion by exploiting the Frisch-Waugh-Lovell theorem.

**Shrinkage methods**

The EN and the RR directly regress the target variable on the predictors.

*Ridge regression*

The ridge estimator solves the penalised regression problem

$$\min_{\Gamma} \boldsymbol{RSS} + \boldsymbol{\nu} \sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \Gamma_{\boldsymbol{i}}^2 \tag{3}$$

and is given by

$$\hat{\Gamma}_{\boldsymbol{h}}^{\boldsymbol{RR}} = (X'X + \boldsymbol{\nu} I_{\boldsymbol{N}})^{-1} X' \boldsymbol{y}^{\boldsymbol{h}}, \tag{4}$$

where $X = \begin{bmatrix} X_1 & \cdots & X_{\boldsymbol{T}-\boldsymbol{h}} \end{bmatrix}'$, $\boldsymbol{y}^{\boldsymbol{h}} = \begin{bmatrix} \boldsymbol{y}_{\boldsymbol{h}+1,1} & \cdots & \boldsymbol{y}_{\boldsymbol{T},\boldsymbol{T}-\boldsymbol{h}} \end{bmatrix}'$, $\Gamma_{\boldsymbol{i}}$ is an element of $\Gamma$, and $\boldsymbol{\nu}$ is the scalar ridge or shrinkage parameter.[5] The RR estimator penalises large parameter estimates and shrinks the LS estimator towards (but not to) zero, thus reducing the variance of the estimates. With RR, all variables enter the forecasting equation. We produce forecasts for $\boldsymbol{\nu}$ = 0.25, $\boldsymbol{N}$, $5\boldsymbol{N}$ and $10\boldsymbol{N}$, following Groen and Kapetanios (2008). $\boldsymbol{\nu}$ = 0.25 imposes much less shrinkage, but is consistent with the parameterisation for EN chosen below and by previous work.

[5] The ridge regression can be interpreted as a Bayesian regression with a Gaussian prior – see De Mol *et al*. (2008).

*Elastic net*

EN is more general than RR. Unlike with RR, some parameters may be shrunk to zero. Hence, EN performs shrinkage and variable selection at the same time (Zou and Hastie 2005).[6] It solves

$$\min_{\Gamma} \boldsymbol{RSS} + \boldsymbol{\nu}_1 \sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \left|\Gamma_{\boldsymbol{i}}\right| + \boldsymbol{\nu}_2 \sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \Gamma_{\boldsymbol{i}}^2 . \tag{5}$$

The EN estimator can be found iteratively with least angle regression (LARS), which efficiently solves the optimization problem (5). For details, see Efron *et al.* (2004). Following Bai and Ng (2008), we set $\boldsymbol{\nu}_2$ to 0.25. As in their application, our results do not change much when we set $\boldsymbol{\nu}_2$ to 0.5 or even to 1.[7] Choosing $\boldsymbol{\nu}_1$ is equivalent to choosing the number of variables with non-zero coefficients which we set to 30, 100 and 200 for our forecasts.

## Factor methods

Approximate factor models (Chamberlain and Rothschild 1983, Stock and Watson 2002a, Forni *et al.* 2000, Bai and Ng 2002, Bai 2003) assume that

[6] EN combines the shrinkage achieved by RR, and the variable selection achieved by LASSO, a method we do not use here. In contrast to EN, the optimization problem in LASSO considers only the first penalisation term of equation (5). While LASSO "tends to select only one variable from the group and does not care which one is selected" (Zou and Hastie 2005), the EN has the advantage that, under certain parameter constellations, it can select groups of (similar) variables. This is the case if $\boldsymbol{\nu}_2/(\boldsymbol{\nu}_1+\boldsymbol{\nu}_2)>0$, i.e. if the EN penalty is a strict convex combination of the LASSO and the RR penalty terms. We have made sure that this is indeed the case for our choices of $\boldsymbol{\nu}_2$ and of the number of variables we keep in our datasets. EN should also select similar variables at each point in time, unlike LASSO. This makes results easier to interpret than with LASSO, and is the main reason why we use the EN here and not LASSO.

[7] A small value for $\boldsymbol{\nu}_2$ reflects the idea that with EN, the focus lies on variable selection (and LASSO shrinkage). We also set $\boldsymbol{\nu}_2$ to $\boldsymbol{N}$ or values larger than $\boldsymbol{N}$, as for the RR case. In this case, the ridge penalty term in equation (5) obtains a very large weight relative to the first (LASSO) penalty term. No noticeable forecast improvements can be obtained compared to the RR case with larger shrinkage parameters, and, hence, we do not present results for EN with large values of $\boldsymbol{\nu}_2$ here.

the (typically large number of) variables in the $\boldsymbol{N} \times 1$ vector $\mathrm{X}_{\boldsymbol{t}} = \left[ \boldsymbol{x}_{1\boldsymbol{t}} \quad \cdots \quad \boldsymbol{x}_{\boldsymbol{Nt}} \right]'$ can be described as

$$\mathrm{X}_{\boldsymbol{t}} = \Lambda \mathrm{F}_{\boldsymbol{t}} + \Xi_{\boldsymbol{t}} . \tag{6}$$

$\Lambda = \left[ \boldsymbol{\lambda}_1 ' \quad \cdots \quad \boldsymbol{\lambda}_{\boldsymbol{N}} ' \right]'$ is the $\boldsymbol{N} \times \boldsymbol{r}$ matrix of factor loadings and $\Xi_{\boldsymbol{t}}$ is the $\boldsymbol{N} \times 1$ vector of idiosyncratic components which can be weakly mutually and serially correlated in the sense of Bai and Ng (2002). $\mathrm{F}_{\boldsymbol{t}}$ is the $\boldsymbol{r} \times 1$ vector of common factors, and $\boldsymbol{r}$, the number of common factors, is typically small.

In all the factor methods, the factors are used to replace the original predictor variables in the forecasting equation.

*Principal components estimation*

Estimation of $\mathrm{F}_{\boldsymbol{t}}$ and $\Lambda$ with PC involves solving the following optimization problem

$$\min_{\Lambda,\mathrm{F}} \frac{1}{\boldsymbol{NT}} \sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \sum_{\boldsymbol{t}=1}^{\boldsymbol{T}} (\boldsymbol{x}_{\boldsymbol{it}} - \boldsymbol{\lambda}_{\boldsymbol{i}} '\mathrm{F}_{\boldsymbol{t}})^2 \tag{7}$$

subject to $\sum_{\boldsymbol{t}=1}^{\boldsymbol{T}} \mathrm{F}_{\boldsymbol{t}} \mathrm{F}_{\boldsymbol{t}} ' / \boldsymbol{T} = \mathrm{I}_{\boldsymbol{r}}$ and $\Lambda ' \Lambda$ being diagonal. This is equivalent to searching for the linear combinations of the data that maximise the share of the total variance explained for each number of combinations up to $\boldsymbol{N}$. A solution to this problem can be found by an eigenvalue-eigenvector decomposition of $\sum_{\boldsymbol{t}=1}^{\boldsymbol{T}} \mathrm{X}_{\boldsymbol{t}} ' \mathrm{X}_{\boldsymbol{t}} / \boldsymbol{T}$. PC estimates for $\Lambda$ and $\mathrm{F}_{\boldsymbol{t}}$ are given by

$$\hat{\Lambda} = \hat{\mathrm{V}} , \tag{8}$$

and

$$\hat{\mathrm{F}}_{\boldsymbol{t}}^{\boldsymbol{PC}} = \hat{\mathrm{V}}' \mathrm{X}_{\boldsymbol{t}} , \tag{9}$$

where $\hat{V}$ is the $N \times r$ matrix of eigenvectors corresponding to the $r$ largest eigenvalues of $\sum_{t=1}^{T} X_t' X_t / T$. We introduce $\hat{F}_t^{PC}$ in equation (1) and estimate the LS regression

$$y_{t+h,t} = b'\hat{F}_t^{PC} + e_{t+h,t}. \tag{10}$$

Our factor-model-based forecasts use a fixed $r$ = 1, 2, 3 and 5. $r = 5$ is suggested by the Bai and Ng (2002) information criterion $IC_{p1}$ for all three (New Zealand, international and combined New Zealand and international) datasets when applied to the whole sample period. In addition, we consider smaller numbers of (up to 3) factors, because previous studies have found that forecasts based on very few factors – often only a single factor – tend to yield better results than less sparsely parameterised factor models.

*Weighted principal components*

Factor forecasting based on PC factors is not always successful in practice. For instance, the PC estimator does not perform well when idiosyncratic components are highly cross-correlated and explain a large part of the variation in the data. To handle this problem, we use Rule 1c suggested by Boivin and Ng (2006) (WPCBN). This involves removing variables from the set that, if included in the PC estimate, would be characterised by highly cross-correlated idiosyncratic components and a low commonality, i.e. the variance explained by the common factors relative to the total variance. With this rule applied here, weights are either zero or one, i.e. variables are either in or out.

In the rule's first step, we estimate by common and idiosyncratic components by PC, using alternately $r$ = 1, 2, 3 and 5. In the second step, we look at each series $i = 1,..., N$ in turn and drop the series $j$ from the rest of the dataset whose idiosyncratic component is most correlated with the idiosyncratic component of series $i$. If the idiosyncratic components of series $i$ and $j$ are most correlated with each other, the series with the lower commonality is selected for dropping. The PCs are then re-estimated from the reduced dataset and included in the forecasting equation.

As we show below, with our dataset WPCBN reduces the amount of cross-correlation in the idiosyncratic components, but does not succeed in increasing commonality. We therefore consider an additional rule (rule SWa as described in Boivin and Ng 2006, WPCSW) that lowers the weight on variables with large idiosyncratic components, as follows. We first estimate with PC the common and idiosyncratic components of $X_t$, again alternately using $\boldsymbol{r}$ = 1, 2, 3 and 5. We then multiply each series by the inverse of its idiosyncratic component's standard deviation, and re-estimate the PCs from the weighted series.

*Targeted predictors*

Another problem of simple or weighted PC for forecasting is that they find the linear combinations of variables that maximise the variance of the total dataset, without directly relating the factors to the target variable. Hence, they do not necessarily improve forecasts of the target variable. TP, by contrast, takes into account the relation between the target variable and the predictors. In TP, PCs are estimated from a reduced set of variables that contains only variables closely related to the target variable. These PCs are then used in the forecasting equation. TP thus combines variable selection and PC. Following Bai and Ng (2008), we select the variables in two ways.

Hard thresholding (TPH) uses a statistical criterion to decide which variables to exclude from the active set. The target variable is regressed on each predictor individually, and only predictors with an absolute *t*-statistic exceeding a specified threshold are retained in the set.[8] We set a threshold of 1.65, the critical value of the two-sided 5% significance level. One weakness of TPH is that it does not take into account the other predictors when deciding whether a variable is included or not. Consequently, TPH may end up selecting "too similar" variables, and we know that pooling over variables is effective only if they have mutually distinct information content.

With soft-thresholding (TPS), other predictors are taken into account. We select 30, 100 and 200 variables for PC factor estimates by solving the EN problem with LARS. Our choice of a minimum of 30 is based on work by Boivin and Ng (2006) who show in simulations that factors can be estimated precisely from datasets containing 30 variables or more, and Bai and Ng

[8] When we analyse the subsets of the international data, in a few cases, *t*-statistics associated with fewer than *r* variables exceed the critical values, and we cannot estimate *r* principal components. In these cases, we include the *r* variables with the largest *t*-statistics in the active set.

(2008) also base their analysis on 30 variables. The parameter $\nu_2$ is set to 0.25, consistent with our parameterisation for EN.

*Partial least squares*

PLS (Wold, 1982) factors are linear combinations of the predictors with weights derived from the covariance of the predictors with the target variable, while being mutually orthogonal.[9] We use the following algorithm to estimate the PLS factors:[10]

i. Set $\boldsymbol{u}_t = \boldsymbol{y}_{t+h,t}$ and $\boldsymbol{\vartheta}_{it} = \boldsymbol{x}_{it}$, $\boldsymbol{i} = 1,...,\boldsymbol{N}$. Set $\boldsymbol{j} = 1$.
ii. Determine the $\boldsymbol{N} \times 1$ vector of indicator variable weights or loadings $\boldsymbol{\omega}_j = \left[\boldsymbol{\omega}_{1j} \quad \cdots \quad \boldsymbol{\omega}_{Nj}\right]'$ by computing individual covariances: $\boldsymbol{\omega}_{ij} = \mathrm{Cov}(\boldsymbol{u}_t, \boldsymbol{\vartheta}_{it})$, $\boldsymbol{i} = 1,...,\boldsymbol{N}$. Construct the $\boldsymbol{j}$th PLS factor by taking the linear combination given by $\boldsymbol{\omega}_j{}'\boldsymbol{\vartheta}_t$ and denote this factor by $\hat{\boldsymbol{f}}_{jt}^{PLS}$.
iii. Regress $\boldsymbol{u}_t$ and $\boldsymbol{\vartheta}_{it}$, $\boldsymbol{i} = 1,...,\boldsymbol{N}$ on $\hat{\boldsymbol{f}}_{jt}^{PLS}$. Denote the residuals of these regressions by $\tilde{\boldsymbol{u}}_t$ and $\tilde{\boldsymbol{\vartheta}}_{it}$, respectively.
iv. If $\boldsymbol{j} = \boldsymbol{k}$, where $\boldsymbol{k}$ is the number of PLS factors, stop, else set $\boldsymbol{u}_t = \tilde{\boldsymbol{u}}_t$ and $\boldsymbol{\vartheta}_{it} = \tilde{\boldsymbol{\vartheta}}_{it}$, $\boldsymbol{i} = 1,...,\boldsymbol{N}$ and $\boldsymbol{j} = \boldsymbol{j} + 1$ and go to step ii.

$\hat{\mathrm{F}}_t^{PLS,h} = \left[\hat{\boldsymbol{f}}_{1t}^{PLS} \quad \cdots \quad \hat{\boldsymbol{f}}_{kt}^{PLS}\right]'$ is the $\boldsymbol{k} \times 1$ matrix of estimated common PLS factors for horizon $\boldsymbol{h}$ that are included in the forecasting equation (1). We set $\boldsymbol{k}$ to 1, 2, 3 and 5.

## 3.3 Trade-weighting approaches to summarising international data

We also look at trade-weighted aggregates of foreign variables as an approach to capturing international data for forecasting purposes. Trade-

[9] PLS has become prominent in natural sciences such as chemical engineering and chemometrics.
[10] A good overview is given in Groen and Kapetanios (2008), and we follow the authors closely.

weighting is often used by practitioners, and, interestingly, also in applications of Pesaran *et al.*'s (2004) Global VAR approach to handling large datasets for modelling international business cycles. In these applications, foreign factors are constructed as trade-weighted aggregates of observable variables before inclusion in a VAR (e.g. Dées *et al.* 2007).

We use two variants of trade-weighted aggregates. In both, we use total merchandise trade (the sum of export and import value) weights for constructing foreign GDP, CPI and interest rate variables, following the Global VAR application. Foreign GDP and CPI are calculated using trade weights on all 12 major trading partners. Foreign long- and short-term interest rates use trade weights for Australia, US, UK, Japan and the euro area (a subset of the 12 trading partners due to data availability). In the first variant, the trade weights are fixed at the average over the entire sample. In the second variant the weights are two-year moving averages.

Table 1 gives an overview of the forecast methods applied here.

**Table 1**
**Overview of specifications**

| | | |
|---|---|---|
| *trade1* | Trade-weighted avgs. | constant trade (export + imports) weights |
| *trade2* | | 2-year moving average trade (exports + imports) weights |
| *PC* | Principal components | $r$ = 1, 2, 3, 5 |
| *WPCBN* | Weighted PC | Rule 1c in Boivin and Ng (2008), $r$ = 1, 2, 3, 5 |
| *WPCSW* | | Rule SWa in Boivin and Ng (2008), $r$ = 1, 2, 3, 5 |
| *TPH* | Targeted predictors | Hard thresholding, r = 1, 2, 3, 5 |
| *TPS* | | Soft thresholding 30,100,200 vbles; $v_2 = 0.25$, $r$ = 1, 2, 3, 5 |
| *PLS* | Partial least squares | $k$ = 1, 2, 3, 5 |
| *RR* | Ridge regression | $v$ = 0.25, N, 5N, 10N |
| *EN* | Elastic net | 30, 100, 200 variables, $v_2 = 0.25$ |

## 3.4 Strengths and weaknesses of the various approaches

It is not clear *a priori* which of the approaches adopted in this paper to handling large amounts of data will lead to the best forecasting results. Each method has its strengths and weaknesses, and the success of each method will depend on the particular forecasting problem at hand, and on the particular characteristics of the data.

**Trade-weighting versus data-rich approaches**

The data-rich approaches to handling the international data have several advantages over the trade-weighted (and other simple weighted-average) aggregation methods. An obvious advantage is that data-rich methods can easily cope with a much greater number and diversity of data compared to the trade-weighting approach. In our international dataset, for example, we include alongside GDP many other real economic variables, such as productivity, capacity utilization, consumption, investment and industrial production. These series may have greater predictive content for New Zealand activity than foreign GDP. The data-rich methods allow for this possibility, while being agnostic about which series among a large number have the greatest predictive content.

A second advantage is that data-rich methods can (implicitly) capture international transmission channels beyond direct trade linkages, such as indirect trade, financial markets, commodity prices and confidence. Those linkages are more difficult to measure directly: data are either not available, or they are very volatile (in the case of financial data), or it is not obvious how to translate them into weights.

Third, the data-rich methods (generally) derive weights from an explicit statistical optimisation problem, which is not usually the case for trade-weights.

However, trade-weighted aggregates also have their appeal. They are often preferred by practitioners, since they provide an intuitive summary of foreign data and may thus make communication with the users of forecasts easier (Robertson 2000, Drew and Frith 1998). In contrast to the data-rich methods (as applied here), trade-weighting can accommodate changing weights, whereas PC and variants of PC as well as PLS, RR and EN approaches are based on constant factor loadings and/or weights.[11] This may be important given changes in trade and financial market integration patterns across time.

**Relative strengths of data-rich methods**

[11] Del Negro and Otrok (2008) suggest a factor model with time-varying loadings which is, however, computationally more demanding than the non-parametric constant parameter factor approaches.

Among the data-rich methods, a disadvantage of PC and WPC compared to other methods is that PC and WPC do not take into account the relationship between the predictors and the target variable. This may be one reason why PC, despite of its ability to use lots of data, does not systematically outperform small-scale models and why other data-rich methods that take the predictors' relationship with the target variable into account tend to outperform factor models (Boivin and Ng 2006, Eickmeier and Ziegler 2008).

Whether pre-selection of the data (EN, TP and WPCBN) or not (PC, WPCSW, PLS and RR) improves performance depends on whether some coefficients are actually exactly zero, i.e. whether some predictors are in fact irrelevant. If this is the case, including all variables in the forecasting model increases sampling uncertainty, but will not improve forecasts, and forecasters may be better off setting these coefficients to zero. Key, of course, is knowing or inferring which coefficients are, or are not, exactly zero.

Finally, if the conditions that guarantee consistent estimation of the factor space in approximate factor models are not satisfied, PC-based methods may tend to perform poorly compared to methods whose success does not depend on the factor structure in the data, such as RR and EN. Consistent estimation with PC requires the factor loadings to remain non-trivial as the number of time series becomes large (so called "strong" factors)[12] and weak serial and cross-correlation of the idiosyncratic components (e.g. Boivin and Ng 2006). In addition, Boivin and Ng (2006) have shown that PC factor estimates become worse as the cross-sectional dispersion of commonality increases. Groen and Kapetanios (2008) have demonstrated in Monte Carlo simulations that PC is outperformed by PLS and RR if factors are "weak". These issues may be particularly relevant for our international dataset, which may contain regional as well as global cycles. This would lead to highly correlated idiosyncratic components and small factor loadings if some countries' variables have substantial correlation with variables from only a subset of other countries.[13]

# 4 Data

[12] Formally, Onatski (2007) defines "weak factors" as factors that have bounded, instead of increasing with $N$, cumulative effects on the cross-sectional units.
[13] See Kose *et al.* (2008) for evidence of global divergence and regional convergence.

We use quarterly data from 1990Q1 to 2007Q4. Our target variable is New Zealand GDP growth. Both the New Zealand and the international datasets are large. Most of our 446 New Zealand series are taken from Matheson (2006).[14] Our international dataset contains 434 series from the US, Canada, euro area, UK, Australia, China, Singapore, Hong Kong, Malaysia, Taiwan, Korea and Japan. The breakdown of our international dataset is shown in table 2.

The set comprises roughly 100 North American, 100 European, 200 Asian, and 42 Australian series. There are 206 real activity, 108 price and 130 monetary and financial series. The real block includes national accounts data, industrial production, productivity and labor market variables, new orders, retail trade, and survey-based expectations about real economic activity. The price block contains consumer prices, producer prices, the GDP deflator and deflators of the main GDP components, unit labor costs and house prices. The monetary and financial variables block includes interest rates, money and credit aggregates, exchange rates and stock prices. In addition, 38 commodity price series (in US dollar terms) are included in the dataset. In building the dataset, we attempted to roughly balance the numbers of series from each region and across the economic types, subject to availability.

**Table 2**
**International dataset - number of series in each class**

| | North Amer. | Europe | Asia | Australia | World | Sum |
|---|---|---|---|---|---|---|
| Real | 50 | 41 | 95 | 20 | - | 206 |
| Prices | 28 | 28 | 41 | 11 | - | 108 |
| Monetary + financial | 23 | 34 | 62 | 11 | - | 130 |
| Commodity prices | - | - | - | - | 38 | 38 |
| Sum | 101 | 103 | 198 | 42 | 38 | 482 |

All data are seasonally adjusted and made stationary by differencing where necessary. Following Stock and Watson (2005), we remove outliers.[15] We

[14] For details on the national dataset see Matheson (2006).
[15] In this approach outliers are defined as observations of the stationary data with absolute deviations from the median larger than 6 times the interquartile range, replacing them with the median value of the preceding 5 observations.

standardise the predictors to have zero mean and unit variance at each recursion. This is needed for the factor methods, so we apply it for the other data-rich methods also for comparability. A detailed overview of the international data and their treatment is given in table A1 in the appendix.

## 4.1 Characteristics of the dataset

Here we summarise the statistical characteristics of our dataset, to illuminate some of the issues relating to the factor structure as discussed above.

First, we compute correlations between the target variable $y_{t+1,t}$ and each predictor $x_{it}$ contained in our New Zealand and international datasets. We show in figure 1, panel (a) box plots of absolute correlations for the full New Zealand, international and combined (New Zealand and international) datasets as well as for datasets that were reduced by either hard- or soft-thresholding.

New Zealand variables tend to be more highly correlated with $y_{t+1,t}$ than international variables. The figure also illustrates the effect of pre-selection based on both hard- and soft-thresholding: the share of variables that are highly correlated with the target variable rises in most cases. Hard thresholding and soft thresholding with 30 variables kept in the active set are most successful in increasing the correlation between the predictors and the target variable, whereas, somewhat surprisingly, the correlation does not change much with soft thresholding with 100 or 200 variables. The dispersion of individual variables' correlations with $y_{t+1,t}$ is smallest with hard-thresholding, which probably reflects that it tends to select rather similar variables.

We next fit factor models to the New Zealand, the international and the combined datasets and look at the first five factors. In table 3, we report the correlations between the factors extracted from $X_t$ and the target variable $y_{t+1,t}$. Three observations are worth highlighting.

First, the first PC is meaningfully correlated with $y_{t+1,t}$ when extracted from the national and the combined datasets, with correlation coefficients of 0.5

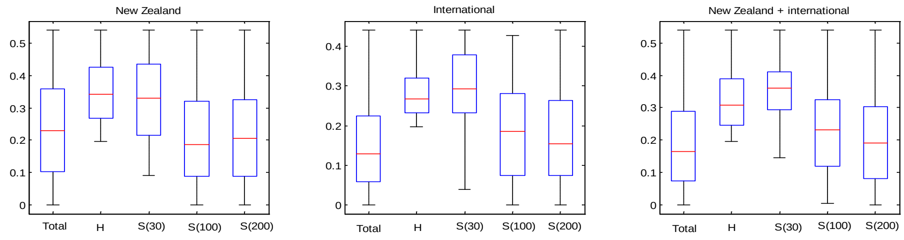
in each case, whereas the correlation coefficient is lower, at 0.3, when the factors are estimated from the international data only.

Second, the correlation does not decline monotonically as the rank of the PC drops. For example, the third PC of the international dataset is most highly correlated with $y_{t+1,t}$ (correlation coefficient: 0.32), followed by the first (0.28) and the fourth PCs (0.27). This is because the PC optimisation problem does not take into account the relationship between target and predictors.

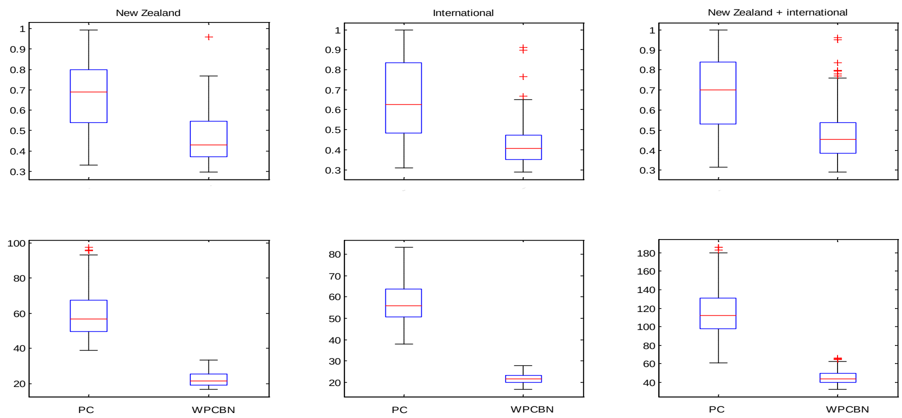
**Figure 1**

**Characteristics of the New Zealand, international-only, and combined datasets**

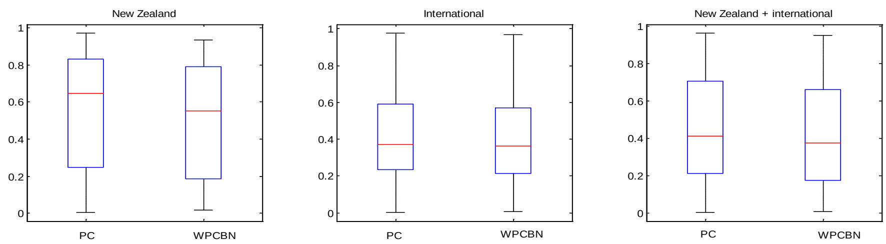
**(a) Absolute correlations between predictors and target variable**




**(b) Absolute cross-correlation of idiosyncratic components**




**(c) Commonality**




Notes: The red lines are the medians, the box indicates the lower and upper quartile values. Whiskers extend to the most extreme values of the data. Red crosses indicate outliers. Results shown in panels (b) and (c) are based on $r$ = 5. H indicates variable selection with hard thresholding. S(30), S(100), S(200) indicate variable selection with soft thresholding with 30, 100 and 200 variables.

**Table 3**
**Correlations between estimated factors and 1-quarter ahead New Zealand GDP growth**

| | New Zealand data | | | | |
|---|---|---|---|---|---|
| | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 |
| PC | 0.53 | 0.04 | 0.15 | 0.02 | 0.06 |
| TPH | 0.54 | 0.05 | 0.14 | 0.16 | 0.22 |
| TPS (30 variables) | 0.73 | 0.31 | 0.14 | 0.19 | 0.22 |
| TPS (100 variables) | 0.54 | 0.03 | 0.52 | 0.01 | 0.06 |
| TPS (200 variables) | 0.53 | 0.04 | 0.31 | 0.02 | 0.28 |
| PLS | 0.59 | 0.60 | 0.25 | 0.29 | 0.28 |
| | International data | | | | |
| | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 |
| PC | 0.28 | 0.03 | 0.32 | 0.27 | 0.06 |
| TPH | 0.45 | 0.36 | 0.09 | 0.00 | 0.26 |
| TPS (30 variables) | 0.59 | 0.10 | 0.60 | 0.21 | 0.00 |
| TPS (100 variables) | 0.21 | 0.30 | 0.34 | 0.15 | 0.54 |
| TPS (200 variables) | 0.31 | 0.10 | 0.40 | 0.20 | 0.23 |
| PLS | 0.62 | 0.52 | 0.47 | 0.24 | 0.19 |
| | New Zealand and international data | | | | |
| | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 |
| PC | 0.46 | 0.28 | 0.08 | 0.19 | 0.09 |
| TPH | 0.56 | 0.12 | 0.13 | 0.20 | 0.15 |
| TPS (30 variables) | 0.86 | 0.09 | 0.09 | 0.27 | 0.12 |
| TPS (100 variables) | 0.55 | 0.58 | 0.15 | 0.16 | 0.11 |
| TPS (200 variables) | 0.51 | 0.51 | 0.08 | 0.23 | 0.12 |
| PLS | 0.64 | 0.53 | 0.40 | 0.30 | 0.17 |

Notes: Abs. correlation between $y_{t+1,t}$ and factors estimated (in sample) from $X_t$ or a reduced version of $X_t$.

Third, pre-selection unsurprisingly helps to extract factors that are more closely linked to the target variable. For all datasets, the correlations of the first PC with the target variable estimated with TPH exceed those estimated with simple PC, and correlations increase further when variable selection is made with TPS and 30 variables. As noted before, TPS with 100 or 200 variables is less successful in raising the correlation. Correlations based on

TPS and 30 variables are comparable with, or even larger than, correlations between the first PLS factors and the target variable.[16]

We then decompose each variable into a common component and an idiosyncratic component based on PC with $\boldsymbol{r} = 5$ and examine, along the lines of Boivin and Ng (2006), the extent to which the assumptions of the approximate factor model are satisfied for our datasets.[17] We first examine whether cross-correlation between the idiosyncratic components could be a problem. We follow Boivin and Ng (2006) and estimate, for each variable, the correlation of its idiosyncratic component with the other variable's idiosyncratic components. Distributions of the maximum absolute correlations are shown in figure 1, panel (b). We also show in figure 1, panel (b) the sums over all absolute correlations. There are more variables with highly cross-correlated errors in the international and combined datasets than in the New Zealand dataset. Moreover, WPCBN clearly reduces the amount of cross-correlation in the errors.

We next assess the commonality. Average commonality ratios of our international data are at 32 percent (based on 3 factors) and 42 percent (based on 5 factors) and are, thus, comparable with those reported in other international business cycle papers (e.g. Eickmeier 2008, Marcellino *et al.* 2000). Figure 1, panel (c) shows box plots of commonalities of all individual variables. There are more variables with low commonality in the international dataset than in the New Zealand dataset. However, the dispersion of the commonality ratios is larger for the New Zealand than for the international dataset, and Boivin and Ng (2006) have shown that this worsens factor estimates. Interestingly, WPCBN does not increase the commonality when applied to our dataset. The reason may be the hierarchical way WPCBN proceeds: it considers only variables with highly cross-correlated errors for elimination. If the common component in eliminated variables is not smaller than the average, WPCBN will not improve the average commonality in the remaining series.

---

[16] At first sight, it seems surprising that the correlation between the target variable and PLS factors does not decline monotonically with lower-ranked factors. The main reason is that the PLS algorithm uses the covariance between the target variable and the predictors for the first PLS factor, but for subsequent factors it uses the covariance between the residual from regressing of the target variable on the previous PLS factor(s) – whereas here we are plotting simple correlations.

[17] We also did this analysis for $\boldsymbol{r} = 3$ and the results were very similar.

Overall, pre-selection appears to relieve most potential difficulties relating to weak factor structure in the dataset, except for the low and dispersed commonality of many variables in our dataset. We consider WPCSW as a means to deal with this latter potential problem.

# 5 Forecasting results

In this section, we look at the predictive content of the international data. We first summarise in subsection 5.1 our forecasting results for New Zealand GDP growth based on data-rich methods exploiting only New Zealand data. This allows a broad comparison with Matheson's (2006) results, using a very similar dataset. We then present in subsection 5.2 our forecast results based on only international data, and then in subsection 5.3 a combined dataset with both New Zealand and international data. These results are shown in table 4, in the form of RMSEs relative to univariate benchmark models for different horizons. Relative RMSEs below 1 indicate that the univariate benchmark model is outperformed.

In subsection 5.4, we document the models that yield the best forecasting accuracy. We show with basic summary statistics how the data-rich methods perform compared to models incorporating trade-weighted aggregates of foreign data, as well as whether models using international data outperform models based on New Zealand data only. For this subsection, as well as using datasets including all international data, we also use our subsets of the international dataset, by region and economic type. We replace the international dataset in the data-rich methods with each of the subsets in turn (for the subsets by type we include the relevant trade-weighted aggregate only). Since the international subsets are much smaller than the full international dataset, we consider for EN and TPS only 30, not 100 or 200 variables. Results are reported in table A.2. of the appendix.

Results obtained based on the subsets of international data are then, in section 6, also used to assess the marginal predictive content of each subset. We also discuss in that section our examination of the regions and types of international data that are most relevant for New Zealand activity forecasting over the sample period. Using subsets of variables amounts to judgemental preselection, and we are interested in whether including or excluding particular classes of variables *a priori* is warranted or not on the basis of their impact on the forecasts.

**Table 4**
**Relative RMSEs**

| | New Zealand | | | | International | | | | New Zealand + international | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | h = 1 | h = 2 | h = 4 | h = 8 | h = 1 | h = 2 | h = 4 | h = 8 | h = 1 | h = 2 | h = 4 | h = 8 |
| Univar. benchm. (RMSE/h) | 0.0061 | 0.0063 | 0.0067 | 0.0069 | 0.0061 | 0.0063 | 0.0067 | 0.0069 | 0.0061 | 0.0063 | 0.0067 | 0.0069 |
| trade1 | - | - | - | - | 0.951 | 1.034 | 0.970 | 1.247 | - | - | - | - |
| trade2 | - | - | - | - | 0.934 | 1.022 | 0.933 | 1.242 | - | - | - | - |
| PC (r = 1) | 0.951 | 0.865 | 0.985 | 1.113 | 1.033 | 1.090 | 1.060 | 0.948 | 0.984 | 1.247 | 1.657 | 2.500 |
| PC (r = 2) | 0.951 | 0.910 | 1.119 | 1.387 | 1.016 | 1.056 | 1.149 | 1.247 | 0.951 | 1.034 | 0.970 | 1.247 |
| PC (r = 3) | **0.902** | 0.899 | 1.127 | 1.381 | 1.082 | 1.034 | 1.134 | 1.361 | 0.934 | 1.022 | 0.933 | 1.242 |
| PC (r = 5) | 0.951 | 0.876 | 1.351 | 1.361 | 1.098 | 1.258 | 1.493 | 1.289 | 1.016 | 1.067 | 1.187 | 1.242 |
| WPCBN (r = 1) | 0.951 | 0.899 | 0.993 | 1.124 | 1.033 | 1.079 | 1.045 | 1.031 | 1.082 | 1.180 | 1.194 | 1.268 |
| WPCBN (r = 2) | 0.951 | 0.854 | 1.082 | 1.392 | 1.016 | 1.079 | 1.149 | 1.227 | 1.082 | 1.180 | 1.351 | 1.284 |
| WPCBN (r = 3) | 0.984 | 0.888 | 1.187 | 1.232 | 1.000 | 1.011 | 1.425 | 1.412 | 1.131 | 1.202 | 1.582 | 1.799 |
| WPCBN (r = 5) | 0.967 | 0.955 | 1.410 | 1.485 | 1.033 | 1.348 | 1.373 | 1.407 | 1.033 | 1.090 | 1.216 | 1.247 |
| WPCSW (r = 1) | 1.033 | 1.056 | 1.037 | 1.026 | 1.016 | 1.022 | 1.000 | **0.851** | 1.131 | 1.225 | 1.291 | 1.232 |
| WPCSW (r = 2) | 0.951 | 0.854 | 0.948 | 1.170 | 0.967 | 0.910 | 0.851 | 1.093 | 1.131 | 1.225 | 1.381 | 1.201 |
| WPCSW (r = 3) | **0.902** | 0.843 | **0.896** | 1.093 | 1.049 | 0.955 | 0.918 | 1.139 | 1.098 | 1.169 | 1.306 | 1.778 |
| WPCSW (r = 5) | 0.984 | 0.921 | **0.896** | 1.026 | 1.066 | 1.225 | 1.224 | 1.139 | 0.934 | 0.933 | 1.045 | 1.113 |
| TPH (r = 1) | 0.951 | 0.966 | 0.963 | 1.021 | 1.082 | 1.101 | 1.127 | 1.103 | 0.984 | 1.045 | 1.194 | 1.191 |
| TPH (r = 2) | 0.951 | 1.022 | 0.948 | 1.325 | 1.049 | 1.112 | 1.194 | 1.320 | 0.984 | 1.135 | 1.246 | 1.196 |
| TPH (r = 3) | 1.000 | 1.056 | 0.933 | 1.206 | 1.197 | 1.157 | 1.179 | 1.521 | 0.934 | 0.989 | 1.194 | 1.387 |
| TPH (r = 5) | 1.180 | 1.112 | 1.261 | 1.237 | 1.180 | 1.146 | 1.373 | 1.665 | 0.984 | 1.034 | 1.269 | 1.562 |
| TPS (30 variables, r = 1) | 1.016 | 1.213 | 1.194 | 1.211 | 1.098 | 1.101 | 1.216 | 1.206 | 1.131 | 1.022 | 1.022 | 1.052 |
| TPS (30 variables, r = 2) | 1.033 | 1.303 | 1.149 | 1.289 | 1.246 | 1.213 | 1.373 | 1.201 | 1.033 | 1.022 | 1.015 | 1.046 |
| TPS (30 variables, r = 3) | 1.033 | 1.225 | 1.224 | 1.273 | 1.311 | 1.202 | 1.261 | 1.263 | 1.049 | 1.045 | 1.015 | 1.062 |
| TPS (30 variables, r = 5) | 1.000 | 1.247 | 1.194 | 1.289 | 1.328 | 1.180 | 1.306 | 1.253 | 1.049 | 1.056 | 0.993 | 0.964 |
| TPS (100 variables, r = 1) | 0.934 | 0.831 | 1.157 | 1.139 | 1.082 | 0.955 | 0.963 | 1.356 | 1.049 | 1.191 | 1.037 | 1.082 |
| TPS (100 variables, r = 2) | 1.098 | 0.854 | 1.261 | 1.160 | 1.164 | 1.000 | 1.112 | 1.273 | 1.033 | 1.157 | 0.985 | 1.175 |
| TPS (100 variables, r = 3) | 1.066 | 0.843 | 1.276 | 1.206 | 1.197 | 1.079 | 1.060 | 1.340 | 1.016 | 1.101 | 1.231 | 1.247 |
| TPS (100 variables, r = 5) | 1.115 | 0.899 | 1.164 | 1.196 | 1.082 | 1.169 | 1.134 | 1.448 | 1.049 | 0.989 | 1.254 | 1.237 |
| TPS (200 variables, r = 1) | 0.934 | **0.820** | 1.067 | 1.186 | 1.066 | 1.056 | 1.022 | 1.129 | 0.934 | 0.820 | 0.955 | 1.144 |
| TPS (200 variables, r = 2) | 0.984 | 0.899 | 1.119 | 1.505 | 1.066 | 1.112 | 1.082 | 1.258 | 0.934 | 0.865 | 0.978 | 1.165 |
| TPS (200 variables, r = 3) | 0.951 | 0.944 | 1.209 | 1.649 | 1.000 | 0.933 | 0.925 | 1.418 | 0.951 | 0.820 | 0.970 | 1.196 |
| TPS (200 variables, r = 5) | 1.000 | 0.933 | 1.284 | 1.691 | 1.131 | 1.180 | 1.179 | 1.521 | 0.934 | 0.809 | 1.045 | 1.129 |
| PLS (k = 1) | 0.951 | 0.843 | 0.940 | 1.108 | 1.000 | 1.067 | 0.784 | 1.098 | 0.951 | 0.865 | 0.925 | 1.057 |
| PLS (k = 2) | 1.066 | 1.056 | 1.336 | 1.351 | 0.869 | 0.944 | 0.761 | 1.196 | 1.000 | 0.854 | 0.806 | 1.021 |
| PLS (k = 3) | 0.934 | **0.787** | 1.007 | 1.412 | 0.869 | 1.045 | 0.836 | 1.124 | **0.852** | 0.831 | 0.731 | 0.948 |
| PLS (k = 5) | 0.951 | 1.034 | 1.209 | 1.361 | **0.787** | 0.955 | 0.761 | 0.923 | **0.852** | 0.944 | 0.784 | 0.804 |
| RR ($v_2$ = 0.25) | 1.049 | 0.966 | 1.239 | 1.371 | 0.803 | 1.011 | 0.903 | 1.216 | 0.885 | 0.865 | 0.873 | 0.969 |
| RR ($v_2$ = N) | 0.918 | 0.820 | 0.955 | 1.186 | 0.836 | **0.899** | **0.716** | 1.057 | **0.852** | 0.775 | **0.701** | 1.000 |
| RR ($v_2$ = 5N) | 0.934 | 0.876 | 0.933 | 1.046 | 0.902 | 0.910 | 0.806 | 1.010 | 0.902 | 0.854 | 0.813 | 0.995 |
| RR ($v_2$ = 10N) | 0.934 | 0.899 | 0.940 | 1.010 | 0.934 | 0.933 | 0.866 | 1.005 | 0.934 | 0.888 | 0.866 | 0.995 |
| EN (30 variables, $v_2$ = 0.25) | 1.016 | 0.910 | 1.239 | 1.077 | 0.951 | 1.000 | 0.993 | 1.021 | 0.934 | **0.764** | 0.873 | **0.716** |
| EN (100 variables, $v_2$ = 0.25) | 1.082 | 1.101 | 1.500 | 1.227 | 0.918 | 0.921 | 0.963 | 1.119 | 0.918 | 0.876 | 1.037 | 0.778 |
| EN (200 variables, $v_2$ = 0.25) | 1.082 | 1.011 | 1.373 | 1.351 | 0.836 | 0.955 | 0.940 | 1.206 | 0.885 | 0.843 | 0.963 | 0.938 |

## 5.1 Forecasts using New Zealand data only

Using New Zealand data only, we find that univariate models deliver forecasts that, in general, are difficult to beat. Their RMSEs lie between 0.6 and 0.7 percentage points. No data-rich method outperforms the univariate model at horizon 8.

The quality of forecasts based on data-rich methods differs widely. Of the factor models, simple PC performs well for short horizons ($h$ = 1 and 2).

Preselection only helps in some cases: TPH yields lower RMSEs than simple PC for the one-year horizon, while TPS with 100 or 200 selected variables beats the benchmark at shorter horizons. It is noticeable that in our setup (and unlike in the US setup of Bai and Ng, 2008), more than 30 variables are necessary for TPS to outperform simple PC, and even the univariate benchmark model. WPCSW is quite successful, and WPCSW with 3 and 5 factors yields the best model for the one-year horizon of all the data-rich methods with the New Zealand dataset. PLS also performs well at shorter horizons, and yields the best model at the six-month horizon, with a reduction of the RMSE by 21 percent.

Of the shrinkage methods, RR with larger shrinkage parameters ($\boldsymbol{\nu}_2 = \boldsymbol{N}$ , $5\boldsymbol{N}$ and $10\boldsymbol{N}$ ) beats the benchmark at horizons of 1, 2 and 4 quarters. RR with $\boldsymbol{\nu}_2 = 0.25$ tends to produce worse forecasts than benchmark. EN with 30 variables (and $\boldsymbol{\nu}_2 = 0.25$) generally outperforms RR with $\boldsymbol{\nu} = 0.25$, but relative RMSEs still exceed 1 in most cases. EN with a larger number of variables having non-zero coefficients is worse than benchmark at all except one horizon.

These results are roughly consistent with Matheson (2006), who found that PC on a mostly New Zealand dataset was more successful for forecasting New Zealand GDP at longer horizons. In that study, variable selection prior to PC estimation improved forecast accuracy at a few longer horizons, but for shorter horizons it was better to exploit all variables.

## 5.2 Forecasts using international data only

Table 4 also shows results with only international data used as predictors – both in trade-weighted aggregate form and with the data-rich methods. This is to test whether the trade-weighted aggregates are clearly outperformed by the data-rich methods, i.e. whether there is sufficient additional predictive power offered by the latter to outweigh the additional complexity of using a large number of international variables. Using only international data also tests whether the data-rich methods on the international-only dataset do better in terms of predictive power relative to using New Zealand data only. Our prior was that a New Zealand-only dataset would outperform an international-only dataset, but this turned out not to be the case for some longer horizons.

The models with trade-weighted aggregates outperform the benchmark only at the one-quarter-ahead horizon. Models based on time-varying trade weights outperform models based on constant trade weights, but the gains are very small. However, the best data-rich methods – the shrinkage methods and PLS – tend to outperform both the benchmark and the models with trade-weighted aggregates. PLS and RR yield the best models for three of the four horizons.

Performance differs markedly across the data-rich methods. One reason for factor methods to perform less well compared to shrinkage methods (and PLS) may be that, as discussed in subsection 4.5., the commonality is rather low in the international dataset, at least compared to that in the national dataset. This would also be consistent with the finding by Groen and Kapetanios (2008) that when there is little factor structure in the data, PLS outperforms PC.[18]

## 5.3 Forecasts using New Zealand and all international data

Finally, table 4 shows forecast results based on the combined dataset of New Zealand and international data. Augmenting the New Zealand dataset with international data generally improves the forecasting performance. The relative forecasting performance results across the data-rich methods are similar as for the international-only dataset, with shrinkage methods and PLS performing very well. For shorter horizons simple PC and TPH also work fairly well, and for horizons up to 4 quarters TPS with 200 variables now outperforms the benchmark.

## 5.4 Best forecasting models and summary of forecasting results

Table 5 reports the best five forecasting models for each horizon out of all models we have considered, including models based on subsets of the international dataset. Consistent with previous results, PLS performs very

[18] Although EN was outperformed by RR and PLS on the international-only dataset, it was marginally better than benchmark. Looking at the variables that EN selected most frequently (not shown), the results were quite stable over recursions, and most make intuitive sense as containing leading information for New Zealand growth. World commodity prices and foreign business and consumer confidence measures were frequently selected.

well: 9 out of the 20 best models were estimated with PLS. RR, EN and PC are also quite successful (3 out of the 20 best models were estimated with each of these methods), followed by WPCBN. Unsurprisingly, models using only New Zealand data do not appear in the set of best models for any horizon. Indeed, 13 out of the 20 best models exploit only international, but no national data, and the remaining 7 best models exploit both New Zealand and international data. Interestingly, 18 out of the 20 best models exploit only subsets of international data (in some cases along with national data).

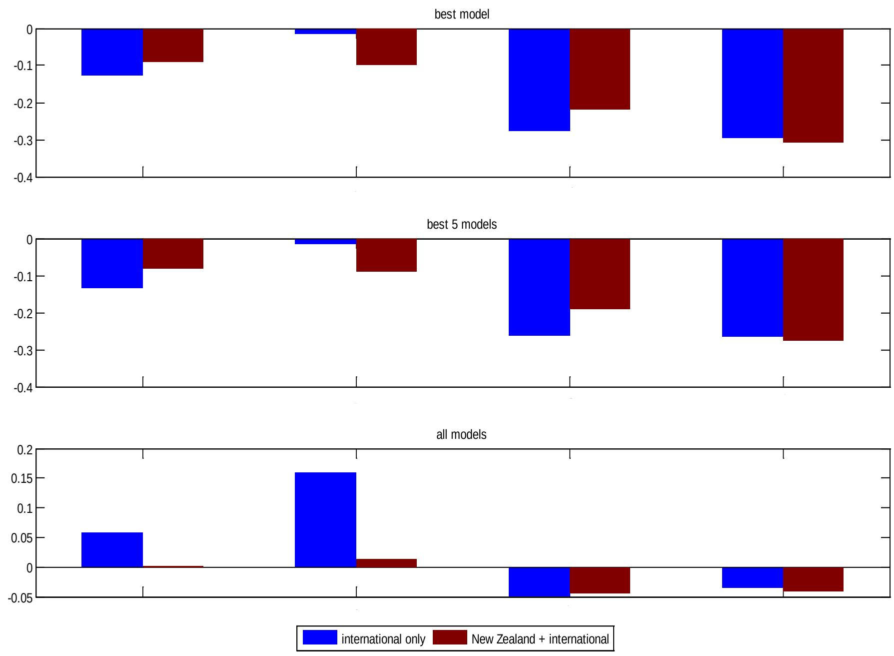
**Table 5**
**Best five models by RMSE**

| | h = 1 | h = 2 |
|---|---|---|
| 1 | int only, all, PLS (k = 5) | New Zealand + int, real data, PLS (k = 3) |
| 2 | int only, Australian data, WPCBN (r = 5) | New Zealand + int, Australian data, PLS (k = 3) |
| 3 | int only, Australian data, PLS (k = 1) | New Zealand + int, European data, PLS (k = 3) |
| 4 | int only, all, RR ($v_2$ = 0.25) | New Zealand + int, EN (30 variables, $v_2$ = 0.25) |
| 5 | int only, price data, PC (r = 5) | int only, European data, PLS (k = 2) |
| | h = 4 | h = 8 |
| 1 | int only, European data, RR ($v_2$ = N) | New Zealand + int, real data, PC (r = 2) |
| 2 | int only, European data, PLS (k = 2) | int only, monetary and financial data, WPCBN (r = 1) |
| 3 | int only, monetary and financial data, PC (r = 3) | New Zealand + int, Asian data, EN (30 variables, $v_2$ = 0.25) |
| 4 | int only, European data, RR ($v_2$ = 5N) | New Zealand + int, EN (30 variables, $v_2$ = 0.25) |
| 5 | int only, European data, PLS ( k = 1) | int only, Asian data, PLS (k = 5) |

The finding that forecast models using only international data, or subsets of the international data, can dominate in forecasting performance is rather surprising at first sight. One might have supposed that more data would be better, or at least no worse, in terms of forecasting accuracy – and that using New Zealand data only would capture the most relevant information for forecasting national activity. These results suggest that there is noise in the New Zealand data that can adversely affect forecasting performance.

Figure 2 compares models exploiting international data with models exploiting only New Zealand data, looking at the best models of each category, the average over the best five models and the average over all models for each horizon. The two upper bar graphs show that it can be worth exploiting international information. The gains are particularly large for long horizons, suggesting that spillovers from international events to the New Zealand economy take some time to materialise. In some cases, it is better to exploit international information only, in some cases international information along with national information. The lower graph shows that on average over all models, results are less clear-cut. Forecast errors differ widely over models, suggesting that careful model selection and specification is crucial for obtaining good forecast results.

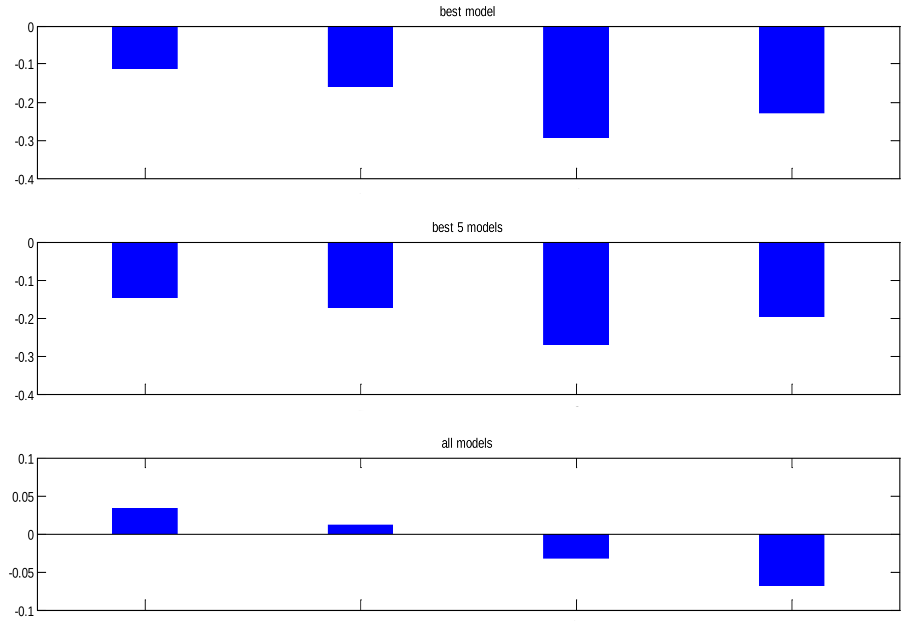
**Figure 2**
**Forecast results – international-only, and combined New Zealand+international, versus New Zealand-only**




Notes: RMSE(models using international-only, or using New Zealand+international, data)/RMSE(models using New Zealand data only)-1; for more details on the forecasting setup, see the text.

It is clear from figure 3 that forecasts based on data-rich methods outperform forecasts based on trade-weighted aggregates (based on models using international data only).

**Figure 3**
**Forecast results - data-rich methods versus trade-weighting**




Notes: RMSE(model based on data-rich methods using international data only)/RMSE(model based on trade-weighting)-1; for more details on the forecasting setup, see the text.

# 6 The relevance of different classes of international data over the sample

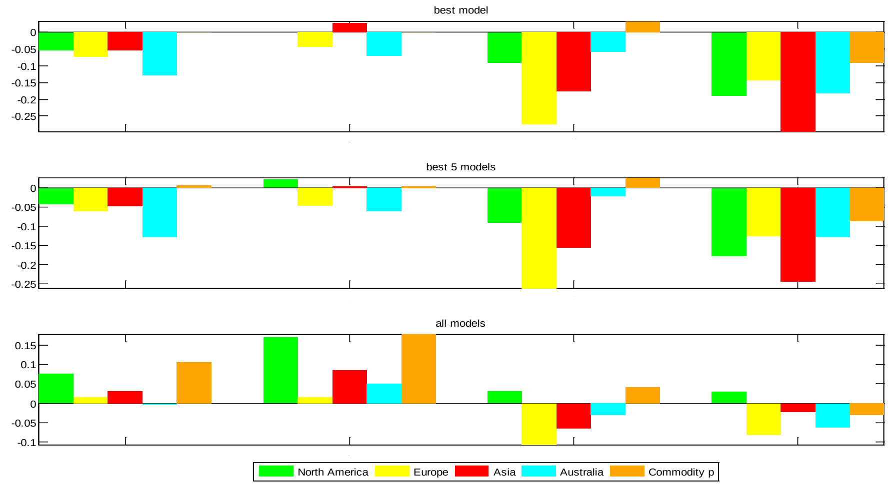
## 6.1 Impact of international subsets on forecasting accuracy

Based on figure 4, we can assess which class of international data yields the greatest improvement over forecasting models using New Zealand data only. Gains can be obtained by including North American, European, Asian, and Australian data (panel (a)). Gains from including Australian data are particularly large at the one-quarter horizon, probably reflecting strong direct linkages between New Zealand and Australia. The large improvement that can be achieved by including European data (relative to data from other regions) is surprising. Europe is a less important trading partner by pure value of trade with New Zealand than Asia or Australia, and the conventional wisdom is that fast-moving international financial and confidence shocks typically emanate from the US rather than Europe. One interpretation would be that the New Zealand survey data proxy to some degree for international – particularly North American – information. This may reflect the dominance of the US in global financial markets and its perceived role as a locomotive for the world economy (e.g. Osborn *et al.* 2005, Dées and Vansteenkiste 2007, Dées and Saint-Guilhem 2009). We will test this explanation in subsection 6.3. Contributions from world commodity prices are generally smaller and positive only for horizon 8.

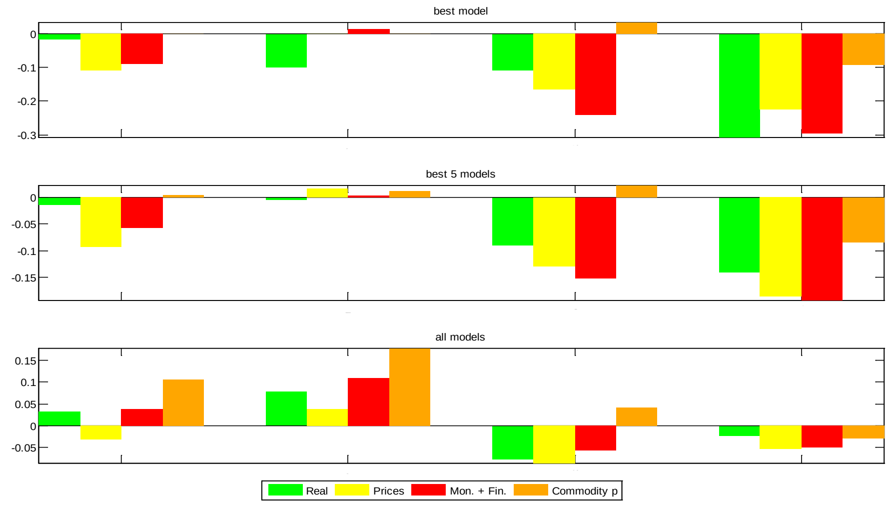
Turning to the split by economic type of data (panel (b)), gains can be achieved by including international real, price and monetary and financial data (except for horizon 2 where only real data seem to help reducing the forecast error). Gains are surprisingly large from including international price data (at horizons 1, 4 and 8) relative to real and monetary and financial data. Again, given the focus on financial markets in the press, information on financial developments might be captured by proxy (or with a better signal/noise ratio) in New Zealand survey data.

**Figure 4**
**Forecast results – New Zealand data only versus international data (regional and economic subsets)**

## (a) Subsets by region




## (b) Subsets by economic type




Notes: RMSE(model based on New Zealand data and subsets of international data)/RMSE(model based on New Zealand data only)-1; for more details on the forecasting setup, see the text.

## 6.2 Historical contributions to New Zealand GDP growth forecasts

We use RR($\boldsymbol{\nu}_2 = \boldsymbol{N}$), which performed very well in terms of forecasting accuracy, to look at the contributions of each subset of the international data to the forecasts, when all data are used.[19] This allows us to interpret the series of forecasts in terms of the predictive content of the different classes of international data. It also provides a plausibility check on the forecasts. This is particularly important for policy making institutions, as the forecasts need to be communicated clearly and credibly, both to decision makers and to the public. We note that, by construction, RR yields biased estimates of the parameters. Although the forecasts can be decomposed into the contributing variable groups, the bias suggests caution in interpreting the absolute and relative magnitudes of the contributions. To check robustness with respect to the data-rich methods, we also computed historical forecast contributions for PC (which also yields biased parameter estimates). Results were similar to those based on RR (not shown, but available upon request).

We discuss in this section the contributions of each subset of the international data to the forecasts, and whether the contributions make sense in terms of the stylised facts of the period. In some cases, the contributions are hard to explain, prompting us to ask in subsection 6.3 whether New Zealand business survey data may be proxying for international information, and whether this may affect our results.

Figure 5 shows the 1-quarter ahead forecasts of New Zealand GDP growth (as deviations from the mean) and the contributions of national and international variables.[20] Looking first at the results for the contribution of New Zealand versus international variables, the relative contribution of national variables (dark blue bars) is quite substantial over the early period from 2001 to 2004. This result seems quite plausible in light of the discussion in RBNZ (2007) suggesting that New Zealand recovered from

[19] We are grateful to Troy Matheson for suggesting this exercise to us.
[20] The optimal model contains 1 lag of the target variable. We take into account that lags of the target variable are explained by past predictors of the large dataset. Differences between the forecasts (black line in figures 5 and 7) and the sums of the contributions (bars in figures 5 and 7) are the sums of GDP growth in the first period and the contribution of the forecast equation's residuals.

the developed world recession of 2000-2001 quite early relative to other countries, for a range of reasons idiosyncratic to New Zealand. In particular, there was a large influx of migrants and returning New Zealanders over this period, partly reflecting terrorism and personal security fears leading expatriate New Zealanders to return home. At the same time, coincidentally, there was a large influx of foreign students of English language. These two factors combined to add strength to the local housing market upturn, which began one or two years earlier than in other countries. Later in the sample, around 2005-2006, the New Zealand economy began slowing, probably dominated by a cooling local housing market and very dry weather conditions adversely affecting farm output.[21]

Looking at the contributions of the international variables by regional subset (panel (a)), we see that the international contribution to growth forecasts early in the sample (2000-2003) is dominated by Asia, offsetting to some degree the negative contributions of North America at this time. The US contribution becomes positive from mid-2003 to 2005. The contribution of Australia is surprisingly small, given its large trade weight. Interestingly (and consistent with the previous subsection), through the whole period, the contribution of fluctuations in the European data is quite substantial. World commodity price fluctuations are, on average, slightly less important than contributions from Australia, North America or Europe.

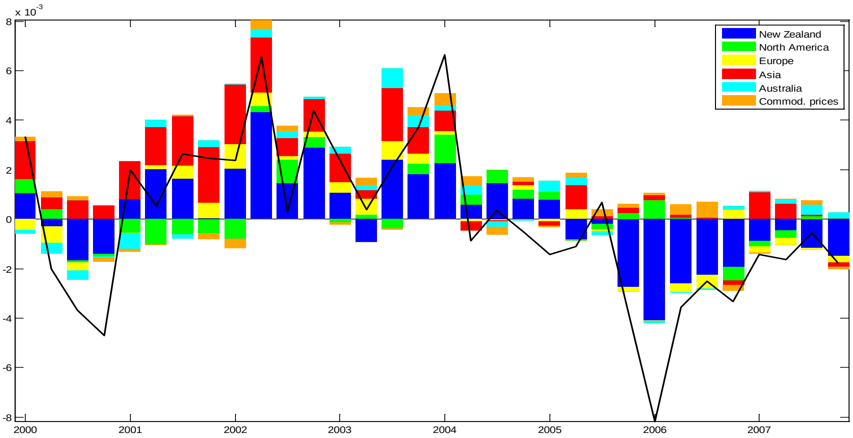
Looking at the international subsets by economic type (panel (b)) also produces interesting results. The pattern of real contributions is not surprising, and appears to coincide with the overall cycle in world activity. The prices pattern resembles the world business cycle and the cycle in oil prices on international markets. The financial variables' contributions are strongly positive through the entire sample – a striking result, lending credence to the view that there is generally a strong signal available in financial prices for forecasting purposes. Over the sample, the financial prices may be capturing predictive information relating to the worldwide "savings glut" that emerged after the recovery from the 2000-2001 world recession.

[21] Weather is captured by the Southern Oscillation Index (SOI) in our dataset. The SOI Southern Oscillation Index (SOI) is derived from the air pressure difference between Tahiti and Darwin, Australia. Bloor and Matheson (2008) found that migration and climate shocks matter for New Zealand GDP.

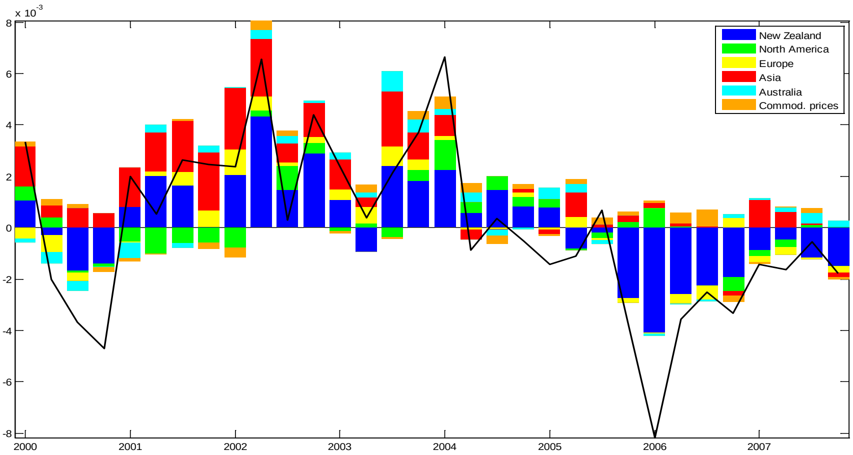
**Figure 5**

**Contributions to forecasts – RR( $\nu_2 = N$ ), New Zealand and international data**

**(a) Subsets by region**




**(b) Subsets by economic type**




Notes: Based on a model using New Zealand and international data, RR( $\nu_2 = N$ ), $h$ = 1; the black line is the forecast; deviations from the mean.

## 6.3 Do national surveys reflect international information?

The presence of business and consumer survey data in the New Zealand dataset bears more discussion, in light of the surprisingly large contributions of the European and price data relative to those of North American and Australian data. One possibility is that the respondents to the surveys pay attention to US and Australian, and real and monetary, developments in accordance with their true signal value for forecasting national activity, whereas they mistakenly downweight European developments and foreign price developments. The data-rich techniques thus pick up the signal in the latter developments directly from the data.

To look at this question a little more formally, we extract $\boldsymbol{r} = 5$ PCs from the New Zealand survey data, the other New Zealand data, the international data combined, and the subsets of international data as defined above.[22] We compute the trace $R^2$ statistics for the factors extracted from the survey data against those extracted from the other New Zealand data and those extracted from the international data. The trace $R^2$ is a multivariate correlation measure defined as the sum of the variances of projections of the variables in one set on the variables in another set, divided by the sum of the variances of the variables in the latter set (Stock and Watson, 1998). The trace $R^2$ lies between 0 and 1.

The New Zealand survey data indeed do seem to reflect international as much as national information. The trace $R^2$ statistic for the survey factors against the international factors is 0.47, a little higher than the 0.43 for the survey factors against the factors extracted from the other New Zealand data. New Zealand survey factors were most highly correlated with North American factors (0.48) followed by Asian (0.47), European (0.42) and Australian factors (0.36). Moreover, they seem to capture international monetary and financial information (0.49) more than foreign real economic activity (0.41) and prices (0.40). The survey factors' correlation with world commodity price factors is very low (0.08). This result is a little surprising for a "commodity economy" such as New Zealand, but is robust when a smaller number of factors is considered and when leads and lags are introduced between the survey factors and the commodity price factors. Overall, this pattern of results supports our conjecture that the surveys

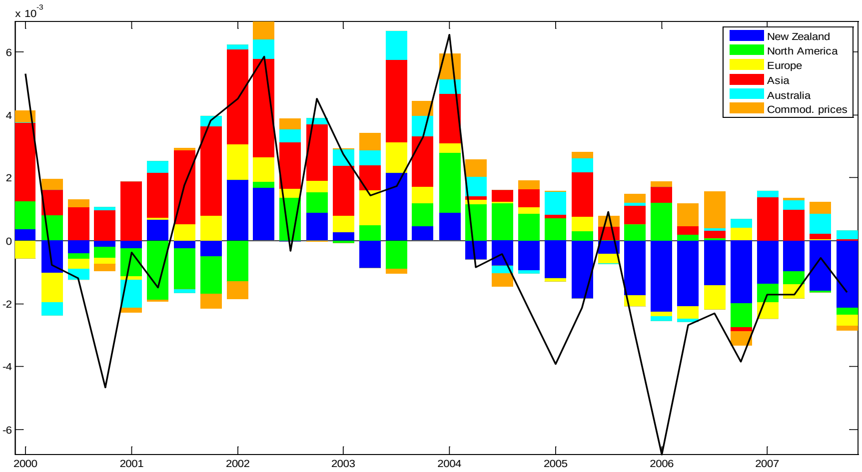
[22] Results were very similar for 3 factors.

effectively capture much of the relevant information in North American and monetary and financial data.

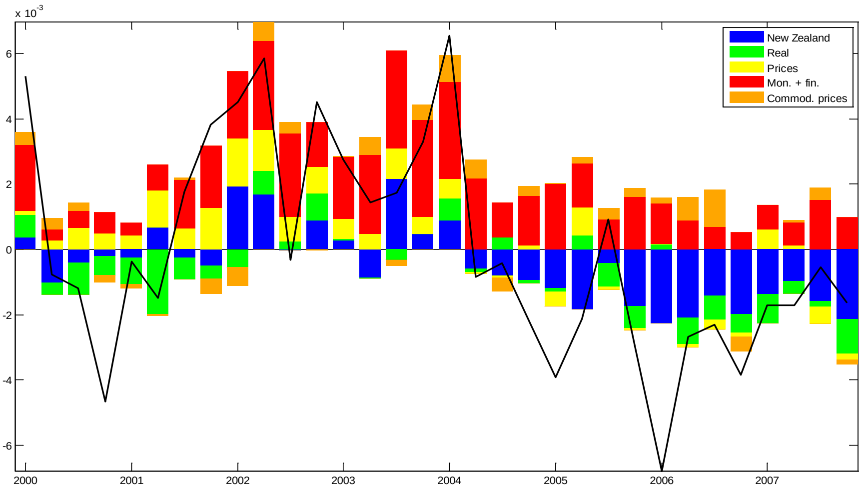
We also test more indirectly the extent to which survey data mask international influences on New Zealand activity by removing survey data from the New Zealand dataset and re-estimating the marginal predictive contents (not shown but available upon request) and the forecast contributions of subgroups of international data (shown in figure 6). The results suggest that the survey data proxy for North American and Asian data, especially at longer horizons, because when the survey data are dropped, the marginal predictive content of North American and Asian data appears to increase relative to that of European and Australian data. The relative contributions to the forecasts also appear to shift somewhat in the direction of the real international data and away from the price data. International data in general have a more important predictive role after the removal of New Zealand business survey data from the datasets.

**Figure 6**
**Contributions to forecasts – RR( $\nu_2 = N$ ), New Zealand excluding survey data, and international data**

## (a) Subsets by region




## (b) Subsets by economic type




Notes: Based on a model using New Zealand and international data, RR( $\nu_2 = N$ ), $h$ = 1; the black line is the forecast; deviations from the mean.

## 7 Conclusions

To recap, this paper’s main contributions were to systematically assess the value of exploiting international information in producing forecasts of New Zealand GDP growth. We looked at various data-rich approaches. Most of them have only been applied to US data, and not very often. We have found it useful to apply them in a wider range of applications and suggest that further work along these lines would be useful to improve understanding on whether these lesser-known techniques would be useful in more general practice. Finally, we showed how some of the data-rich techniques might fill a gap between structural econometric work and forecasting, by enabling assessment of the marginal predictive content of subsets of international data, and calculation of historical contributions to GDP growth forecasts. This is important for policy makers, among others, who usually want to explain the forecasts in a consistent and accessible way as a basis for policy decisions.

Our main findings were as follows. International information drawn from large international datasets can substantially improve forecasts of New Zealand GDP growth and outperform forecasts based on trade weighted aggregates of international variables. The gains are particularly large at long forecast horizons.

The forecasting performance of data-rich methods differs widely. Shrinkage methods (RR and EN) and PLS perform particularly well on our international dataset, whereas PC-based methods perform poorly. One reason may be the rather weak factor structure and, more specifically, the low commonality of the international dataset. We suggest that this result would be relevant for other examples of forecasting using international datasets, since the international dataset we use here has comprehensive coverage of the economically major regions of the world. The factor structure of our national dataset, by contrast, is stronger, and PC or variants of PC work better as means of summarising the predictive content of this dataset. We suggest that the choice of technique in any particular application, and whether pre-selection or other weighting schemes should be used, should be guided by considerations of the strength of the factor structure, as illustrated here.

Historical decompositions based on the data-rich techniques seem to be consistent with the economic experience over the sample as documented by policymakers. A relevant caution here is that the decomposition approach taken here does not correspond to a structural decomposition with identified shocks. Related to this point, New Zealand business survey data seem to capture a substantial proportion of the signal in offshore developments for forecasting purposes, and are thus ascribed a high weight by the data-rich techniques. Only a fully identified approach (e.g. Bernanke *et al.* 2005) can resolve the causal influences on national activity in a more fundamental sense.

## References

Bai, J. (2003), "Inferential theory for factor models of large dimensions", *Econometrica*, 71, 135-171.

Bai J, S. Ng (2002), "Determining the number of factors in approximate factor models", *Econometrica*, 70(1), 191-221.

Bai, J., S. Ng (2008), "Forecasting economic time series using targeted predictors", *Journal of Econometrics*, 146 (2008), 304-317.

Banerjee, A., M. Marcellino, I. Masten (2006), "Forecasting macroeconomic variables for the new member states" in: Artis, M. J., A. Banerjee, M. Marcellino (eds.), The central and eastern European countries and the European Union, Cambridge University Press, Cambridge, Chapter 4, 108-134.

Bedford, P. (2008) "The global financial crisis and its transmission to New Zealand – an external balance sheet analysis", *RBNZ Bulletin*, 71(4), 18-28.

Bernanke B, J. Boivin, P. Eliasz (2005), "Measuring the effects of monetary policy: a Factor-Augmented Vector Autoregressive (FAVAR) approach", *The Quarterly Journal of Economics*, 120(1), 387-422.

Bloor, C., T. Matheson (2008), "Analyzing shock transmission in a data-rich environment: a large BVAR for New Zealand", RBNZ Discussion Paper 2008/09.

Boivin J, S. Ng (2006), "Are more data always better for factor analysis", *Journal of Econometrics*, 132, 169-194.

Brisson, M., B. Campbell, J. W. Galbraith (2003), "Forecasting some low-predictability time series using diffusion indices", *Journal of Forecasting*, 22, 515-531.

Buckle, R. A., K. Kim, H. Kirkham, N. McLellan, J. Sharma (2007), "A structural VAR business cycle model for a volatile small open economy", *Economic Modelling*, 24, 990-1017.

Chamberlain G, M. Rothschild (1983), “Arbitrage factor structure and mean-variance analysis in large asset markets”, *Econometrica* 51, 1305-1324.

Chen, Y. K. Rogoff (2003), “Commodity currencies”, *Journal of International Economics*, 60(1), 133-160.

Cheung, C., F. Demers (2007), “Evaluating Forecasts from Factor Models for Canadian GDP Growth and Core Inflation”, Bank of Canada Working Paper 8.

Dées, S., F. di Mauro, H. Pesaran, V. Smith (2007), “Exploring the international linkages of the euro area: a Global VAR analysis”, *Journal of Applied Econometrics*, 22(1), 1-38.

Dées, S., A. Saint-Guilhem (2009), “The role of the United States in the global economy and its evolution over time”, ECB Working Paper 1034.

Dées, S., I. Vansteenkiste (2007), “The transmission of US cyclical developments to the rest of the world”, ECB Working Paper 798.

Del Negro M, C. Otrok (2008), “Dynamic factor models with time-varying parameters: measuring changes in international business cycles”, revised version of Federal Reserve Bank of New York Staff Report 326 (2005).

De Mol, C., D., Giannone, L. Reichlin (2008), “Forecasting using a large number of predictors: is Bayesian regression a valid alternative to principal components?”, *Journal of Econometrics*, 146(2), 318-328.

Drew, A., M. Frith (1998), “Forecasting at the Reserve Bank of New Zealand”, RBNZ Bulletin, 61(4), 317-327.

Dungey, M., R. Fry (2007), “The identification of fiscal and monetary policy in a structural VAR”, revised version of CAMA Working Paper 29/2007.

Efron, B., T., Hastie, I. Johnstone, R. Tibshirani (2004), “Least angle regression”, *Annals of Statistics*, 32, 407-499.

Osborn, D., P. Perez, M. Sensier (2005), “Business cycle linkages for the G7 countries: Does the US lead the world?”, CGBCR Discussion Paper 50, University of Manchester.

Eickmeier, S. (2008), “Comovements and heterogeneity analyzed in a non-stationary dynamic factor model”, *Journal of Applied Econometrics*, forthcoming.

Eickmeier, S., C. Ziegler (2008), “How successful are dynamic factor models at forecasting output and inflation? A meta-analytic approach”, *Journal of Forecasting*, 27(3), 237-265.

Forni, M., M. Hallin, M. Lippi, L. Reichlin (2000), “The generalized dynamic factor model: identification and estimation”, *The Review of Economic and Statistics*, 82, 540-554.

Forni, M., D. Giannone, M. Lippi, L. Reichlin (2008), “Opening the black box: structural factor models versus structural VARs”, *Econometric Theory*, forthcoming.

Groen, J. J., G. Kapetanios (2008), “Revisiting useful approaches to data-rich macroeconomic forecasting”, Federal Reserve Bank of New York Staff Report 327, May.

Gosselin, M.-A., G. Tkacz (2001), “Evaluating factor models: an application to forecasting inflation in Canada”, Bank of Canada Working Paper 18.

Kose, A., C. Otrok, E. S. Prasad (2008), “Global business cycles: convergence and decoupling?”, IMF WP/08/143.

Lin, J., R. S. Tsay (2006), “Comparisons of forecasting methods with many predictors”, mimeo.

Marcellino M., J. H. Stock, M. W. Watson (2000), “A dynamic factor analysis of the EMU”, mimeo. http://www.igier.uni-bocconi.it/whos.php?vedi=1139&tbn=albero &id_doc=177.

Matheson, T., (2006), “Factor model forecasts for New Zealand”, International Journal of Central Banking, June.

Onatski, A. (2007), "Asymptotics of the principal components estimator of large factor models with weak factors and i.i.d. Gaussian noise", mimeo, Columbia University.

Pesaran M. H., T. Schuermann, S. M. Weiner (2004), „Modelling regional interdependencies using a global error-correcting macroeconometric model", *Journal of Business and Economic Statistics*, 22, 129-162.

RBNZ (2007), "A review of economic developments and monetary policy since 2000", paper A2 in *Submission to Finance and Expenditure Select Committee's inquiry into the future monetary policy framework*. Mimeo at www.rbnz.govt.nz

Robertson, J. C. (2000), "Central bank forecasting: an international comparison", *Federal Reserve Bank of Atlanta Economic Review*, Second Quarter 2000, 21-32.

Schumacher, C. (2007), "Forecasting German GDP using alternative factor models based on large datasets", *Journal of Forecasting*, 26(4), 271-302.

Schumacher, C. (2009), "Factor forecasting using international targeted predictors: the case of German GDP", Bundesbank Discussion Paper 10/2009.

Stock, J., M. Watson (1998), "Diffusion indexes", NBER Working Paper 6702.

Stock, J., M. Watson (2002a), "Macroeconomic forecasting using diffusion indexes", *Journal of Business and Economic Statistics*, 20,147-162.

Stock, J., M. Watson (2002b), "Forecasting using principal components from a large number of predictors", *Journal of the American Statistical Association*, 97, 1167-1179.

Stock, J., M. Watson (2004), "Combination forecasts of output growth in a seven-country data set", *Journal of Forecasting*, 23, 405-430.

Stock, J., M., Watson (2005), "Implications of dynamic factor models for VAR analysis", NBER Working Paper 11467.

Wold (1982), „Soft modeling. The basic design and some extensions“, in: K.-G. Jöreskog and H. Wold (eds.), *Systems under indirect observation*, 2, North-Holland, Amsterdam.

Zou, H., T. Hastie (2005), „Regularization and variable selection via the elastic net”, *Journal of Royal Statistical Society*, Series B, 67(2), 301-320.

# Appendix

## Table A1
## International dataset

| # | Country | Variable | Treatment | Source |
|---|---|---|---|---|
| 1 | US | Gross domestic product, real | 4 | OECD, Main Economic Indicators |
| 2 | | Private final consumption, real | 4 | OECD, Main Economic Indicators |
| 3 | | Gross fixed capital formation, real | 4 | OECD, Main Economic Indicators |
| 4 | | Government final consumption expenditure, real | 4 | OECD, Main Economic Indicators |
| 5 | | Exports, volume index | 4 | OECD, Main Economic Indicators |
| 6 | | Imports, volume index | 4 | OECD, Main Economic Indicators |
| 7 | | Employment | 4 | OECD, Main Economic Indicators |
| 8 | | Personal consumption, ex food and energy | 4 | OECD, Main Economic Indicators |
| 9 | | Capacity utilization | 3 | OECD, Main Economic Indicators |
| 10 | | Industrial production | 4 | OECD, Main Economic Indicators |
| 11 | | Income, nominal | 4 | OECD, Main Economic Indicators |
| 12 | | Orders of manufactured goods | 4 | OECD, Main Economic Indicators |
| 13 | | Labour force | 4 | OECD, Main Economic Indicators |
| 14 | | Total retail trade | 4 | OECD, Main Economic Indicators |
| 15 | | Dwelling productions | 4 | OECD, Main Economic Indicators |
| 16 | | Weekly hours worked | 4 | OECD, Main Economic Indicators |
| 17 | | Machinery production | 4 | OECD, Main Economic Indicators |
| 18 | | Intermediate goods production | 4 | OECD, Main Economic Indicators |
| 19 | | Non-durable goods production | 4 | OECD, Main Economic Indicators |
| 20 | | Total manufacturing production | 4 | OECD, Main Economic Indicators |
| 21 | | Total wholesale trade | 4 | OECD, Main Economic Indicators |
| 22 | | Ratio of inventories to shipments | 2 | OECD, Main Economic Indicators |
| 23 | | Unemployment rate, male | 4 | OECD, Main Economic Indicators |
| 24 | | Unemployment rate | 1 | OECD, Main Economic Indicators |
| 25 | | Consumer confidence index | 3 | OECD, Main Economic Indicators |
| 26 | | Purchasing managers index | 3 | OECD, Main Economic Indicators |
| 27 | | Consumer price index | 4 | OECD, Main Economic Indicators |
| 28 | | Consumer price index, ex food and energy | 4 | OECD, Main Economic Indicators |
| 29 | | GDP deflator | 4 | OECD, Main Economic Indicators |
| 30 | | Personal consumption expenditures deflator | 4 | Bureau of Economic Analysis |
| 31 | | Durable goods deflator | 4 | Bureau of Economic Analysis |
| 32 | | Nondurable goods deflator | 4 | Bureau of Economic Analysis |
| 33 | | Gross private domestic investment deflator | 4 | Bureau of Economic Analysis |
| 34 | | Fixed investment deflator | 4 | Bureau of Economic Analysis |
| 35 | | Nonresidential investment deflator | 4 | Bureau of Economic Analysis |
| 36 | | Residential investment deflator | 4 | Bureau of Economic Analysis |
| 37 | | Government consumption expenditures and gross investment deflator | 4 | Bureau of Economic Analysis |
| 38 | | Producer price index | 4 | OECD, Main Economic Indicators |
| 39 | | Total labour costs | 4 | OECD, Main Economic Indicators |
| 40 | | Unit labour costs | 4 | OECD, Main Economic Indicators |
| 41 | | Export price index | 4 | OECD, Main Economic Indicators |
| 42 | | Import price index | 4 | OECD, Main Economic Indicators |
| 43 | | Benchmarked real output, total | 4 | OECD, Main Economic Indicators |
| 44 | | Hourly earnings, manufacturing | 4 | OECD, Main Economic Indicators |
| 45 | | CPI housing | 4 | OECD, Main Economic Indicators |
| 46 | | 3-month Certificates of deposit rate | 1 | OECD, Main Economic Indicators |
| 47 | | 10-year federal government securities (composite) rate | 1 | OECD, Main Economic Indicators |
| 48 | | 3-month euro-dollar deposit rate | 1 | OECD, Main Economic Indicators |
| 49 | | 10-year federal government bond yield | 1 | OECD, Main Economic Indicators |
| 50 | | Federal funds rate | 1 | OECD, Main Economic Indicators |
| 51 | | Prime rate | 1 | OECD, Main Economic Indicators |
| 52 | | M3 | 4 | OECD, Main Economic Indicators |
| 53 | | M2 | 4 | OECD, Main Economic Indicators |
| 54 | | M1 | 4 | OECD, Main Economic Indicators |
| 55 | | Real effective exchange rate | 4 | OECD, Main Economic Indicators |
| 56 | | Share price | 4 | IMF, International Financial Statistics |
| 57 | Canada | Gross domestic product, real | 4 | OECD, Main Economic Indicators |
| 58 | | Private final consumption, real | 4 | OECD, Main Economic Indicators |
| 59 | | Gross fixed capital formation, real | 4 | OECD, Main Economic Indicators |
| 60 | | Government final consumption expenditure, real | 4 | OECD, Main Economic Indicators |
| 61 | | Exports, volume index | 4 | OECD, Main Economic Indicators |
| 62 | | Imports, volume index | 4 | OECD, Main Economic Indicators |
| 63 | | Change in inventories | 1 | OECD, Main Economic Indicators |
| 64 | | Employment | 4 | OECD, Main Economic Indicators |
| 65 | | Labour force | 4 | OECD, Main Economic Indicators |
| 66 | | Capacity utilisation | 3 | OECD, Main Economic Indicators |
| 67 | | Total production | 4 | OECD, Main Economic Indicators |
| 68 | | CLI total industry, ex construction | 4 | OECD, Main Economic Indicators |
| 69 | | Unemployment level | 4 | OECD, Main Economic Indicators |
| 70 | | Unemployment rate | 1 | OECD, Main Economic Indicators |
| 71 | | Total retail trade | 4 | OECD, Main Economic Indicators |
| 72 | | Manufacturing, finished goods stocks level | 2 | OECD, Main Economic Indicators |
| 73 | | Manufacturing, order books level | 2 | OECD, Main Economic Indicators |
| 74 | | Manufacturing, orders, inflow/demand tendency | 1 | OECD, Main Economic Indicators |
| 75 | | Manufacturing, production, future tendency | 1 | OECD, Main Economic Indicators |
| 76 | | Employees, manufacturing | 4 | OECD, Main Economic Indicators |
| 77 | | Total employees | 4 | OECD, Main Economic Indicators |
| 78 | | Permits issued for buildings | 4 | OECD, Main Economic Indicators |
| 79 | | Permits issued for dwellings | 4 | OECD, Main Economic Indicators |
| 80 | | Orders for total manufactured goods | 4 | OECD, Main Economic Indicators |
| 81 | | Consumer price index | 4 | OECD, Main Economic Indicators |
| 82 | | Consumer price index, ex food and energy | 4 | OECD, Main Economic Indicators |
| 83 | | GDP deflator | 4 | OECD, Main Economic Indicators |
| 84 | | Total labour costs | 4 | OECD, Main Economic Indicators |
| 85 | | Producer price index | 4 | OECD, Main Economic Indicators |
| 86 | | Consumer price index, ex housing | 4 | OECD, Main Economic Indicators |
| 87 | | CPI services less housing | 4 | OECD, Main Economic Indicators |
| 88 | | Hourly earnings, manufacturing | 4 | OECD, Main Economic Indicators |
| 89 | | Wages and salaries, manufacturing | 4 | OECD, Main Economic Indicators |
| 90 | | 3-month prime corporate paper rate | 1 | OECD, Main Economic Indicators |
| 91 | | 10-year government bonds yield | 1 | OECD, Main Economic Indicators |
| 92 | | Central bank interest rate, < 24 hours | 1 | OECD, Main Economic Indicators |
| 93 | | Overnight money market financing rate | 1 | OECD, Main Economic Indicators |
| 94 | | M2+, gross | 4 | OECD, Main Economic Indicators |
| 95 | | M3, gross | 4 | OECD, Main Economic Indicators |
| 96 | | M1+, gross | 4 | OECD, Main Economic Indicators |
| 97 | | Narrow money M1 | 4 | OECD, Main Economic Indicators |
| 98 | | Real effective exchange rate, CPI based | 4 | OECD, Main Economic Indicators |
| 99 | | Real effective exchange rate, ULC based | 4 | OECD, Main Economic Indicators |
| 100 | | CAD/USD exchange rate, monthly average | 4 | OECD, Main Economic Indicators |

| | | | | |
|---|---|---|---|---|
| 101 | | Share price index | 4 | OECD, Main Economic Indicators |
| 102 | Euro area | Gross domestic product, real | 4 | AWM database, see Fagan *et al.* (2007) |
| 103 | | Total demand, real | 4 | AWM database, see Fagan *et al.* (2007) |
| 104 | | Consumption, real | 4 | AWM database, see Fagan *et al.* (2007) |
| 105 | | Gross investment, real | 4 | AWM database, see Fagan *et al.* (2007) |
| 106 | | Government consumption, real | 4 | AWM database, see Fagan *et al.* (2007) |
| 107 | | Net public investment, real | 4 | AWM database, see Fagan *et al.* (2007) |
| 108 | | Labour force | 4 | AWM database, see Fagan *et al.* (2007) |
| 109 | | Total employment | 4 | AWM database, see Fagan *et al.* (2007) |
| 110 | | Labour productivity, real | 4 | AWM database, see Fagan *et al.* (2007) |
| 111 | | Exports, volume index | 4 | AWM database, see Fagan *et al.* (2007) |
| 112 | | Imports, volume index | 4 | AWM database, see Fagan *et al.* (2007) |
| 113 | | Household disposable income, real | 4 | AWM database, see Fagan *et al.* (2007) |
| 114 | | Wealth | 4 | AWM database, see Fagan *et al.* (2007) |
| 115 | | Employees, level | 4 | AWM database, see Fagan *et al.* (2007) |
| 116 | | Retail sales | 4 | AWM database, see Fagan *et al.* (2007) |
| 117 | | Industrial production, manufacturing | 4 | AWM database, see Fagan *et al.* (2007) |
| 118 | | Industrial production, ex construction | 4 | AWM database, see Fagan *et al.* (2007) |
| 119 | | Unemployment, level | 4 | AWM database, see Fagan *et al.* (2007) |
| 120 | | Industrial confidence | 1 | European Commission |
| 121 | | Consumer price index | 4 | AWM database, see Fagan *et al.* (2007) |
| 122 | | Consumer price index, energy | 4 | AWM database, see Fagan *et al.* (2007) |
| 123 | | Consumer price index, ex energy | 4 | AWM database, see Fagan *et al.* (2007) |
| 124 | | Growth of consumption deflator | 1 | AWM database, see Fagan *et al.* (2007) |
| 125 | | Import of goods and services deflator | 4 | AWM database, see Fagan *et al.* (2007) |
| 126 | | Consumption deflator | 4 | AWM database, see Fagan *et al.* (2007) |
| 127 | | Unit labour costs | 4 | AWM database, see Fagan *et al.* (2007) |
| 128 | | Exports of goods and services deflator | 4 | AWM database, see Fagan *et al.* (2007) |
| 129 | | Compensation to employees | 4 | AWM database, see Fagan *et al.* (2007) |
| 130 | | Producer price index, manufacturing | 4 | AWM database, see Fagan *et al.* (2007) |
| 131 | | Producer price index | 4 | AWM database, see Fagan *et al.* (2007) |
| 132 | | Wage rate | 2 | AWM database, see Fagan *et al.* (2007) |
| 133 | | GDP deflator | 4 | AWM database, see Fagan *et al.* (2007) |
| 134 | | Short-term nominal interest rate | 1 | AWM database, see Fagan *et al.* (2007) |
| 135 | | Long-term interest rate | 1 | AWM database, see Fagan *et al.* (2007) |
| 136 | | 10-year interest rate | 1 | AWM database, see Fagan *et al.* (2007) |
| 137 | | 5-year interest rate | 1 | AWM database, see Fagan *et al.* (2007) |
| 138 | | 2 -year interest rate | 1 | AWM database, see Fagan *et al.* (2007) |
| 139 | | 2-year yield spread | 1 | AWM database, see Fagan *et al.* (2007) |
| 140 | | 5-year yield spread | 1 | AWM database, see Fagan *et al.* (2007) |
| 141 | | 10-year yield spread | 1 | AWM database, see Fagan *et al.* (2007) |
| 142 | | Household's savings ratio | 4 | AWM database, see Fagan *et al.* (2007) |
| 143 | | Consumer loans | 4 | AWM database, see Fagan *et al.* (2007) |
| 144 | | Loans to NFCs | 4 | AWM database, see Fagan *et al.* (2007) |
| 145 | | M1 | 4 | AWM database, see Fagan *et al.* (2007) |
| 146 | | M2 | 4 | AWM database, see Fagan *et al.* (2007) |
| 147 | | M2-M1 | 4 | AWM database, see Fagan *et al.* (2007) |
| 148 | | M3 | 4 | AWM database, see Fagan *et al.* (2007) |
| 149 | | M3-M2 | 4 | AWM database, see Fagan *et al.* (2007) |
| 150 | | M3-M1 | 4 | AWM database, see Fagan *et al.* (2007) |
| 151 | | Nominal effective exchange rate | 4 | AWM database, see Fagan *et al.* (2007) |
| 152 | | Real effective exchange rate | 4 | AWM database, see Fagan *et al.* (2007) |
| 153 | | Stock price | 4 | AWM database, see Fagan *et al.* (2007) |
| 154 | UK | Gross domestic product, real | 4 | OECD, Main Economic Indicators |
| 155 | | Private final consumption, real | 4 | OECD, Main Economic Indicators |
| 156 | | Gross fixed capital formation, real | 4 | OECD, Main Economic Indicators |
| 157 | | Government final consumption expenditure, real | 4 | OECD, Main Economic Indicators |
| 158 | | Exports, volume index | 4 | OECD, Main Economic Indicators |
| 159 | | Imports, volume index | 4 | OECD, Main Economic Indicators |
| 160 | | Industrial production | 4 | OECD, Main Economic Indicators |
| 161 | | Total retail trade | 4 | OECD, Main Economic Indicators |
| 162 | | Household disposable income | 4 | Office for National Statistics |
| 163 | | Consumer spending | 4 | Office for National Statistics |
| 164 | | Workforce jobs | 4 | Office for National Statistics |
| 165 | | Productivity, whole economy | 4 | Office for National Statistics |
| 166 | | Industrial production index, manufacturing | 4 | Office for National Statistics |
| 167 | | Consumer confidence | 1 | Office for National Statistics |
| 168 | | Unemployment level | 4 | OECD, Main Economic Indicators |
| 169 | | Unemployment rate | 1 | OECD, Main Economic Indicators |
| 170 | | Unemployment rate, survey-based | 1 | OECD, Main Economic Indicators |
| 171 | | Passenger car registrations | 4 | OECD, Main Economic Indicators |
| 172 | | Work started for dwellings | 4 | OECD, Main Economic Indicators |
| 173 | | Composite leading indicator | 4 | OECD, Main Economic Indicators |
| 174 | | Consumer confidence | 1 | Office for National Statistics |
| 175 | | Business optimism | 1 | Confederation of British Industry |
| 176 | | Consumer price index | 4 | OECD, Main Economic Indicators |
| 177 | | Consumer price index, ex food and energy | 4 | OECD, Main Economic Indicators |
| 178 | | Consumer price index, HICP all items | 4 | OECD, Main Economic Indicators |
| 179 | | Consumer price index, services less housing | 4 | OECD, Main Economic Indicators |
| 180 | | GDP deflator | 4 | OECD, Main Economic Indicators |
| 181 | | Producer price index, manufacturing output | 4 | OECD, Main Economic Indicators |
| 182 | | Total labour costs | 4 | OECD, Main Economic Indicators |
| 183 | | Unit labour costs | 4 | OECD, Main Economic Indicators |
| 184 | | Average earning index | 4 | Office for National Statistics |
| 185 | | Weekly earnings, manufacturing | 4 | OECD, Main Economic Indicators |
| 186 | | Weekly earnings, private sector | 4 | OECD, Main Economic Indicators |
| 187 | | Export price index | 4 | Office for National Statistics |
| 188 | | Retail price index | 4 | OECD, Main Economic Indicators |
| 189 | | Retail price index, less mortgage interest rates | 4 | OECD, Main Economic Indicators |
| 190 | | CPI housing | 4 | OECD, Main Economic Indicators |
| 191 | | 3-month mean, LIBID/LIBOR rate | 1 | OECD, Main Economic Indicators |
| 192 | | 3-month treasury bills discount rate | 1 | OECD, Main Economic Indicators |
| 193 | | 10-year central government securities yield | 1 | OECD, Main Economic Indicators |
| 194 | | Sterling overnight interbank rate | 1 | OECD, Main Economic Indicators |
| 195 | | Bank base rate, 4 UK banks | 1 | OECD, Main Economic Indicators |
| 196 | | 3-month treasury bills discount rate, sterling | 1 | Bank of England |
| 197 | | Sterling overnight interbank rate, mean LIBID/LIBOR | 1 | OECD, Main Economic Indicators |
| 198 | | Prime lending rate, major banks | 1 | Bank of England |
| 199 | | M2 | 4 | OECD, Main Economic Indicators |
| 200 | | M4 | 4 | OECD, Main Economic Indicators |

| | | | |
|---|---|---|---|
| 201 | Real effective exchange rate, CPI based | 4 | OECD, Main Economic Indicators |
| 202 | Real effective exchange rate, ULC based | 4 | OECD, Main Economic Indicators |
| 203 | GBP/ USD exchange rate, monthly average | 4 | OECD, Main Economic Indicators |
| 204 | Share price index, FTSE 100 | 4 | OECD, Main Economic Indicators |
| 205 Australia | Gross domestic product, real | 4 | OECD, Main Economic Indicators |
| 206 | Private final consumption, real | 4 | OECD, Main Economic Indicators |
| 207 | Gross fixed capital formation, real | 4 | OECD, Main Economic Indicators |
| 208 | Government final consumption expenditure, real | 4 | OECD, Main Economic Indicators |
| 209 | Exports, volume index | 4 | OECD, Main Economic Indicators |
| 210 | Imports, volume index | 4 | OECD, Main Economic Indicators |
| 211 | Total employment | 4 | OECD, Main Economic Indicators |
| 212 | Employees,household survey | 4 | OECD, Main Economic Indicators |
| 213 | Labor force | 4 | OECD, Main Economic Indicators |
| 214 | Manufacturers and wholesale trade sales | 4 | Australian Bureau of Statistics |
| 215 | Gross national income | 4 | Australian Bureau of Statistics |
| 216 | Productivity, GDP per employed person | 4 | Australian Bureau of Statistics |
| 217 | Production in total manufacturing, level | 4 | OECD, Main Economic Indicators |
| 218 | Production in total manufacturing, index | 4 | OECD, Main Economic Indicators |
| 219 | Production in total service sector | 4 | OECD, Main Economic Indicators |
| 220 | Total retail trade | 4 | OECD, Main Economic Indicators |
| 221 | Unemployment level | 4 | OECD, Main Economic Indicators |
| 222 | Unemployment rate | 2 | OECD, Main Economic Indicators |
| 223 | Melbourne Westpac consumer sentiment index | 3 | Westpac Melbourne Institute |
| 224 | 10-year central government securities yield | 4 | Westpac Melbourne Institute |
| 225 | Consumer price index | 4 | OECD, Main Economic Indicators |
| 226 | GDP deflator | 4 | OECD, Main Economic Indicators |
| 227 | Consumer price index, ex food and energy | 4 | OECD, Main Economic Indicators |
| 228 | Export price index | 4 | Australian Bureau of Statistics |
| 229 | Import price index | 4 | Australian Bureau of Statistics |
| 230 | Producer price index, food, beverage and tobacco | 4 | OECD, Main Economic Indicators |
| 231 | Producer price index, manufacturing | 4 | OECD, Main Economic Indicators |
| 232 | Total labour costs | 4 | OECD, Main Economic Indicators |
| 233 | Unit labour costs | 4 | OECD, Main Economic Indicators |
| 234 | Real output, total | 4 | OECD, Main Economic Indicators |
| 235 | CPI housing | 4 | OECD, Main Economic Indicators |
| 236 | 90-day bank accepted bills yield | 1 | OECD, Main Economic Indicators |
| 237 | 10-year government bonds yield | 1 | OECD, Main Economic Indicators |
| 238 | M3 | 4 | OECD, Main Economic Indicators |
| 239 | Broad money | 4 | OECD, Main Economic Indicators |
| 240 | M1 | 4 | OECD, Main Economic Indicators |
| 241 | Narrow money | 4 | OECD, Main Economic Indicators |
| 242 | Real effective exchange rates, CPI based | 4 | OECD, Main Economic Indicators |
| 243 | Real effective exchange rates, ULC based | 4 | OECD, Main Economic Indicators |
| 244 | AUD/USD exchange rate, monthly average | 4 | OECD, Main Economic Indicators |
| 245 | Share price index, S&P ASX 200 | 4 | OECD, Main Economic Indicators |
| 246 | Share price index, S&P ASE industrials | 4 | OECD, Main Economic Indicators |
| 247 Japan | Gross domestic product, real | 4 | OECD, Main Economic Indicators |
| 248 | Private final consumption, real | 4 | OECD, Main Economic Indicators |
| 249 | Private residential investment, real | 4 | OECD, Main Economic Indicators |
| 250 | Private non-residential investment, real | 4 | OECD, Main Economic Indicators |
| 251 | Private inventory, real | 2 | OECD, Main Economic Indicators |
| 252 | Government final consumption expenditure, real | 4 | OECD, Main Economic Indicators |
| 253 | Public investment, real | 4 | OECD, Main Economic Indicators |
| 254 | Exports, volume index | 4 | OECD, Main Economic Indicators |
| 255 | Imports, volume index | 4 | OECD, Main Economic Indicators |
| 256 | Consumer confidence | 3 | OECD, Main Economic Indicators |
| 257 | Total employment | 4 | OECD, Main Economic Indicators |
| 258 | Labour force | 4 | OECD, Main Economic Indicators |
| 259 | Capacity utilisation | 3 | OECD, Main Economic Indicators |
| 260 | Total production | 4 | OECD, Main Economic Indicators |
| 261 | Retail trade | 4 | OECD, Main Economic Indicators |
| 262 | Unemployment level | 4 | OECD, Main Economic Indicators |
| 263 | Unemployment rate | 2 | OECD, Main Economic Indicators |
| 264 | Manufactured goods orders | 4 | OECD, Main Economic Indicators |
| 265 | Business condition survey | 1 | Ministry of Finance, Japan |
| 266 | Consumer price index | 4 | OECD, Main Economic Indicators |
| 267 | Consumer price index, ex food and energy | 4 | OECD, Main Economic Indicators |
| 268 | Unit labor costs | 4 | OECD, Main Economic Indicators |
| 269 | Producer price index, manufacturing | 4 | OECD, Main Economic Indicators |
| 270 | CPI housing | 4 | OECD, Main Economic Indicators |
| 271 | GDP deflator | 4 | OECD, Main Economic Indicators |
| 272 | Export unit price | 4 | Bank of Japan |
| 273 | Import unit price | 4 | Bank of Japan |
| 274 | 3-month interest rate, certificates of deposit | 1 | OECD, Main Economic Indicators |
| 275 | 10-year interest bearing government bonds yield | 1 | OECD, Main Economic Indicators |
| 276 | Central bank discount rate | 1 | OECD, Main Economic Indicators |
| 277 | Overnight call rate, uncollateralized | 1 | OECD, Main Economic Indicators |
| 278 | Broad money, M4 | 4 | OECD, Main Economic Indicators |
| 279 | M2 | 4 | OECD, Main Economic Indicators |
| 280 | M2 + Certificates of deposit | 4 | OECD, Main Economic Indicators |
| 281 | Broadly defined liquidity | 4 | OECD, Main Economic Indicators |
| 282 | M1 | 4 | OECD, Main Economic Indicators |
| 283 | Real effective exchange rate, CPI based | 4 | OECD, Main Economic Indicators |
| 284 | Real effective exchange rate, ULC based | 4 | OECD, Main Economic Indicators |
| 285 | JPY/USD exchange rate, monthly average | 4 | OECD, Main Economic Indicators |
| 286 | Share price index, TSE TOPIX | 4 | OECD, Main Economic Indicators |
| 287 Korea | Gross domestic product, real | 4 | OECD, Main Economic Indicators |
| 288 | Private final consumption expenditure, real | 4 | OECD, Main Economic Indicators |
| 289 | Gross fixed capital formation, real | 4 | OECD, Main Economic Indicators |
| 290 | Government final consumption expenditure, real | 4 | OECD, Main Economic Indicators |
| 291 | Changes in inventories | 1 | OECD, Main Economic Indicators |
| 292 | Exports, volume index | 4 | OECD, Main Economic Indicators |
| 293 | Imports, volume index | 4 | OECD, Main Economic Indicators |
| 294 | Total employment | 4 | OECD, Main Economic Indicators |
| 295 | Composite leading indicators, excluding constructions | 4 | OECD, Main Economic Indicators |
| 296 | Machinery orders received | 4 | National Statistical Office |
| 297 | Labour productivity index | 4 | National Statistical Office |
| 298 | Industrial production | 4 | Bank of Korea |
| 299 | Manufacturing production index | 4 | National Statistical Office |
| 300 | Retail sales | 4 | Bank of Korea |

| | | | | |
|---|---|---|---|---|
| 301 | | Labour force | 4 | OECD, Main Economic Indicators |
| 302 | | Capacity utilisation | 3 | OECD, Main Economic Indicators |
| 303 | | Total retail trade | 4 | OECD, Main Economic Indicators |
| 304 | | Unemployment level | 4 | OECD, Main Economic Indicators |
| 305 | | Unemployment rate | 1 | OECD, Main Economic Indicators |
| 306 | | Leading composite index | 4 | National Statistical Office |
| 307 | | Consumer price index | 4 | OECD, Main Economic Indicators |
| 308 | | Housing purchase price index | 4 | Bank of Korea |
| 309 | | Export price index | 4 | Bank of Korea |
| 310 | | Import price index | 4 | Bank of Korea |
| 311 | | Consumer price index, ex food and energy | 4 | OECD, Main Economic Indicators |
| 312 | | GDP deflator | 4 | IMF, International Financial Statistics |
| 313 | | Producer price index | 4 | OECD, Main Economic Indicators |
| 314 | | Unit labour costs | 4 | OECD, Main Economic Indicators |
| 315 | | Benchmarked real output, total | 4 | OECD, Main Economic Indicators |
| 316 | | CPI housing | 4 | OECD, Main Economic Indicators |
| 317 | | 10-year government bond yields | 1 | OECD, Main Economic Indicators |
| 318 | | M2 | 4 | OECD, Main Economic Indicators |
| 319 | | M3 | 4 | OECD, Main Economic Indicators |
| 320 | | M1 | 4 | OECD, Main Economic Indicators |
| 321 | | Real effective exchange rate, ULC based | 4 | OECD, Main Economic Indicators |
| 322 | | KRW/USD exchange rate, monthly average | 4 | OECD, Main Economic Indicators |
| 323 | | Share price index, Kse KOSPI index | 4 | OECD, Main Economic Indicators |
| 324 | China | Gross domestic product, real | 4 | National Bureau of Statistics, China |
| 325 | | Exports, volume index | 4 | National Bureau of Statistics, China |
| 326 | | Imports, volume index | 4 | National Bureau of Statistics, China |
| 327 | | Employment | 4 | National Bureau of Statistics, China |
| 328 | | Saving rate | 2 | National Bureau of Statistics, China |
| 329 | | Unemployment rate | 2 | National Bureau of Statistics, China |
| 330 | | Unemployment level | 4 | National Bureau of Statistics, China |
| 331 | | Disposable income | 4 | National Bureau of Statistics, China |
| 332 | | Industrial production | 4 | National Bureau of Statistics, China |
| 333 | | Production of cement | 4 | OECD, Main Economic Indicators |
| 334 | | Composite leading indicator | 4 | National Bureau of Statistics, China |
| 335 | | Consumer price index (%YOY) | 1 | National Bureau of Statistics, China |
| 336 | | Average wage | 4 | National Bureau of Statistics, China |
| 337 | | Overnight interest rate | 1 | OECD, Main Economic Indicators |
| 338 | | Prime lending rate | 1 | People's Bank of China |
| 339 | | Discount rate | 1 | People's Bank of China |
| 340 | | M2 | 4 | OECD, Main Economic Indicators |
| 341 | | M1 | 4 | OECD, Main Economic Indicators |
| 342 | | SDR reserve assets | 4 | OECD, Main Economic Indicators |
| 343 | | M0, Currency in circulation | 4 | OECD, Main Economic Indicators |
| 344 | | CNY/USD exchange rate | 4 | OECD, Main Economic Indicators |
| 345 | Hong Kong | Gross domestic product, real | 4 | Census and Statistics Department of Hong Kong |
| 346 | | Private consumption expenditure, real | 4 | Census and Statistics Department of Hong Kong |
| 347 | | Gross fixed capital formation, real | 4 | IMF, International Financial Statistics |
| 348 | | Government consumption expenditure, real | 4 | Census and Statistics Department of Hong Kong |
| 349 | | Exports, volume index | 4 | IMF, International Financial Statistics |
| 350 | | Imports, volume index | 4 | IMF, International Financial Statistics |
| 351 | | Retail sales | 4 | Census and Statistics Department of Hong Kong |
| 352 | | Labour force | 4 | Census and Statistics Department of Hong Kong |
| 353 | | Unemployment level | 4 | Census and Statistics Department of Hong Kong |
| 354 | | Unemployment rate | 1 | Census and Statistics Department of Hong Kong |
| 355 | | Merchandise trade balance | 2 | Census and Statistics Department of Hong Kong |
| 356 | | Industrial production, manufacturing | 4 | Census and Statistics Department of Hong Kong |
| 357 | | Consumer price index | 4 | IMF, International Financial Statistics |
| 358 | | GDP deflator | 4 | IMF, International Financial Statistics |
| 359 | | Export unit value index | 4 | Census and Statistics Department of Hong Kong |
| 360 | | Import unit value index | 4 | Census and Statistics Department of Hong Kong |
| 361 | | Producer price index, manufacturing industries | 4 | Census and Statistics Department of Hong Kong |
| 362 | | 3-month interbank offered rate | 1 | Hong Kong Monetary Authority |
| 363 | | Prime lending rate | 1 | Hong Kong Monetary Authority |
| 364 | | M0 | 4 | Hong Kong Monetary Authority |
| 365 | | M1 | 4 | Hong Kong Monetary Authority |
| 366 | | HKD/USD exchange rate | 4 | IMF, International Financial Statistics |
| 367 | | Effective exchange rate indices, trade-weighted | 4 | Census and Statistics Department of Hong Kong |
| 368 | | Share price index, Hang Seng | 4 | Census and Statistics Department of Hong Kong |
| 369 | Malaysia | Gross domestic product, real | 4 | IMF, International Financial Statistics |
| 370 | | Industrial production | 4 | IMF, International Financial Statistics |
| 371 | | Exports, volume index | 4 | IMF, International Financial Statistics |
| 372 | | Imports, volume index | 4 | IMF, International Financial Statistics |
| 373 | | Industrial production, manufacturing | 4 | Department of Statistics, Malaysia |
| 374 | | Consumer price index | 4 | IMF, International Financial Statistics |
| 375 | | Producer price index | 4 | IMF, International Financial Statistics |
| 376 | | Manufacturing sector salaries and wages paid | 4 | Department of Statistics, Malaysia |
| 377 | | 3-month fixed deposit rate | 1 | IMF, International Financial Statistics |
| 378 | | 3-month treasury bills rate | 1 | IMF, International Financial Statistics |
| 379 | | Overnight interbank rate | 1 | IMF, International Financial Statistics |
| 380 | | Reserve money | 4 | IMF, International Financial Statistics |
| 381 | | M0 | 4 | Bank of Malaysia |
| 382 | | M1 | 4 | Bank of Malaysia |
| 383 | | M2 | 4 | Bank of Malaysia |
| 384 | | M3 | 4 | Bank of Malaysia |
| 385 | | MYR/USD official exchange rate | 4 | IMF, International Financial Statistics |
| 386 | | Share price index | 4 | IMF, International Financial Statistics |
| 387 | Singapore | Gross domestic product, real | 4 | Department of Statistics, Singapore |
| 388 | | Private consumption expenditure, real | 4 | Department of Statistics, Singapore |
| 389 | | Gross fixed capital formation, real | 4 | Department of Statistics, Singapore |
| 390 | | Government consumption expenditure, real | 4 | Department of Statistics, Singapore |
| 391 | | Composite leading indicator | 4 | Department of Statistics, Singapore |
| 392 | | Exports, volume index | 4 | Department of Statistics, Singapore |
| 393 | | Imports, volume index | 4 | Department of Statistics, Singapore |
| 394 | | Unemployment rate | 4 | Department of Statistics, Singapore |
| 395 | | Retail sales index | 4 | Department of Statistics, Singapore |
| 396 | | Industrial productions, ex rubber processing | 4 | Department of Statistics, Singapore |
| 397 | | Business expectations, manufacturing next 6 months | 1 | Department of Statistics, Singapore |
| 398 | | Composite leading indicators | 4 | Department of Statistics, Singapore |
| 399 | | Consumer price index | 4 | IMF, International Financial Statistics |
| 400 | | Producer price index | 4 | IMF, International Financial Statistics |

| | | | | |
|---|---|---|---|---|
| 401 | | Export unit value | 4 | IMF, International Financial Statistics |
| 402 | | Import unit value | 4 | IMF, International Financial Statistics |
| 403 | | Domestic supply price index | 4 | Department of Statistics, Singapore |
| 404 | | Unit labour costs | 4 | Department of Statistics, Singapore |
| 405 | | 3-month interbank rate | 1 | IMF, International Financial Statistics |
| 406 | | 3-month deposit rate | 1 | IMF, International Financial Statistics |
| 407 | | 3-month treasury bill rate | 1 | Monetary Authority of Singapore |
| 408 | | Prime lending rate | 1 | Monetary Authority of Singapore |
| 409 | | M0 | 4 | Monetary Authority of Singapore |
| 410 | | M1 | 4 | Monetary Authority of Singapore |
| 411 | | M2 | 4 | Monetary Authority of Singapore |
| 412 | | M3 | 4 | Monetary Authority of Singapore |
| 413 | | SGD/USD exchange rate | 4 | Monetary Authority of Singapore |
| 414 | | Share price index | 4 | IMF, International Financial Statistics |
| 415 | Taiwan | Gross domestic product, real | 4 | Directorate General of Budget, Accounting and Statistics |
| 416 | | Private consumption, real | 4 | Directorate General of Budget, Accounting and Statistics |
| 417 | | Gross domestic fixed capital formation, real | 4 | Directorate General of Budget, Accounting and Statistics |
| 418 | | Gross national production | 4 | Directorate General of Budget, Accounting and Statistics |
| 419 | | Government consumption, real | 4 | Directorate General of Budget, Accounting and Statistics |
| 420 | | Exports, volume index | 4 | Directorate General of Budget, Accounting and Statistics |
| 421 | | Imports, volume index | 4 | Directorate General of Budget, Accounting and Statistics |
| 422 | | Industrial production index | 4 | Ministry of Economic Affairs |
| 423 | | Industrial production index, manufacturing | 4 | Ministry of Economic Affairs |
| 424 | | Export orders received | 4 | Directorate General of Budget, Accounting and Statistics |
| 425 | | Unemployment rate | 1 | Directorate General of Budget, Accounting and Statistics |
| 426 | | Labour force | 4 | Directorate General of Budget, Accounting and Statistics |
| 427 | | Employment | 4 | Directorate General of Budget, Accounting and Statistics |
| 428 | | Unemployment level | 4 | Directorate General of Budget, Accounting and Statistics |
| 429 | | Labour productivity index | 4 | Directorate General of Budget, Accounting and Statistics |
| 430 | | Composite leading indicators | 4 | Directorate General of Budget, Accounting and Statistics |
| 431 | | Consumer price index | 4 | Directorate General of Budget, Accounting and Statistics |
| 432 | | Consumer price index, ex food and energy | 4 | Directorate General of Budget, Accounting and Statistics |
| 433 | | Average monthly earnings, manufacturing | 4 | Directorate General of Budget, Accounting and Statistics |
| 434 | | Unit labour costs | 4 | Directorate General of Budget, Accounting and Statistics |
| 435 | | Export price index | 4 | Directorate General of Budget, Accounting and Statistics |
| 436 | | Import price index | 4 | Directorate General of Budget, Accounting and Statistics |
| 437 | | GDP deflator | 4 | Directorate General of Budget, Accounting and Statistics |
| 438 | | Discount rate | 1 | Central Bank of China |
| 439 | | 90-day money market rate | 1 | Central Bank of China |
| 440 | | Prime lending rate, 5 major banks | 1 | Central Bank of China |
| 441 | | M0 | 4 | Central Bank of China |
| 442 | | M1 | 4 | Central Bank of China |
| 443 | | M2 | 4 | Central Bank of China |
| 444 | | TWD/USD exchange rate | 4 | Central Bank of China |
| 445 | Commodity | Aluminum | 4 | London Metal Exchange |
| 446 | | Cooper | 4 | London Metal Exchange |
| 447 | | Lead | 4 | London Metal Exchange |
| 448 | | Nickel | 4 | London Metal Exchange |
| 449 | | Tin | 4 | London Metal Exchange |
| 450 | | Zinc | 4 | London Metal Exchange |
| 451 | | Cotton | 4 | US Department of Agriculture |
| 452 | | Nylon yarn | 4 | Taiwan Economic Journal |
| 453 | | Polyester | 2 | Taiwan Economic Journal |
| 454 | | Wool | 4 | Australian Wool Council |
| 455 | | Fuel oil | 4 | Dow Jones energy services |
| 456 | | Gas oil | 4 | ICIS Pricing |
| 457 | | Gasoline | 4 | Dow Jones energy services |
| 458 | | Jet kerosene-cargos | 4 | ICIS Pricing |
| 459 | | Crude oil | 4 | ICIS Pricing |
| 460 | | Palm oil | 4 | Public Ledger |
| 461 | | Sunflower oil | 4 | Public Ledger |
| 462 | | Soya oil | 4 | Public Ledger |
| 463 | | Peanut oil | 4 | Public Ledger |
| 464 | | Linseed oil | 4 | Public Ledger |
| 465 | | Raw sugar | 4 | Public Ledger |
| 466 | | Rubber | 4 | Malaysian Rubber Exchange |
| 467 | | Coffee | 4 | International Coffee Organization |
| 468 | | Cocoa | 4 | International Cocoa Organization |
| 469 | | Soybeans | 4 | US Department of Agriculture |
| 470 | | Rapeseed | 4 | Public Ledger |
| 471 | | Wheat (hard Kansas, Cts./Bu) | 4 | US Department of Agriculture |
| 472 | | Wheat 2 (soft) | 4 | US Department of Agriculture |
| 473 | | Rice | 4 | Public Ledger |
| 474 | | Platinum | 4 | Metal Bulletin |
| 475 | | Silver | 4 | London Metal Exchange |
| 476 | | Palladium | 4 | Metal Bulletin |
| 477 | | Corn | 4 | US Department of Agriculture |
| 478 | | Gold | 4 | London Metal Exchange |
| 479 | | Pork bellies | 4 | US Department of Agriculture |
| 480 | | Eggs | 4 | US Department of Agriculture |
| 481 | | Oats | 4 | US Department of Agriculture |
| 482 | | Live hogs | 4 | Standard & Poor's |

Notes: Series are treated as follows. 1: no transformation, 2: first difference, 3: log, 4: log difference.

## Table A2
## Forecast results for subsets of international data

### (a) International subset = North American data only

| | International | | | | New Zealand + international | | | |
|---|---|---|---|---|---|---|---|---|
| | h = 1 | h = 2 | h = 4 | h = 8 | h = 1 | h = 2 | h = 4 | h = 8 |
| Univar. benchm. (RMSE/h) | 0.0061 | 0.0063 | 0.0067 | 0.0069 | 0.0061 | 0.0063 | 0.0067 | 0.0069 |
| trade1 | 1.115 | 1.416 | 1.955 | 2.655 | - | - | - | - |
| trade2 | 1.115 | 1.416 | 1.955 | 2.660 | - | - | - | - |
| PC (r = 1) | 1.033 | 1.045 | 0.836 | **0.825** | 0.984 | 0.933 | 1.030 | 1.170 |
| PC (r = 2) | 1.049 | 1.056 | 0.948 | 1.077 | 1.016 | 0.978 | 1.142 | 1.160 |
| PC (r = 3) | 1.082 | 1.090 | 0.978 | 1.119 | 1.016 | 1.000 | 1.149 | 1.180 |
| PC (r = 5) | 1.148 | 1.382 | 1.418 | 1.948 | 1.033 | 0.876 | 1.119 | 0.928 |
| WPCBN (r = 1) | 1.049 | 1.079 | **0.828** | 0.871 | 0.984 | 0.989 | 1.030 | 0.959 |
| WPCBN (r = 2) | 1.082 | 1.101 | 0.940 | 1.139 | 1.000 | 0.944 | 1.045 | 0.938 |
| WPCBN (r = 3) | 1.000 | 1.067 | 0.925 | 1.392 | **0.869** | 1.000 | 0.933 | **0.820** |
| WPCBN (r = 5) | 1.049 | 1.236 | 1.127 | 1.464 | 0.852 | 0.955 | 1.425 | 1.165 |
| WPCSW (r = 1) | 1.016 | 1.067 | 0.925 | 0.871 | 1.066 | 1.202 | 1.187 | 1.134 |
| WPCSW (r = 2) | 1.000 | 1.000 | 0.993 | 1.170 | 0.967 | 1.022 | 1.037 | 0.948 |
| WPCSW (r = 3) | 1.000 | 1.045 | 0.978 | 1.093 | 1.049 | 1.000 | 1.157 | 1.314 |
| WPCSW (r = 5) | **0.984** | 1.056 | 0.851 | 1.134 | 1.016 | 1.011 | 1.194 | 1.031 |
| TPH (r = 1) | 1.066 | 1.236 | 1.209 | 1.206 | 0.918 | 0.910 | 1.134 | 1.175 |
| TPH (r = 2) | 1.131 | 1.337 | 1.336 | 1.521 | 0.885 | 0.899 | 1.134 | 1.155 |
| TPH (r = 3) | 1.164 | 1.404 | 1.313 | 1.515 | 0.902 | 0.978 | 1.119 | 1.191 |
| TPH (r = 5) | 1.344 | 1.449 | 1.396 | 1.701 | 0.918 | 1.101 | 1.164 | 1.340 |
| TPS (30 variables, r = 1) | 1.016 | 1.056 | 0.963 | 1.072 | 1.131 | 1.157 | 1.134 | 1.005 |
| TPS (30 variables, r = 2) | 1.131 | 1.056 | 1.388 | 1.402 | 1.066 | 1.135 | 1.224 | 1.242 |
| TPS (30 variables, r = 3) | 1.098 | 1.135 | 1.396 | 1.454 | 0.984 | 1.079 | 1.164 | 1.258 |
| TPS (30 variables, r = 5) | 1.131 | 1.236 | 1.500 | 1.675 | 1.016 | 1.011 | 1.104 | 1.206 |
| PLS (k = 1) | 1.098 | 1.180 | 0.873 | 1.160 | 0.967 | 0.876 | 0.978 | 1.129 |
| PLS (k = 2) | 1.328 | 1.416 | 1.194 | 1.608 | 1.115 | 1.011 | 1.052 | 1.186 |
| PLS (k = 3) | 1.475 | 1.697 | 1.545 | 1.876 | 0.967 | **0.787** | **0.813** | 1.160 |
| PLS (k = 5) | 1.410 | 1.607 | 1.560 | 1.670 | 0.984 | 1.090 | 1.052 | 1.098 |
| RR ($v_2$ = 0.25) | 1.836 | 1.910 | 2.142 | 2.670 | 1.033 | 1.000 | 1.104 | 1.165 |
| RR ($v_2$ = N) | 1.098 | 1.225 | 1.127 | 1.330 | 0.918 | 0.820 | 0.851 | 1.082 |
| RR ($v_2$ = 5N) | 1.033 | 1.056 | 0.948 | 1.067 | 0.934 | 0.888 | 0.896 | 1.015 |
| RR ($v_2$ = 10N) | 1.016 | 1.022 | 0.955 | 1.031 | 0.951 | 0.910 | 0.925 | 1.000 |
| EN (30 variables, $v_2$ = 0.25) | 1.311 | 1.584 | 1.970 | 1.794 | 0.984 | 0.933 | 1.224 | 1.005 |

### (b) International subset = European data only

| | International | | | | New Zealand + international | | | |
|---|---|---|---|---|---|---|---|---|
| | h = 1 | h = 2 | h = 4 | h = 8 | h = 1 | h = 2 | h = 4 | h = 8 |
| Univar. benchm. (RMSE/h) | 0.0061 | 0.0063 | 0.0067 | 0.0069 | 0.0061 | 0.0063 | 0.0067 | 0.0069 |
| trade1 | 1.049 | 1.079 | 1.127 | 1.113 | - | - | - | - |
| trade2 | 1.049 | 1.067 | 1.127 | 1.119 | - | - | - | - |
| PC (r = 1) | 1.000 | 1.045 | 1.060 | 1.021 | 0.951 | 0.865 | 1.007 | 1.129 |
| PC (r = 2) | 1.000 | 0.955 | 0.836 | 1.124 | 0.951 | 0.843 | 1.067 | 1.134 |
| PC (r = 3) | 1.016 | 0.944 | 0.873 | 1.139 | 0.951 | 0.888 | 1.075 | 1.299 |
| PC (r = 5) | 1.000 | 0.876 | 1.045 | 1.309 | 0.984 | 0.955 | 1.239 | 1.572 |
| WPCBN (r = 1) | 1.000 | 1.011 | 1.015 | **0.887** | 0.951 | 0.978 | 0.948 | **0.866** |
| WPCBN (r = 2) | 1.000 | 0.910 | 0.724 | 0.938 | 0.934 | 1.056 | 0.970 | 1.144 |
| WPCBN (r = 3) | 0.934 | 0.865 | 0.769 | 1.119 | 0.951 | 1.079 | 1.239 | 1.624 |
| WPCBN (r = 5) | 1.066 | 0.944 | 1.075 | 1.077 | 1.115 | 1.000 | 1.403 | 1.804 |
| WPCSW (r = 1) | 1.033 | 1.067 | 1.037 | 1.021 | 1.066 | 1.135 | 1.082 | 1.082 |
| WPCSW (r = 2) | 0.934 | 0.910 | 0.955 | 1.155 | 0.984 | 0.865 | 1.007 | 0.923 |
| WPCSW (r = 3) | 1.000 | 1.034 | 1.030 | 1.186 | 0.984 | 0.899 | 1.030 | 1.222 |
| WPCSW (r = 5) | 0.967 | 0.955 | 1.022 | 1.170 | 0.934 | 0.820 | 1.007 | 1.232 |
| TPH (r = 1) | 0.967 | 1.000 | 0.948 | 0.995 | 0.885 | 0.944 | 1.112 | 1.211 |
| TPH (r = 2) | 0.951 | 0.989 | 1.030 | 1.196 | 0.852 | 0.921 | 1.224 | 1.134 |
| TPH (r = 3) | 0.951 | 1.000 | 1.187 | 1.072 | **0.836** | 0.933 | 1.194 | 1.232 |
| TPH (r = 5) | 0.951 | 1.011 | 1.291 | 1.180 | 0.967 | 1.000 | 1.119 | 1.232 |
| TPS (30 variables, r = 1) | 1.000 | 1.045 | 1.007 | 1.175 | 1.246 | 1.146 | 1.201 | 1.144 |
| TPS (30 variables, r = 2) | 1.000 | 1.169 | 1.060 | 1.299 | 1.213 | 1.135 | 1.209 | 1.119 |
| TPS (30 variables, r = 3) | 1.033 | 1.090 | 1.201 | 1.284 | 1.230 | 1.146 | 1.261 | 1.134 |
| TPS (30 variables, r = 5) | 1.016 | 1.079 | 1.224 | 1.381 | 1.246 | 1.191 | 1.284 | 1.113 |
| PLS (k = 1) | 0.918 | 0.854 | 0.701 | 1.031 | 0.934 | 0.831 | 0.910 | 1.072 |
| PLS (k = 2) | **0.869** | **0.775** | 0.672 | 1.175 | 1.000 | 0.910 | 1.030 | 1.253 |
| PLS (k = 3) | 1.033 | 0.899 | 0.799 | 1.088 | 0.918 | **0.753** | **0.716** | 1.242 |
| PLS (k = 5) | 1.279 | 1.079 | 0.828 | 0.969 | 0.967 | 1.034 | 0.925 | 1.216 |
| RR ($v_2$ = 0.25) | 1.770 | 1.461 | 1.164 | 1.304 | 1.000 | 0.910 | 0.925 | 1.278 |
| RR ($v_2$ = N) | 0.902 | 0.809 | **0.649** | 1.041 | 0.902 | 0.787 | 0.784 | 1.119 |
| RR ($v_2$ = 5N) | 0.902 | 0.843 | 0.694 | 0.995 | 0.918 | 0.854 | 0.851 | 1.021 |
| RR ($v_2$ = 10N) | 0.918 | 0.876 | 0.776 | 0.985 | 0.934 | 0.876 | 0.896 | 1.000 |
| EN (30 variables, $v_2$ = 0.25) | 1.016 | 1.022 | 0.903 | 0.948 | 1.016 | 0.831 | 1.045 | 1.031 |

## (c) International subset = Asian data only

| | International | | | | New Zealand + international | | | |
|---|---|---|---|---|---|---|---|---|
| | h = 1 | h = 2 | h = 4 | h = 8 | h = 1 | h = 2 | h = 4 | h = 8 |
| Univar. benchm. (RMSE/h) | 0.0061 | 0.0063 | 0.0067 | 0.0069 | 0.0061 | 0.0063 | 0.0067 | 0.0069 |
| trade1 | 1.115 | 1.213 | 0.978 | 1.294 | - | - | - | - |
| trade2 | 1.115 | 1.213 | 0.978 | 1.294 | - | - | - | - |
| PC (r = 1) | 0.984 | 0.944 | 0.851 | 1.000 | 0.967 | 0.933 | 1.075 | 1.165 |
| PC (r = 2) | 1.115 | 1.258 | 0.910 | 1.216 | 0.984 | 0.876 | 1.052 | 1.376 |
| PC (r = 3) | 1.033 | 1.101 | 0.828 | 1.129 | 0.951 | 0.876 | 0.918 | 1.309 |
| PC (r = 5) | 1.098 | **0.899** | 0.873 | 1.423 | 0.984 | **0.809** | **0.828** | 1.742 |
| WPCBN (r = 1) | 0.984 | 0.955 | 0.881 | 0.969 | 0.984 | 1.011 | 1.119 | 1.196 |
| WPCBN (r = 2) | 1.115 | 1.202 | 0.896 | 1.186 | 0.984 | 0.933 | 1.157 | 1.490 |
| WPCBN (r = 3) | 1.000 | 1.169 | 1.067 | 1.268 | 0.967 | 0.899 | 1.127 | 1.289 |
| WPCBN (r = 5) | 0.951 | 1.056 | 1.000 | 1.345 | 0.934 | 0.888 | 1.216 | 1.443 |
| WPCSW (r = 1) | 1.016 | 0.944 | **0.739** | 0.923 | 1.000 | 1.067 | 1.045 | 1.067 |
| WPCSW (r = 2) | 1.066 | 1.157 | 0.806 | 1.005 | 0.934 | 0.820 | 0.910 | 1.211 |
| WPCSW (r = 3) | 1.066 | 1.180 | 0.873 | 1.124 | 0.967 | 0.843 | 1.082 | 1.284 |
| WPCSW (r = 5) | 1.049 | 1.146 | 0.993 | 1.356 | 1.000 | 0.944 | 1.179 | 1.531 |
| TPH (r = 1) | 1.180 | 1.191 | 1.187 | 1.959 | 0.934 | 0.843 | 1.030 | 1.129 |
| TPH (r = 2) | 1.213 | 1.213 | 1.396 | 1.985 | 0.934 | 0.854 | 1.045 | 1.237 |
| TPH (r = 3) | 1.213 | 1.213 | 1.418 | 1.979 | 0.967 | 0.989 | 1.179 | 1.227 |
| TPH (r = 5) | 1.279 | 1.315 | 1.634 | 2.041 | 0.984 | 0.989 | 1.194 | 1.572 |
| TPS (30 variables, r = 1) | 0.951 | 1.022 | 1.254 | 0.923 | 1.066 | 1.124 | 1.381 | 1.144 |
| TPS (30 variables, r = 2) | 1.115 | 1.202 | 1.455 | 1.412 | 1.098 | 1.247 | 1.433 | 1.247 |
| TPS (30 variables, r = 3) | 1.377 | 1.292 | 1.440 | 1.387 | 1.098 | 1.258 | 1.463 | 1.258 |
| TPS (30 variables, r = 5) | 1.377 | 1.270 | 1.478 | 1.392 | 1.180 | 1.236 | 1.410 | 1.191 |
| PLS (k = 1) | 1.082 | 1.213 | 1.060 | 1.082 | 0.951 | 0.843 | 0.940 | 1.052 |
| PLS (k = 2) | **0.852** | 0.966 | 0.799 | 1.093 | 0.984 | 0.854 | 0.948 | 1.242 |
| PLS (k = 3) | 0.885 | 0.933 | 0.761 | 0.881 | **0.852** | 0.865 | 0.896 | 1.046 |
| PLS (k = 5) | 0.984 | 1.270 | 0.940 | **0.722** | 0.967 | 1.112 | 0.918 | 0.907 |
| RR ($v_2$ = 0.25) | 1.115 | 1.225 | 1.254 | 0.969 | 0.967 | 0.933 | 1.015 | 1.062 |
| RR ($v_2$ = N) | 0.902 | 1.011 | 0.799 | 0.923 | 0.885 | **0.809** | **0.828** | 1.046 |
| RR ($v_2$ = 5N) | 0.918 | 0.933 | 0.813 | 0.943 | 0.918 | 0.865 | 0.851 | 1.000 |
| RR ($v_2$ = 10N) | 0.934 | 0.944 | 0.851 | 0.974 | 0.934 | 0.888 | 0.881 | 0.995 |
| EN (30 variables, $v_2$ = 0.25) | 0.918 | 1.067 | 1.060 | 1.186 | 0.951 | 0.933 | 1.045 | **0.711** |

## (d) International subset = Australian data only

| | International | | | | New Zealand + international | | | |
|---|---|---|---|---|---|---|---|---|
| | h = 1 | h = 2 | h = 4 | h = 8 | h = 1 | h = 2 | h = 4 | h = 8 |
| Univar. benchm. (RMSE/h) | 0.0061 | 0.0063 | 0.0067 | 0.0069 | 0.0061 | 0.0063 | 0.0067 | 0.0069 |
| trade1 | 0.984 | 1.011 | 0.955 | 0.928 | - | - | - | - |
| trade2 | 0.984 | 1.011 | 0.955 | 0.928 | - | - | - | - |
| PC (r = 1) | 0.934 | 1.000 | 1.007 | 1.005 | 1.000 | 1.000 | 1.201 | 1.325 |
| PC (r = 2) | 0.902 | 1.011 | 1.060 | 1.031 | 1.000 | 1.034 | 1.321 | 1.655 |
| PC (r = 3) | 0.902 | 0.955 | 1.067 | 1.046 | 0.984 | 1.056 | 1.381 | 1.552 |
| PC (r = 5) | 0.820 | 0.989 | 1.134 | 1.113 | 0.918 | 1.056 | 1.552 | 1.531 |
| WPCBN (r = 1) | 0.918 | 1.034 | 1.007 | 0.979 | 0.934 | 0.865 | 1.000 | 1.139 |
| WPCBN (r = 2) | 0.902 | 0.978 | 1.067 | 1.077 | 0.934 | 0.876 | 1.067 | 1.361 |
| WPCBN (r = 3) | 0.885 | 0.888 | 1.075 | 1.093 | 0.934 | 0.865 | 1.104 | 1.067 |
| WPCBN (r = 5) | **0.787** | 1.034 | 0.985 | 1.170 | 1.000 | 0.933 | 1.164 | 1.474 |
| WPCSW (r = 1) | 0.852 | 0.854 | 1.030 | 1.026 | 1.246 | 1.315 | 1.276 | 1.082 |
| WPCSW (r = 2) | 0.918 | 0.933 | 1.060 | 1.021 | 1.098 | 1.079 | 1.022 | 1.376 |
| WPCSW (r = 3) | 1.033 | 1.022 | 1.045 | 1.077 | 1.098 | 1.112 | 1.269 | 1.608 |
| WPCSW (r = 5) | 0.984 | 1.011 | 1.075 | 1.010 | 1.016 | 0.978 | 1.067 | 1.335 |
| TPH (r = 1) | 0.951 | 0.989 | 0.993 | 1.088 | 0.951 | 0.955 | 0.963 | 1.000 |
| TPH (r = 2) | 1.000 | 1.045 | 0.948 | 0.964 | 0.951 | 0.989 | 1.007 | 1.304 |
| TPH (r = 3) | 0.984 | 1.056 | 0.940 | 1.505 | 0.934 | 1.011 | 1.052 | 1.335 |
| TPH (r = 5) | 1.016 | 1.146 | 1.336 | 1.758 | 1.016 | 1.124 | 1.313 | 1.376 |
| TPS (30 variables, r = 1) | 1.016 | 1.067 | 1.052 | 0.985 | 1.016 | 1.056 | 1.284 | 1.258 |
| TPS (30 variables, r = 2) | 1.016 | 1.045 | 1.037 | 0.990 | 1.148 | 1.135 | 1.284 | 1.392 |
| TPS (30 variables, r = 3) | 1.049 | 1.056 | 1.060 | 1.041 | 1.295 | 1.180 | 1.231 | 1.448 |
| TPS (30 variables, r = 5) | 0.984 | 1.090 | 0.955 | 0.985 | 1.295 | 1.315 | 1.216 | 1.418 |
| PLS (k = 1) | **0.787** | 0.831 | 1.104 | 1.072 | 0.934 | 0.831 | 0.940 | 1.103 |
| PLS (k = 2) | 0.869 | 0.899 | 0.925 | 1.005 | 1.016 | 1.000 | 1.306 | 1.345 |
| PLS (k = 3) | 0.918 | 0.888 | 0.903 | 0.959 | 0.902 | **0.730** | 0.970 | 1.402 |
| PLS (k = 5) | 1.066 | 1.124 | 0.918 | 0.990 | 0.902 | 0.944 | 1.119 | 1.284 |
| RR ($v_2$ = 0.25) | 1.803 | 1.831 | 1.776 | 1.005 | 1.016 | 0.933 | 1.157 | 1.366 |
| RR ($v_2$ = N) | 0.803 | **0.775** | **0.843** | **0.825** | **0.869** | 0.775 | 0.933 | 1.180 |
| RR ($v_2$ = 5N) | 0.836 | 0.854 | 0.955 | 0.912 | 0.918 | 0.865 | **0.925** | 1.036 |
| RR ($v_2$ = 10N) | 0.869 | 0.888 | 0.985 | 0.948 | 0.934 | 0.888 | 0.940 | 1.005 |
| EN (30 variables, $v_2$ = 0.25) | 1.246 | 1.281 | 1.261 | 1.026 | 1.000 | 0.820 | 1.246 | 1.134 |

## (e) International subset = real data only

| | International | | | | New Zealand + international | | | |
|---|---|---|---|---|---|---|---|---|
| | h = 1 | h = 2 | h = 4 | h = 8 | h = 1 | h = 2 | h = 4 | h = 8 |
| Univar. benchm. (RMSE/h) | 0.0061 | 0.0063 | 0.0067 | 0.0069 | 0.0061 | 0.0063 | 0.0067 | 0.0069 |
| trade1 | 1.049 | 1.090 | 0.948 | 0.933 | - | - | - | - |
| trade2 | 1.049 | 1.079 | 0.940 | 0.923 | - | - | - | - |
| PC (r = 1) | 1.066 | 1.056 | 0.970 | 0.990 | 0.951 | 0.888 | 1.037 | 1.149 |
| PC (r = 2) | 1.066 | 1.146 | 0.985 | **0.912** | 0.967 | 0.921 | 1.194 | 1.387 |
| PC (r = 3) | 1.049 | 1.045 | 0.866 | 1.412 | 0.984 | 0.966 | 1.231 | 1.443 |
| PC (r = 5) | 1.148 | 1.146 | 1.187 | 1.608 | 1.000 | 1.000 | 1.254 | 1.464 |
| WPCBN (r = 1) | 1.049 | 1.034 | 0.970 | 1.026 | 0.934 | 0.899 | 1.030 | 1.170 |
| WPCBN (r = 2) | 1.066 | 1.112 | 0.970 | 0.938 | 0.951 | 0.933 | 1.142 | 1.077 |
| WPCBN (r = 3) | 1.082 | 1.034 | 0.963 | 1.309 | 0.967 | 0.910 | 1.119 | 1.160 |
| WPCBN (r = 5) | 1.131 | 1.124 | 1.030 | 1.325 | 0.934 | 0.933 | 1.358 | 1.320 |
| WPCSW (r = 1) | 1.049 | 1.101 | 1.045 | 0.979 | 1.033 | 1.056 | 1.134 | 1.103 |
| WPCSW (r = 2) | 1.066 | 1.124 | 1.030 | 1.005 | 0.967 | 0.933 | 1.172 | 1.289 |
| WPCSW (r = 3) | 1.033 | 1.112 | 1.075 | 1.418 | 0.984 | 0.966 | 1.284 | 1.603 |
| WPCSW (r = 5) | 1.016 | 1.180 | 0.933 | 1.186 | 0.951 | 0.910 | 1.104 | 1.402 |
| TPH (r = 1) | 1.066 | 1.079 | 1.097 | 1.124 | 0.984 | 0.933 | 1.149 | 1.253 |
| TPH (r = 2) | 1.066 | 1.045 | 1.299 | 1.423 | 0.984 | 0.910 | 1.164 | 1.402 |
| TPH (r = 3) | 1.180 | 1.112 | 1.254 | 1.314 | 1.016 | 0.978 | 1.134 | 1.423 |
| TPH (r = 5) | 1.180 | 1.157 | 1.254 | 1.351 | 1.098 | 1.101 | 1.246 | 1.381 |
| TPS (30 variables, r = 1) | 1.016 | 1.022 | 0.948 | 1.345 | 1.213 | 1.180 | 1.037 | 1.103 |
| TPS (30 variables, r = 2) | 1.033 | 1.079 | 1.112 | 1.273 | 1.197 | 1.348 | 1.075 | 1.031 |
| TPS (30 variables, r = 3) | 1.098 | 1.079 | 1.149 | 1.459 | 1.180 | 1.337 | 1.000 | 1.021 |
| TPS (30 variables, r = 5) | 1.262 | 1.404 | 1.291 | 1.536 | 1.148 | 1.371 | 0.963 | 1.062 |
| PLS (k = 1) | 1.066 | 1.045 | **0.851** | 1.242 | 0.967 | 0.843 | 0.963 | 1.124 |
| PLS (k = 2) | 0.967 | 0.966 | 0.940 | 1.330 | 1.049 | 0.933 | 0.978 | 1.222 |
| PLS (k = 3) | **0.885** | **0.933** | 0.881 | 1.299 | **0.902** | **0.708** | 0.821 | 1.046 |
| PLS (k = 5) | 0.967 | 1.034 | **0.851** | 1.139 | 0.918 | 0.955 | 0.903 | 1.031 |
| RR ($v_2$ = 0.25) | 0.934 | 1.067 | 1.000 | 1.381 | 0.951 | 0.865 | 0.993 | 1.103 |
| RR ($v_2$ = N) | 0.934 | 1.067 | 0.993 | 1.381 | 0.902 | 0.798 | **0.799** | 1.046 |
| RR ($v_2$ = 5N) | 0.918 | 1.045 | 0.978 | 1.361 | 0.934 | 0.888 | 0.866 | 0.995 |
| RR ($v_2$ = 10N) | 0.918 | 1.034 | 0.963 | 1.340 | 0.951 | 0.910 | 0.910 | 0.990 |
| EN (30 variables, $v_2$ = 0.25) | 1.082 | 0.978 | 0.896 | 1.278 | 0.984 | 0.865 | 0.918 | **0.701** |

## (f) International subset = price data only

| | International | | | | New Zealand + international | | | |
|---|---|---|---|---|---|---|---|---|
| | h = 1 | h = 2 | h = 4 | h = 8 | h = 1 | h = 2 | h = 4 | h = 8 |
| Univar. benchm. (RMSE/h) | 0.0061 | 0.0063 | 0.0067 | 0.0069 | 0.0061 | 0.0063 | 0.0067 | 0.0069 |
| trade1 | 0.885 | 0.933 | 0.918 | 0.985 | - | - | - | - |
| trade2 | 0.885 | 0.921 | 0.925 | 0.979 | - | - | - | - |
| PC (r = 1) | 0.902 | **0.888** | 0.821 | 0.866 | 0.951 | 0.888 | 1.015 | 1.134 |
| PC (r = 2) | 0.951 | 0.966 | 0.828 | 0.809 | 0.984 | 0.933 | 1.127 | 1.098 |
| PC (r = 3) | 0.869 | 0.955 | 0.940 | 1.155 | 0.967 | 0.978 | 1.127 | 1.268 |
| PC (r = 5) | **0.803** | 1.101 | 1.373 | 1.459 | 0.934 | 0.921 | 1.090 | 1.500 |
| WPCBN (r = 1) | 0.918 | 0.910 | 0.858 | 0.897 | 0.951 | 0.921 | 0.896 | 1.129 |
| WPCBN (r = 2) | 0.918 | 1.079 | 1.082 | **0.784** | 0.967 | 0.910 | 1.015 | 1.211 |
| WPCBN (r = 3) | 0.967 | 1.056 | 1.276 | 1.696 | 0.918 | 0.966 | 1.157 | 1.412 |
| WPCBN (r = 5) | 1.098 | 1.056 | 1.231 | 1.892 | 1.016 | 1.045 | 1.463 | 1.562 |
| WPCSW (r = 1) | 0.984 | 0.989 | 0.963 | 0.933 | 1.049 | 1.191 | 1.149 | 1.093 |
| WPCSW (r = 2) | 0.951 | 0.978 | 0.888 | 0.825 | 0.934 | 0.876 | 0.955 | **0.985** |
| WPCSW (r = 3) | 0.934 | 1.011 | 1.022 | 0.964 | 1.000 | 0.888 | 0.925 | 1.170 |
| WPCSW (r = 5) | 0.934 | 1.067 | 1.090 | 0.979 | 0.951 | 0.876 | **0.836** | 1.103 |
| TPH (r = 1) | 0.869 | 1.022 | 0.940 | 1.000 | 0.984 | 0.854 | 0.970 | 1.072 |
| TPH (r = 2) | 0.885 | 1.079 | 1.082 | 1.144 | 0.984 | 0.854 | 0.970 | 1.196 |
| TPH (r = 3) | 0.902 | 1.202 | 0.933 | 1.474 | 1.000 | 0.888 | 0.985 | 1.072 |
| TPH (r = 5) | 0.984 | 1.337 | 1.187 | 1.680 | 1.049 | 0.888 | 1.321 | 1.273 |
| TPS (30 variables, r = 1) | 0.967 | 1.067 | 0.978 | 0.959 | 1.131 | 1.157 | 1.269 | 1.227 |
| TPS (30 variables, r = 2) | 0.967 | 1.090 | 1.291 | 1.340 | 1.164 | 1.090 | 1.269 | 1.242 |
| TPS (30 variables, r = 3) | 1.016 | 1.202 | 1.433 | 1.536 | 1.230 | 1.090 | 1.299 | 1.278 |
| TPS (30 variables, r = 5) | 0.984 | 1.326 | 1.500 | 1.588 | 1.230 | 1.157 | 1.321 | 1.206 |
| PLS (k = 1) | 0.852 | 0.910 | 0.799 | 0.923 | 0.934 | 0.843 | 0.940 | 1.062 |
| PLS (k = 2) | 0.852 | 1.022 | 0.888 | 1.495 | 0.984 | 0.899 | 1.067 | 1.387 |
| PLS (k = 3) | 0.885 | 0.989 | 0.828 | 1.356 | 0.934 | 0.843 | 0.851 | 1.206 |
| PLS (k = 5) | 0.951 | 1.090 | 0.851 | 0.990 | 0.967 | 1.056 | 0.955 | 1.124 |
| RR ($v_2$ = 0.25) | 1.098 | 1.247 | 1.007 | 1.330 | 0.984 | 0.933 | 1.007 | 1.268 |
| RR ($v_2$ = N) | **0.803** | 0.921 | **0.746** | 1.129 | **0.869** | **0.787** | 0.866 | 1.149 |
| RR ($v_2$ = 5N) | 0.852 | **0.888** | 0.813 | 0.990 | 0.902 | 0.843 | 0.873 | 1.031 |
| RR ($v_2$ = 10N) | 0.902 | 0.910 | 0.858 | 0.979 | 0.918 | 0.876 | 0.903 | 1.010 |
| EN (30 variables, $v_2$ = 0.25) | 0.967 | 1.056 | 1.022 | 1.345 | 0.951 | 0.876 | 1.022 | 1.175 |

## (g) International subset = monetary and financial data only

| | International | | | | New Zealand + international | | | |
|---|---|---|---|---|---|---|---|---|
| | h = 1 | h = 2 | h = 4 | h = 8 | h = 1 | h = 2 | h = 4 | h = 8 |
| Univar. benchm. (RMSE/h) | 0.0061 | 0.0063 | 0.0067 | 0.0069 | 0.0061 | 0.0063 | 0.0067 | 0.0069 |
| trade1 | 1.000 | 1.011 | 1.052 | 1.196 | - | - | - | - |
| trade2 | 1.000 | 1.011 | 1.045 | 1.191 | - | - | - | - |
| PC (r = 1) | 1.082 | 1.112 | 0.933 | 0.742 | 1.000 | 1.000 | 1.119 | 1.211 |
| PC (r = 2) | 1.016 | 0.978 | 0.739 | 0.979 | 0.967 | 0.899 | 1.127 | 1.474 |
| PC (r = 3) | 1.066 | 1.000 | **0.679** | 1.015 | 0.984 | 0.921 | 1.149 | 1.603 |
| PC (r = 5) | 1.148 | 1.079 | 0.873 | 1.222 | 1.082 | 0.978 | 1.388 | 1.742 |
| WPCBN (r = 1) | 1.033 | 1.022 | 0.873 | **0.711** | 1.000 | 1.034 | 1.157 | 1.186 |
| WPCBN (r = 2) | 1.049 | 1.112 | 1.194 | 0.871 | 0.918 | 0.910 | 1.134 | 1.031 |
| WPCBN (r = 3) | 1.049 | 1.169 | 1.082 | 1.273 | 0.967 | 0.910 | 1.164 | 1.381 |
| WPCBN (r = 5) | 1.115 | 1.135 | 1.246 | 1.222 | 1.033 | 1.090 | 1.052 | 1.562 |
| WPCSW (r = 1) | 1.066 | 1.101 | 1.000 | 0.923 | 1.000 | 1.067 | 1.045 | 1.077 |
| WPCSW (r = 2) | 1.082 | 1.169 | 1.037 | 1.242 | 0.951 | 0.831 | 0.903 | 1.299 |
| WPCSW (r = 3) | 1.197 | 1.315 | 1.276 | 1.335 | 0.951 | 0.921 | 0.970 | 1.227 |
| WPCSW (r = 5) | 1.180 | 1.270 | 1.209 | 1.057 | 0.984 | 0.888 | 1.082 | 1.325 |
| TPH (r = 1) | 1.115 | 1.191 | 1.194 | 1.247 | 0.951 | 0.865 | 1.104 | 1.227 |
| TPH (r = 2) | 1.197 | 1.258 | 1.127 | 1.345 | 0.984 | 0.809 | 1.149 | 1.289 |
| TPH (r = 3) | 1.180 | 1.258 | 1.030 | 1.366 | 0.984 | 0.843 | 1.067 | 1.139 |
| TPH (r = 5) | 1.098 | 1.494 | 1.224 | 1.351 | **0.820** | 0.831 | 1.015 | 1.273 |
| TPS (30 variables, r = 1) | 1.000 | 1.022 | 0.910 | 1.165 | 0.934 | 1.213 | 1.030 | 1.088 |
| TPS (30 variables, r = 2) | 0.902 | 1.079 | 0.918 | 1.247 | 1.033 | 1.146 | 1.045 | 1.093 |
| TPS (30 variables, r = 3) | **0.820** | 1.169 | 1.194 | 1.330 | 1.016 | 1.270 | 1.164 | 0.943 |
| TPS (30 variables, r = 5) | 1.033 | 1.315 | 1.194 | 1.325 | 1.016 | 1.191 | 1.097 | **0.897** |
| PLS (k = 1) | 1.180 | 1.315 | 1.351 | 1.186 | 0.951 | 0.854 | 0.940 | 1.077 |
| PLS (k = 2) | 1.066 | 1.157 | 1.127 | 1.253 | 1.049 | 0.933 | 1.015 | 1.253 |
| PLS (k = 3) | 1.049 | 1.247 | 1.216 | 1.103 | 0.885 | 0.843 | **0.791** | 1.134 |
| PLS (k = 5) | 1.148 | 1.303 | 1.187 | 1.304 | 0.934 | 1.056 | 0.940 | 1.057 |
| RR ($v_2$ = 0.25) | 1.689 | 1.494 | 1.470 | 1.876 | 0.967 | 0.910 | 0.963 | 1.149 |
| RR ($v_2$ = N) | 0.984 | 1.056 | 1.067 | 1.088 | 0.902 | **0.798** | 0.821 | 1.082 |
| RR ($v_2$ = 5N) | 0.984 | 1.000 | 0.970 | 1.010 | 0.934 | 0.865 | 0.881 | 1.021 |
| RR ($v_2$ = 10N) | 0.967 | **0.966** | 0.933 | 1.010 | 0.934 | 0.888 | 0.896 | 1.005 |
| EN (30 variables, $v_2$ = 0.25) | 1.033 | 1.247 | 1.358 | 1.206 | 1.049 | 0.888 | 0.993 | 1.113 |

## (h) International subset = world commodity prices only

| | International | | | | New Zealand + international | | | |
|---|---|---|---|---|---|---|---|---|
| | h = 1 | h = 2 | h = 4 | h = 8 | h = 1 | h = 2 | h = 4 | h = 8 |
| Univar. benchm. (RMSE/h) | 0.0061 | 0.0063 | 0.0067 | 0.0069 | 0.0061 | 0.0063 | 0.0067 | 0.0069 |
| PC (r = 1) | 0.984 | 1.034 | 1.037 | 1.031 | 0.951 | 0.865 | 0.993 | 1.119 |
| PC (r = 2) | 1.082 | 1.067 | 1.075 | 1.041 | 0.984 | 0.910 | 1.097 | 1.284 |
| PC (r = 3) | 1.082 | 1.079 | 1.060 | 1.026 | 1.000 | 0.910 | 1.276 | 1.325 |
| PC (r = 5) | 1.049 | 1.090 | 1.104 | 1.144 | 1.016 | 0.989 | 1.366 | 1.686 |
| WPCBN (r = 1) | 0.984 | 1.022 | **0.985** | 0.943 | 0.951 | 0.910 | 1.007 | 1.134 |
| WPCBN (r = 2) | 1.033 | 1.067 | 1.015 | 0.948 | 0.934 | 0.831 | 1.194 | 1.144 |
| WPCBN (r = 3) | 1.066 | 1.079 | 1.015 | 0.974 | 1.016 | 0.854 | 1.142 | 1.134 |
| WPCBN (r = 5) | 1.000 | 1.146 | 1.097 | 1.010 | 1.033 | 0.921 | 1.224 | 1.232 |
| WPCSW (r = 1) | 1.033 | 1.090 | 1.075 | 0.995 | 1.066 | 1.180 | 1.134 | 1.077 |
| WPCSW (r = 2) | 1.016 | 1.056 | 1.015 | 0.954 | 0.967 | 0.876 | 1.030 | 1.134 |
| WPCSW (r = 3) | 1.033 | 1.079 | 1.067 | 0.954 | 0.934 | 0.888 | 1.022 | 1.325 |
| WPCSW (r = 5) | 1.049 | 1.101 | 1.075 | 1.067 | 1.016 | 0.899 | 1.112 | 1.294 |
| TPH (r = 1) | 1.049 | 1.180 | 1.231 | 1.242 | 0.951 | 0.978 | 0.970 | 1.015 |
| TPH (r = 2) | **0.951** | 1.225 | 1.246 | 1.057 | 0.967 | 0.955 | 0.955 | 1.320 |
| TPH (r = 3) | 1.180 | 1.213 | 1.090 | 1.000 | 0.984 | 1.034 | 0.978 | 1.273 |
| TPH (r = 5) | 1.164 | 1.079 | 1.149 | 1.175 | 1.131 | 1.000 | 1.470 | 1.402 |
| TPS (30 variables, r = 1) | 0.984 | 1.079 | 1.037 | **0.918** | 1.213 | 1.292 | 1.231 | 1.093 |
| TPS (30 variables, r = 2) | 0.984 | 1.067 | 1.015 | 0.995 | 1.164 | 1.281 | 1.254 | 1.196 |
| TPS (30 variables, r = 3) | 1.000 | 1.045 | 1.097 | 0.933 | 1.115 | 1.169 | 1.306 | 1.284 |
| TPS (30 variables, r = 5) | 0.967 | 1.101 | 1.142 | 1.031 | 1.148 | 1.236 | 1.239 | 1.314 |
| PLS (k = 1) | 1.049 | 1.236 | 1.119 | 1.196 | 0.951 | 0.854 | 0.940 | 1.098 |
| PLS (k = 2) | 1.295 | 1.618 | 1.328 | 1.479 | 1.049 | 1.045 | 1.299 | 1.356 |
| PLS (k = 3) | 1.492 | 1.596 | 1.478 | 1.536 | **0.902** | 0.787 | 0.970 | 1.351 |
| PLS (k = 5) | 1.770 | 1.966 | 1.784 | 1.701 | 0.934 | 1.034 | 1.194 | 1.273 |
| RR ($v_2$ = 0.25) | 2.951 | 3.382 | 3.396 | 3.227 | 1.016 | 0.989 | 1.194 | 1.335 |
| RR ($v_2$ = N) | 1.148 | 1.247 | 1.104 | 1.093 | **0.902** | **0.820** | 0.948 | 1.165 |
| RR ($v_2$ = 5N) | 1.016 | 1.067 | 1.000 | 0.995 | 0.934 | 0.876 | **0.925** | 1.036 |
| RR ($v_2$ = 10N) | 1.016 | 1.034 | 0.993 | 0.990 | 0.934 | 0.899 | 0.933 | 1.005 |
| EN (30 variables, $v_2$ = 0.25) | 1.934 | 2.112 | 1.746 | 2.325 | 1.049 | 0.933 | 1.299 | 1.057 |

Notes: RMSE(model)/RMSE(univariate). Minima are in bold, and relative RMSEs < 1 are in gray. For the trade-weighted aggregates, we consider the following information: real: GDPs of all 12 countries; prices: CPIs of 12 countries; monetary and financial: interest rates of 5 countries; North America: GDPs and CPIs of the US and Canada and US interest rates; Europe: GDPs, CPIs and interest rates of the euro area and the UK; Asia: GDPs and CPIs of all Asian countries and interest rates of Japan; Australia: Australian GDP, CPI and interest rates. For more details on the forecasting setup, see the text.