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Abstract

A popular approach to forecasting macroeconomic variables is to utilize a large number of predictors. Several regularization and shrinkage methods can be used to exploit such high-dimensional datasets, and have been shown to improve forecast accuracy for the US economy. To assess whether similar results hold for economies with different characteristics, an Australian dataset containing observations on 151 aggregate and disaggregate economic series as well as 185 international variables, is introduced. An extensive empirical study is carried out investigating forecasts at different horizons, using a variety of methods and with information sets containing an increasing number of predictors. In contrast to other countries the results show that it is difficult to forecast Australian key macroeconomic variables more accurately than some simple benchmarks. In line with other studies we also find that there is little to no improvement in forecast accuracy when the number of predictors is expanded beyond 20–40 variables and international factors do not seem to help.

Keywords: Bayesian VAR, bagging, dynamic factor model, ridge regression, least angular regression, shrinkage, regularization.

1 Introduction

Forecasts of macroeconomic variables, in particular key indicators such as GDP growth, inflation and interest rates, are necessary inputs for government budget planning, central bank policy making and business decisions. Forming forecasts based on lags of other macroeconomic variables is an approach that dates back at least as far as efforts by Mitchell and Burns (1938) and Burns and Mitchell (1946) to find leading indicators of the business cycle. The use of time series approaches for macroeconomic forecasting gained impetus in the 1970s and 1980s as forecasts from univariate ARIMA models (Box & Jenkins, 1970) and vector autoregressions (VARs) (Sims, 1980) were shown to outperform structural macroeconomic models (for a discussion of this history see Diebold, 1997, and references therein). During this era, the information sets used to form forecasts typically contained only a small number of variables.

This situation changed in the early 2000s as researchers began to compose high-dimensional macroeconomic datasets. Two of the earliest and most widely used examples are the US dataset containing 149 variables measured at a monthly frequency featured in Stock and Watson (2002) (hereafter referred to as the 'Stock and Watson data'), and the Euro area dataset containing 447 variables measured at a monthly frequency featured in Forni, Hallin, Lippi and Reichlin (2003).

In both studies, utilising a large number of predictors in a dynamic factor modelling (DFM) framework (see Geweke, 1977; Sargent & Sims, 1977) leads to improved forecasts of industrial production relative to standard benchmarks. A key factor in the popularity of this approach is its simplicity; principal components provide consistent estimates of the dynamic factors and can subsequently be used in auxiliary predictive regressions. There is an extensive literature that establishes how the DFM, when used with a large number of predictors, yields good forecasts for macroeconomic variables such as output and inflation for a number of different economies (see Eickmeier & Ziegler, 2008, for an overview).

Despite its success, the DFM is by no means the only framework for forecasting with a large number of predictors. Advances from the statistics and machine learning literature have also been exploited in the macroeconomic context. For example, De Mol, Giannone and Reichlin (2008) consider both ridge regression and the LASSO (see Tibshirani, 1996) for the Stock and Watson data and obtain forecasts that have a similar performance to those obtained from a DFM. Bai and Ng (2008) use least angular regression or LARS (Efron, Hastie, Johnstone & Tibshirani, 2004) to select a set of 'targeted predictors'. Forecasts are then produced using either these targeted predictors on their own, or alternatively by using the principal components of the targeted predictors. Bai and Ng (2008) show that at least for some periods of the data, methods based on LARS produces better forecasts of CPI, personal income, retail sales, industrial production and total employment compared to the case where principal components are formed using the full information set. Methods that account for model uncertainty such as bootstrap aggregation or 'bagging' (see Breiman, 1996; Bühlmann & Yu, 2002; Lee & Yang, 2006) have been successful in forecasting inflation by Inoue and Kilian (2008). Finally, in the class of multivariate forecasting there has been a focus on "big" VARs estimated using Bayesian techniques. Examples include Kadiyala and Karlsson (1997), and more recently Bańbura, Giannone and Reichlin (2010), Carriero, Kapetanios and Marcellino (2011) and Koop (2013) who utilize shrinkage priors including the so-called Minnesota prior of Doan, Litterman and Sims (1984) and Litterman (1986).

Although the literature on macroeconomic forecasting with a large number of predictors is vast, it is possible to make some general conclusions. First, somewhat unsurprisingly, there is no single method that dominates all alternatives for every series at every horizon. Second, the benefit from expanding the information set beyond 20–40 variables is often small, a conclusion particularly supported by Bai and Ng (2008), Bańbura et al. (2010) and Koop (2013). Third, forecasts based on principal components are highly competitive. In a thorough empirical study

Stock and Watson (2012) conclude that *"it will be difficult to improve systematically upon DFM forecasts using time-invariant linear functions of the principal components of large macro datasets like the one considered here."*.

Since these conclusions have been formed on the basis of using only US data, it is worthwhile questioning whether the same results can be found for other economies with vastly different characteristics to the US. A major contribution of this paper is to introduce an extensive Australian macroeconomic data set comparable in size to that of the US, comprising 151 quarterly Australian macroeconomic variables which naturally divide into 12 categories of macroeconomic activity. To the best of our knowledge, such a dataset has not been analysed previously, and since Australia is a small open economy it provides an interesting point of contrast with the excessively mined Stock and Watson US data. A notable exception is Eickmeier and Ng (2011) who focus on New Zealand, a small open economy similar to Australia. Eickmeier and Ng (2011) find that adding international predictors assisted substantially in forecasting New Zealand GDP. We investigate here if this conclusion is also applicable to Australia by adding to the predictor set another 185 international variables.

Using these variables we undertake an empirical comparison of the aforementioned approaches, including the dynamic factor model, in the context of forecasting Australian macroeconomic variables. We focus our attention on forecasting three key variables, namely Gross Domestic Product (GDP) growth, Consumer Price Index (CPI) inflation and the overnight IBR (interbank rate). The IBR is closely related to the 'cash rate', the main monetary policy instrument targeted by the Australian central bank. We use the IBR here as the cash rate series only begins in August 1990. The two series are essentially identical over the period for which they are both available. To investigate the value of expanding the number of predictors, we consider information sets of increasing sizes similar to Bańbura et al. (2010) and Koop (2013). To facilitate this analysis, we complement tabulated results with a set of scatter plots which assist in effectively visualising a large amount of information.

The rest of the paper is organised as follows. In Section 2, we provide the details of the Australian macroeconomic data set. Section 3 describes the alternative forecasting approaches we implement in this paper. Section 4 introduces the measures of forecast accuracy we use and Section 5 gives the main empirical results.

2 An Australian Macroeconomic Data Set

The Australian macroeconomic data set compiled for this study comprises 151 variables collected from the Australian Bureau of Statistics (ABS) and the Reserve Bank of Australia (RBA). The series IDs assigned by either the ABS or the RBA are recorded in Table 5. The variables naturally divide into 12 categories shown in Table 6. Each variable consists of 123 quarterly observations spanning the period Q4 1984 to Q2 2015. Variables which are observed at a monthly frequency are aggregated to quarterly by averaging over the 3 months in a quarter (as in Koop, 2013). Each variable is transformed to stationary (similar to Stock & Watson, 2012), with the transformations listed in Table 7.

The complete data set is available from the Australian Macro Database (AMD) at http://ausmacrodata.org/research.php. This link provides two files. The first contains the variables as used in this paper. Hence, the file contains all the variables observed over the above mentioned time span and after transformation to stationarity. The second file contains an up-to-date version for each of the raw (untransformed) variables. Each variable is updated automatically when new updates are released by the ABS or the RBA. For more details see Behlul, Panagiotelis, Athanasopoulos, Hyndman and Vahid (2017).

Let $\mathcal{I}_K$ denote an *information set* containing K macroeconomic variables with $|\mathcal{I}_K| = K$. In this paper, we evaluate the empirical performance of the competing forecasting methods with nested subsets of predictors with different values of K, specifically $\mathcal{I}_3 \subset \mathcal{I}_{13} \subset \mathcal{I}_{23} \subset \mathcal{I}_{43} \subset \mathcal{I}_{151} \subset \mathcal{I}_{336}$. This allows us to investigate the impact of utilizing information sets of differing sizes.

The motivation for considering these nested sets is similar to that of Bańbura et al. (2010) and Koop (2013). Tables 8–12 provide a detailed description of each variable, along with the transformation applied to achieve stationarity, as well as the category to which each variable belongs.

To further illustrate, the smallest of the information subsets $\mathcal{I}_3$ (see Table 8) contains real GDP growth, CPI inflation and IBR (the interbank overnight cash rate equivalent to the Federal funds rate in the US). These are widely considered as three of the more important variables in macroeconomic forecasting and they have been used in many simple DSGE models (see for example An & Schorfheide, 2007; Bańbura et al., 2010; Christiano, Eichenbaum & Evans, 1999). The information subset $\mathcal{I}_{13}$ (see Table 9) includes in addition to the three variables in $\mathcal{I}_3$, the Australian versions of those variables modelled in: the small VAR of Bańbura et al.

(2010) (the total number of persons employed); the medium VAR of Koop (2013) (the industrial production index, private dwelling approvals and the S&P ASX AllOrds stock price index); and the monetary model of Christiano et al. (1999) (the commodity price index of Australia, M1 and total credit). Since Australia, in contrast to the US, is a small open economy we also include in this set, terms of trade, import and export volumes (Dungey & Pagan, 2009).

The set $\mathcal{I}_{23}$ (see Table 10) contains the remaining 10 variables which are mostly aggregate information, e.g., consumption, labour, money, exchange rates. These variables account for other aspects of the economy not accounted for in $\mathcal{I}_{13}$. In general, the variables chosen in this scenario are analogous to those selected by Koop (2013) who refer to these as "medium" scale models.

Combining the variables included in the preceding information subsets with an additional 20 variables leads to the information set $\mathcal{I}_{43}$ (see Table 11). It consists of the majority of aggregate variables in the information set. Koop (2013) refers to these as "medium-large" scale models. Finally, we consider the largest information set $\mathcal{I}_{151}$ (see Table 12) by adding the remaining 108 variables which are mostly disaggregate variables.

2.1 International Data

We have also compiled an international data set containing 134 economic variables from China, the Euro Area, Japan and the US which together account for almost half of Australia's total trade and an additional 51 commodity prices. These international variables combined with the Australian data leads to an extended information set $\mathcal{I}_{336}$ (see Table 13). In a recent paper, Bjørnland, Ravazzolo and Thorsrud (2017) investigate the marginal predictive power of a global factor extracted from real GDP growth rate of 33 countries for forecasting real GDP growth in each country. Australia and New Zealand are two countries where this global factor does not reduce the root mean squared error relative to the autoregressive benchmark. However, Eickmeier and Ng (2011) compile a more "supervised" international data set for New Zealand (in the sense that the countries are selected judiciously to have relevance to the New Zealand economy), and they find that including the international data does improve forecasts. We therefore follow Eickmeier and Ng (2011) in assembling our international data set.

3 Forecasting Methods

We investigate a wide range of forecasting methods applied to the Australian macroeconomic data set described in the previous section. These techniques include univariate benchmarks such as a naïve forecast and the AR model, and some more advanced approaches for forecasting high-dimensional data sets such as the dynamic factor model, ridge regression and least angle regression as well as multivariate Bayesian VARs.

Let $\boldsymbol{x}_t$ be a K-vector with elements $x_{i,t} : i \in \mathcal{I}_K$, where $x_{i,t}$ is the value of macroeconomic variable i at time t, after it has (i) been transformed to stationarity, (ii) centered by subtracting the mean, and (iii) standardised by dividing by the standard deviation. Also define $\boldsymbol{z}_t := \left(\boldsymbol{x}_t', \boldsymbol{x}_{t-1}', \ldots, \boldsymbol{x}_{t-p+1}'\right)'$ as a Kp-vector containing all the information (including lagged information) available at time t. Finally define y_t as the target variable which will be an element of $\boldsymbol{x}_t$. All methods that we consider provide forecasts which are linear combinations of the predictors, allowing us to use the following general form

$$\hat{y}_{t+1}^M = \boldsymbol{x}_t'\hat{\boldsymbol{\theta}}_1^M + \boldsymbol{x}_{t-1}'\hat{\boldsymbol{\theta}}_2^M + \cdots + \boldsymbol{x}_{t-p+1}'\hat{\boldsymbol{\theta}}_p^M \tag{3.1}$$

where $\hat{y}_{t+1}^M$ is an one-step-ahead forecast of the target variable using forecasting method M and $\hat{\boldsymbol{\theta}}_\ell^M := \left(\hat{\theta}_{1,\ell}, \hat{\theta}_{2,\ell}, \ldots, \hat{\theta}_{K,\ell}\right)'$ where $\hat{\theta}_{i,\ell}$ is the weight placed on the ℓth lag of the ith variable in information set $\mathcal{I}_K$. This can also be expressed in terms of the stacked form as

$$\hat{y}_{t+1}^M = \boldsymbol{z}_t'\hat{\boldsymbol{\theta}}^M \tag{3.2}$$

where $\hat{\boldsymbol{\theta}}^M := \left(\hat{\boldsymbol{\theta}}_1^{M'}, \hat{\boldsymbol{\theta}}_2^{M'}, \ldots, \hat{\boldsymbol{\theta}}_p^{M'}\right)'$ is a Kp-vector. Note that Equations (3.1) and (3.2) specify a one-step-ahead forecast. Although our focus is on GDP growth, CPI inflation and IBR, we produce forecasts of all predictors in $\mathcal{I}_k$ so that they can subsequently be used as inputs to form multistep ahead forecasts in a recursive fashion. Marcellino, Stock and Watson (2006) provide some justification for using iterated forecasts rather than direct forecasts as do Hsu, Hung and Chang (2008), in the context of LARS. For our data, direct forecasts were not appreciably better than iterated forecasts and are thus not considered in what follows. For the DFM producing forecasts in an indirect fashion would also require the specification of a forecasting model for the factors. Since our results will be sensitive to the choice of forecasting model for the factors we follow what is typically implemented in the literature and employ a direct forecasting method for the DFM instead. We discuss this further in Section 3.2.

3.1 Benchmarks

Two benchmark models are used to facilitate the empirical evaluation undertaken in this paper. The first benchmark we consider is the sample mean which in this setting forms a natural naïve benchmark. Since the data are mean corrected, $\hat{y}_{t+1}^{\text{naive}} = 0$ implying $\hat{\boldsymbol{\theta}}^{\text{naive}} = 0$. It is worth noting that for macroeconomic variables of interest such as GDP and the interbank overnight cash rate which usually require first-differencing for stationarity, the sample mean forecast is equivalent to assuming a random walk model with drift for the original variable.

The second benchmark we consider is the standard AR(p) model. Recalling that $y_t = x_{j,t}$, in the general framework of Equation (3.2),

$$\begin{aligned} \hat{\theta}_{i,\ell}^{AR} &\neq 0 \quad \text{if} \quad i = j \\ \hat{\theta}_{i,\ell}^{AR} &= 0 \quad \text{if} \quad i \neq j. \end{aligned}$$

The non-zero weights are found as estimates of an AR(p) model. It is worth noting that AR(p) forecasts only utilize the information in the target series and therefore form a natural benchmark against the univariate forecast procedures which extract information from a large number of predictors. We select p by minimising the BIC with a maximum lag of $p = 4$. These are denoted as "AR" in the results that follow.

3.2 Dynamic Factor Model (DFM)

The dynamic factor model assumes that r_D unobserved dynamic factors can summarize the information set of the predictors $\boldsymbol{x_t}$ where $r_D \ll K$. More precisely we assume that $\boldsymbol{x}_t$ admits the approximate factor structure

$$\boldsymbol{x}_t = \boldsymbol{\Lambda} \boldsymbol{f}_t + \boldsymbol{\xi}_t$$

in which $\boldsymbol{\Lambda}$ is a $K \times r_D$ matrix of factor loadings, $\boldsymbol{f}_t$ are the r_D unobserved factors and $\boldsymbol{\xi}_t$ is a vector of idiosyncratic errors which can be weakly inter-correlated (e.g., Fan, Liao & Mincheva, 2013). Stock and Watson (2002) show that the first r_D principal components of the data can consistently estimate the r_D unobserved factors under the assumptions of the DFM. If $\boldsymbol{W}$ is a

$K \times r_D$ matrix with columns given by the first r_D eigenvectors of $S_X = (T-1)^{-1} \sum_{t=1}^{T} \boldsymbol{x}_t \boldsymbol{x}_t'$, then the factors at time t are estimated by

$$\hat{\boldsymbol{f}}_t = \boldsymbol{W}' \boldsymbol{x}_t \tag{3.3}$$

To operationalize this framework as a forecasting model for h-step-ahead forecasting, y_{t+h} is regressed upon $\hat{\boldsymbol{f}}_t, \hat{\boldsymbol{f}}_{t-1}, \ldots \hat{\boldsymbol{f}}_{t-p+1}$. The h-step-ahead forecasts from the dynamic factor model are derived directly as

$$\hat{y}_{t+h}^{\mathrm{DFM}} = \hat{\boldsymbol{f}}_t' \hat{\boldsymbol{\delta}}_1 + \hat{\boldsymbol{f}}_{t-1}' \hat{\boldsymbol{\delta}}_2 + \cdots + \hat{\boldsymbol{f}}_{t-p+1}' \hat{\boldsymbol{\delta}}_p, \tag{3.4}$$

where $\hat{\boldsymbol{\delta}}_\ell$ is an r_D-vector of coefficients estimated by least squares, that corresponds to the ℓth lag of the factors in the auxillary regression. Despite the use of a two-step procedure, the forecast is still a linear function of the predictors. Substituting Equation (3.3) into Equation (3.4) and using the notation of Equation (3.1) yields

$$\hat{\boldsymbol{\theta}}_\ell^{\mathrm{DFM}} = \hat{\boldsymbol{W}} \hat{\boldsymbol{\delta}}_\ell.$$

3.3 Ridge Regression

Ridge regression is a method that shrinks the estimates of regression coefficients towards zero relative to the least squares solution. It can be motivated by adding a penalty on the L_2 norm of the coefficients to the usual sum of squared errors objective function, or in a Bayesian context by assuming a conjugate Gaussian prior on the coefficients. In our context, ridge regression implies that the forecasts weights have the following closed form

$$\hat{\boldsymbol{\theta}}^{\mathrm{ridge}} = \left(\sum_{t=p}^{T} \boldsymbol{z}_{t-1} \boldsymbol{z}_{t-1}' + r_R \boldsymbol{I}_{Kp} \right)^{-1} \left(\sum_{t=p}^{T} \boldsymbol{z}_{t-1} y_t \right),$$

where $r_R \geq 0$ is a parameter the controls the amount of shrinkage on the ridge coefficients and $\boldsymbol{I}_{Kp}$ is a $Kp \times Kp$ identity matrix.

It is worth noting some similarities between the dynamic factor modelling approach, which is effectively a principal components regression, and ridge regression. Principal components analysis considers a rotated version of the predictor space and shrinks the coefficients corresponding to smaller eigenvalues to be exactly zero. When ridge regression is considered in this rotated space, coefficients are shrunk by a factor of $d_i^2/(d_i^2 + r_R)$ where d_i is the ith largest eigenvalue of $S_Z = (T-p-1)^{-1}\sum_{t=p}^{T} \boldsymbol{z}_{t-1}\boldsymbol{z}'_{t-1}$. Since the $d_i^2/(d_i^2+r_R)$ is close to zero for small d_i, ridge regression shrinks the coefficients corresponding to smaller eigenvalues towards zero to a greater degree than coefficients corresponding to large eigenvalues, but in contrast to principal components regression, ridge regression does not shrink any of these coefficients exactly to zero.

3.4 Least Angle Regression (LARS)

Least angle regression is a shrinkage and variable selection method proposed by Efron et al. (2004) and is motivated by the forward selection and the forward stagewise methods for selecting regression models (e.g., Hastie, Tibshirani & Friedman, 2009). A comprehensive formulation of the technical details underlying the LARS algorithm can be found in Efron et al. (2004), but we summarise the main features here. The LARS algorithm is initialised at a null model that includes no predictors. In our context, the dependent variable is y_t and the set of potential predictors is $\boldsymbol{z}_{t-1}$, although in the following discussion, the time index t and $t-1$ will be dropped for convenience. Let $\mathcal{S}_k$ be the set of predictors included at step k of the LARS algorithm. At step k of the algorithm, the coefficients of the predictors are updated in an equiangular fashion towards the least squares solution of a regression of y on $z_i : z_i \in \mathcal{S}_k$, with the residual given by e_k. This proceeds until the correlations between e_k and the $z_i : z_i \in \mathcal{S}_k$ are equal to the correlation between e_k and some $z_{i'} \notin \mathcal{S}_k$. The algorithm proceeds to step $k+1$, we define $\mathcal{S}_{k+1} = \{\mathcal{S}_k, z_{i'}\}$ and the coefficients are now updated in the direction of the least squares solution of a regression of y on $z_i \in \mathcal{S}_{k+1}$.

It is worth noting that the selection process of the LARS algorithm actually delivers a ranking of the predictors. This is a great advantage when forecasting with a handful of economic variables as practitioners can get a feel for which variables are more important than the others. Moreover, at no further computational cost, the LARS algorithm can be used to implement forward stagewise selection. In practice, the LARS algorithm often provides a solution to the LASSO objective function

$$\hat{\boldsymbol{\theta}}_i^{\mathrm{LARS}} = \underset{\boldsymbol{\theta}}{argmin} \sum_{t=1}^{T} (y_t - \boldsymbol{z}'_{t-1}\boldsymbol{\theta})^2 + r_{LARS}\sum_{j=1}^{Kp} |\theta_j|,$$

where a minor modification to the LARS algorithm guarantees equivalence. The total level of shrinkage is controlled by the number of variables selected which we denote as r_L. This implies that for LARS the forecasts in Equation (3.2) are given by a sparse linear combination of the predictors where,

$$\hat{\theta}_i^{\text{LARS}} \neq 0 \quad \forall i : z_{i,t-1} \in \mathcal{S}_{r_L}$$
$$\hat{\theta}_i^{\text{LARS}} = 0 \quad \forall i : z_{i,t-1} \notin \mathcal{S}_{r_L}.$$

3.5 Bagging LARS

Bootstrap aggregation or bagging (e.g., Breiman, 1996) is a prevalent device for improving the accuracy and stability of statistical learning algorithms. Rather than training the parameters once, bootstrap samples are taken, the parameters are trained on each bootstrap sample and are then averaged.

In macroeconomic forecasting, bagging has been used in conjunction with pretest methods for variable selection whereby variables are included only if their corresponding t-statistics exceed some hard threshold (see Inoue & Kilian, 2008; Stock & Watson, 2012, for more details). Rather than follow Inoue and Kilian (2008) and Stock and Watson (2012) we use bagging in conjunction with LARS rather than the pretest method for three main reasons. First, for $K = 151$, the number of predictors is larger than the number of observations, a scenario that cannot be handled by the pretest methods but can be handled by LARS. Second, pretest methods can select predictors that are highly correlated with one another, which as Bai and Ng (2008) point out, can be avoided by LARS. Selecting highly correlated predictors reduces the benefit from bagging since model averaging is most effective when the predictors carry distinct information. Third, bagging with LARS has a computational cost of the same order as ordinary least squares. In the empirical evaluation that follows we refer to forecasts generated from bagging LARS as "BagL" or "Bag-LARS". If we let $\hat{\theta}_b^{\text{LARS}}$ be the coefficients obtained in the manner described in Section 3.4 but for bootstrap sample b then by the linearity of our forecasts

$$\hat{\theta}^{\text{BagL}} = \sum_{b=1}^{B} \hat{\theta}_b^{\text{LARS}},$$

where B is the total number of bootstrap samples. Given the similarities between LASSO and LARS our approach is similar to Bach (2008).

3.6 A Bayesian VAR

The multivariate forecast method we focus on is a Bayesian VAR (see for example, Bańbura et al., 2010; Carriero et al., 2011; Koop, 2013). Unlike the conventional VARs that only include a small number of variables (typically less than ten), such Bayesian VARs can allow for quite a large number of predictors. For instance, the BVAR of Bańbura et al. (2010) contains 131 predictors.

In the previous sections we have let $\boldsymbol{x}_t$ be the K-dimensional vector the elements of which are the macroeconomic variables in the information set $\mathcal{I}_K$. Thus, a multivariate VAR(p) can be expressed as

$$\boldsymbol{x}_{t+1} = \boldsymbol{A}_1\boldsymbol{x}_t + \boldsymbol{A}_2\boldsymbol{x}_{t-1} + \cdots + \boldsymbol{A}_p\boldsymbol{x}_{t-p+1} + \boldsymbol{e}_{t+1}, \tag{3.5}$$

where $\boldsymbol{e}_{t+1}$ is a vector of errors distributed independently $N(0,\Sigma)$ across t and $\{\boldsymbol{A}_i; i = 1,2,\ldots,p\}$ are $K \times K$ autoregressive coefficient matrices. As in the previous sections trends and means are assumed to have been properly removed.

Recalling $\boldsymbol{z}_t = \left(\boldsymbol{x}_t', \boldsymbol{x}_{t-1}', \ldots, \boldsymbol{x}_{t-p+1}'\right)'$ and denoting $\boldsymbol{A} = (\boldsymbol{A}_1, \boldsymbol{A}_2, \ldots, \boldsymbol{A}_p)'$, the model (3.5) can be alternatively expressed as

$$\underset{(T^*\times K)}{\boldsymbol{X}} = \underset{(T^*\times Kp)}{\boldsymbol{Z}}\;\underset{(Kp\times K)}{\boldsymbol{A}} + \underset{(T^*\times K)}{\boldsymbol{\mathcal{E}}},$$

where $\boldsymbol{X} = \left(\boldsymbol{x}_{p+1}, \ldots, \boldsymbol{x}_T\right)'$, $\boldsymbol{Z} = \left(\boldsymbol{z}_p, \ldots, \boldsymbol{z}_{T-1}\right)'$ and $\boldsymbol{\mathcal{E}} = \left(\boldsymbol{e}_{p+1}, \ldots, \boldsymbol{e}_T\right)'$ such that $\mathrm{vec}(\boldsymbol{\mathcal{E}}) \sim N(0, \Sigma \otimes \boldsymbol{I}_{T^*})$.

We employ a normal-inverted Wishart prior proposed by Kadiyala and Karlsson (1997)

$$\mathrm{vec}(\boldsymbol{A})|\Sigma \sim N(\mathrm{vec}(\boldsymbol{A}_0), \Sigma \otimes \boldsymbol{\Omega}_0), \qquad \Sigma \sim iW(\boldsymbol{v}_0, \boldsymbol{S}_0), \tag{3.6}$$

where the parameters $\boldsymbol{v}_0, \boldsymbol{S}_0, \boldsymbol{A}_0, \boldsymbol{\Omega}_0$ are hyper-parameters set as follows. The values of $\boldsymbol{A}_0$ and $\boldsymbol{\Omega}_0$ are set according to the Minnesota prior (Litterman, 1986):

$$\mathrm{E}\left[A_\ell^{(i,j)}\right] = \begin{cases} 0, & i = j,\ \ell = 1; \\ 0 & \text{otherwise}; \end{cases} \qquad \mathrm{Var}\left[A_\ell^{(i,j)}\right] = \begin{cases} \frac{r_V^2}{\ell^2}, & i = j; \\ \frac{r_v^2}{\ell^2}\frac{\sigma_i^2}{\sigma_j^2} & \text{otherwise}; \end{cases}$$

where $A_\ell^{(i,j)}$ is element (i,j) of the coefficient matrix $\boldsymbol{A}_\ell$. Our formulation here differs slightly from the original paper by Litterman (1986) who shrinks all non-stationary variables to a random walk by setting $\mathrm{E}[A_\ell^{(i,j)}] = 1$ for all i corresponding to non-stationary variables. Since we transform all variables to be stationarity, this is not relevant in our context. The shrinkage on the coefficients is determined by the hyper-parameter r_V. The values of ν_0 and $\boldsymbol{S}_0$ are chosen such that the prior expectation of Σ is the fixed residual covariance matrix $\mathrm{diag}\{\sigma_1^2, \sigma_2^2, \dots, \sigma_K^2\}$. This a priori expected value of Σ is the same as for the Minnesota prior, however in contrast to the Minnesota prior, there is some prior support for non-zero correlations between error terms under the normal-inverted Wishart prior.

The prior given in (3.6) together with the likelihood given in 3.5 lead to the conditional posteriors which are also normal-inverted Wishart,

$$\mathrm{vec}(\boldsymbol{A}) \mid \Sigma, \boldsymbol{X}, \boldsymbol{Z} \sim N(\mathrm{vec}(\overline{\boldsymbol{A}}), \Sigma \otimes \overline{\boldsymbol{\Omega}}), \qquad \Sigma \mid \boldsymbol{X}, \boldsymbol{Z} \sim iW(\overline{\boldsymbol{v}}, \overline{\boldsymbol{S}})$$

where $\overline{\boldsymbol{A}} = (\boldsymbol{\Omega}_0^{-1} + \boldsymbol{Z}'\boldsymbol{Z})^{-1}(\boldsymbol{\Omega}_0^{-1}\boldsymbol{A}_0 + \boldsymbol{Z}'\boldsymbol{X})$, $\overline{\boldsymbol{\Omega}} = (\boldsymbol{\Omega}_0^{-1} + \boldsymbol{Z}'\boldsymbol{Z})^{-1}$. Due to conjugacy, Σ can be integrated out analytically leading to a multivariate t distribution for $\mathrm{vec}(\boldsymbol{A}) \mid \boldsymbol{X}$ with posterior expectation $\mathrm{vec}(\overline{\boldsymbol{A}}) = \mathrm{vec}\Big((\boldsymbol{\Omega}_0^{-1} + \boldsymbol{Z}'\boldsymbol{Z})^{-1}(\boldsymbol{\Omega}_0^{-1}\boldsymbol{A}_0 + \boldsymbol{Z}'\boldsymbol{X})\Big)$ (Zellner, 1971).

The Bayesian VAR also generates forecasts that are linear combinations of the predictors. To express this in the form of Equation 3.2 we isolate a single element of $\boldsymbol{x}_t$, namely $y_t = x_{j,t}$, and the weights on the predictors for a one-step-ahead forecast are given by

$$\hat{\theta}^{\mathrm{BVAR}} = \overline{\boldsymbol{a}}_j\,,$$

where $\overline{\boldsymbol{a}}_j$ denotes the jth column of $\overline{\boldsymbol{A}}$

3.7 Setting Regularisation Parameters

The levels of regularization in the dynamic factor modelling approach, the ridge regression, LARS and Bayesian VAR depend on a parameter denoted r_D, r_R and r_L and r_B respectively. In the case of the dynamic factor model we employ the maximum eigenvalue ratio estimator of Ahn and Horenstein (2013) $r_D = \underset{k}{argmax}\frac{\lambda_k}{\lambda_{k+1}}$, where λ_k is the k^{th} eigenvalue of $\boldsymbol{Z}'\boldsymbol{Z}$, while the number of lags used to form $\boldsymbol{Z}$ is determined by minimising BIC. For ridge and LARS we use cross-validation, a choice supported by the conclusion in Bergmeir, Hyndman and Koo (2015) that cross validation is valid when statistical learning methods are applied to purely autoregressive models. The default setting of 10-fold cross validation was used in the R-packages, glmnet (version 2.0.5) and lars (version 1.2) for estimating ridge and LARS respectively. As an alternative, for LARS we also implemented the C_p-type selection criterion proposed by Efron et al. (2004). However, its performance was inferior to that of cross validation and therefore we do not report the results. Finally, for selecting the shrinkage parameter of the Bayesian VAR we follow Bańbura et al. (2010) and Koop (2013). All forecast approaches make use of a maximum of 4 lags of the predictors which includes 4 lags of the dependent variable as well. For all methods, regularisation parameters are re-evaluated for every rolling window.

4 Forecast evaluation

We consider $h = 1$ to 4-steps ahead forecasts for each of the six information sets described in Section 2. We should reemphasise that all the estimation and calculations that follow are based on the variables after transformation to stationarity. The forecast evaluation begins using a training window of 10 years, i.e., 40 observations. Each model is estimated within this window from which $h = 1$ to 4–steps-ahead forecasts are generated. The window is then rolled forward one quarter at a time until the end of the sample (similar to Stock & Watson, 2012). Sample means, sample variances and models are re-estimated and forecasts are generated with each step. This results in $75 - h$ out-of-sample forecasts for each forecast horizon h, which are used to evaluate the forecast performances of the competing models.

We consider two measures of forecasting accuracy: RMSE (root mean squared error) and MASE (mean absolute scaled error) (see Hyndman & Koehler, 2006, for further details). As mentioned in Section 3, each variable is standardised using the sample mean and variance of each estimation window before the methods are applied. The RMSE and MASE vary in nature in that the former is a scale dependent measure while the latter is a scale independent measure. We calculate both forecast error measures on the standardised variables.

An important issue to be aware of is the stability of forecast performance over time. In the context of macroeconomic data, even when a useful predictor or method is found for a certain subsample of data, its performance may deteriorate in the future due to a structural break. Rerunning all selection algorithms over the running window may mitigate this to some extent. However, to further investigate the stability of forecasting algorithms we conduct the forecast breakdown test of Giacomini and Rossi (2009) which is based on the distance between in-sample and out of sample values of the loss function. In all cases a one-sided test is performed with a 5% level of significance.

5 Empirical results

Table 1: *Forecast accuracy for $h = 1$ to 4. Each entry shows RMSE relative to the naïve benchmark. K denotes the number of predictors in the information set used. BagL denotes Bagging-LARS. Bold entries indicate the lowest error measure achieved by the competing approaches for the variable of interest across each row, i.e., using an increasing number of predictors.*

	$K = 3$	13	23	43	151	336	3	13	23	43	151	336	3	13	23	43	151	336
	GDP growth						CPI inflation						IBR					
								h=1										
DFM	1.11	1.14	1.16	**1.07**	1.16	1.34	**1.00**	1.05	1.12	1.03	1.07	1.07	0.80	**0.75**	0.81	0.78	0.80	0.93
Ridge	1.03	**1.00**	1.01	1.01	1.05	1.05	1.06	1.00	1.00	0.99	**0.96**	1.03	0.81	0.85	0.84	**0.77**	0.79	0.79
LARS	1.02	**1.00**	1.05	1.00	1.01	1.00	1.02	1.01	1.01	**1.00**	**1.00**	1.01	0.92	0.93	0.93	**0.85**	0.86	0.88
BLAR	1.04	1.02	1.03	1.02	1.02	**1.01**	**0.92**	0.99	0.96	0.95	0.97	0.99	0.82	0.82	0.82	**0.73**	0.78	0.76
BVAR	1.34	1.02	**1.01**	**1.01**	**1.01**	**1.01**	**0.91**	0.98	1.01	0.99	0.98	0.98	0.97	**0.82**	0.86	0.84	0.87	0.87
AR			*1.06*						*0.89*						*0.77*			
								h=2										
DFM	1.18	1.10	1.20	**1.06**	**1.06**	1.13	**1.01**	1.09	1.25	1.07	1.08	1.07	0.96	0.99	1.06	0.99	**0.92**	0.98
Ridge	1.09	1.02	1.03	1.01	1.03	**0.92**	1.15	1.01	1.00	**0.99**	1.02	1.03	0.95	0.94	0.96	**0.93**	0.94	1.01
LARS	1.04	1.00	1.00	1.01	1.04	**0.89**	1.05	1.00	1.01	1.01	1.00	**0.99**	0.97	0.97	1.00	0.97	**0.95**	0.98
BLAR	1.04	1.03	1.03	1.01	1.01	**0.90**	1.02	1.01	1.01	**1.00**	1.01	**1.00**	0.95	**0.94**	0.97	**0.94**	0.96	0.95
BVAR	1.35	**1.00**	1.01	**1.00**	**1.00**	**1.00**	1.12	1.01	1.01	1.00	**1.00**	**1.00**	1.10	**0.95**	0.97	0.96	0.96	0.96
AR			*1.00*						*1.03*						*0.97*			
								h=3										
DFM	1.18	1.14	1.28	**1.04**	**1.04**	1.18	**1.02**	1.07	1.33	1.06	**1.02**	**1.02**	1.03	1.10	1.28	**0.91**	1.19	1.11
Ridge	1.09	1.03	**1.00**	1.02	1.02	**1.00**	1.11	1.00	**0.98**	0.99	1.00	1.01	1.03	0.98	1.00	**0.97**	0.99	1.07
LARS	**1.00**	**1.00**	1.01	1.05	1.01	**1.00**	1.05	**1.00**	1.01	**1.00**	1.03	1.02	1.00	1.01	1.02	1.01	**0.99**	**0.99**
BLAR	1.03	1.02	1.03	1.01	**0.99**	**0.99**	1.01	1.00	1.00	1.00	1.01	**0.99**	**0.98**	**0.98**	1.01	**0.98**	**0.98**	**0.98**
BVAR	1.34	1.01	**1.00**	**1.00**	**1.00**	**1.00**	1.09	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	1.11	**0.99**	1.00	**0.99**	1.00	1.00
AR			*1.01*						*1.02*						*1.05*			
								h=4										
DFM	1.09	1.12	1.20	1.15	**1.07**	1.14	1.07	1.04	1.21	1.05	1.01	**1.00**	1.03	1.07	1.14	**1.00**	1.14	1.14
Ridge	1.04	1.02	1.02	**1.01**	1.02	1.02	1.05	0.99	**0.98**	0.99	0.99	1.00	1.05	0.99	1.00	**0.98**	1.01	1.05
LARS	1.00	1.00	1.01	1.00	1.01	**0.99**	1.00	1.00	1.00	1.00	1.00	**0.99**	1.00	1.01	1.01	1.00	**0.99**	1.01
BLAR	**1.00**	1.01	1.01	**1.00**	1.01	1.01	1.00	0.99	0.99	1.00	1.00	**0.98**	**0.99**	1.00	1.01	**0.99**	**0.99**	1.00
BVAR	1.24	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	1.20	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	1.19	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
AR			*1.01*						*1.01*						*1.06*			

Table 1 presents the forecast accuracy for $h = 1$ to 4-steps ahead of the alternative approaches across the three key macroeconomic variables of interest: GDP growth, CPI inflation and IBR. Each entry shows the RMSE of the forecast approach relative to the naïve benchmark. K denotes the number of variables included in the information set as defined in Section 2. The entries in bold show the minimum RMSE achieved by each alternative approach using information sets of varying sizes. Our interest here is to assess the value added to forecasting key Australian macroeconomic variables by increasing the size of the information set and by also including international variables. The results based on the MASE are presented in Table 2. The results are

Table 2: *Forecast accuracy for $h = 1$ to 4. Each entry shows MASE relative to the naïve benchmark. K denotes the number of predictors in the information set used. BagL denotes Bagging-LARS. Bold entries indicate the lowest error measure achieved by the competing approaches for the variable of interest across each row, i.e., using an increasing number of predictors.*

	$K = 3$	13	23	43	151	336	3	13	23	43	151	336	3	13	23	43	151	336
	GDP growth						CPI inflation						IBR					
							h=1											
DFM	**1.08**	1.12	1.19	1.09	1.14	1.29	**1.01**	1.06	1.13	1.04	1.05	1.08	0.79	0.85	0.85	**0.75**	0.80	0.89
Ridge	**1.02**	**1.02**	1.03	1.04	1.06	1.05	1.05	1.01	0.97	**0.96**	0.97	1.04	0.88	0.86	0.83	**0.74**	0.79	0.83
LARS	1.03	**1.00**	1.05	1.01	1.02	1.01	**0.99**	1.03	1.02	1.01	1.01	1.00	0.87	0.93	0.94	**0.77**	0.80	0.83
BLAR	**1.04**	1.05	1.05	1.05	**1.04**	**1.04**	**0.93**	0.98	0.95	0.94	0.94	0.97	0.77	0.83	0.79	**0.71**	0.74	0.74
BVAR	1.34	1.03	**1.02**	**1.02**	**1.02**	**1.02**	**0.95**	0.96	1.00	0.98	0.97	0.97	1.06	0.82	0.83	**0.80**	0.84	0.84
AR	*1.06*						*0.90*						*0.75*					
							h=2											
DFM	1.19	1.13	1.22	**1.11**	**1.11**	1.17	**1.03**	1.13	1.20	**1.03**	1.08	1.06	**0.96**	1.03	1.14	1.03	0.98	1.01
Ridge	1.10	1.06	1.06	1.04	1.03	**0.96**	1.23	1.04	0.99	**0.97**	1.03	1.04	1.02	**0.95**	0.98	**0.95**	1.01	1.10
LARS	1.04	1.00	1.00	1.02	1.06	**0.93**	1.06	1.02	1.02	1.02	**0.97**	0.98	0.97	0.97	1.01	1.01	**0.95**	0.97
BLAR	1.06	1.06	1.05	1.03	1.02	**0.96**	1.02	1.02	0.98	0.98	0.98	**0.97**	**0.93**	0.95	0.97	**0.93**	0.96	**0.93**
BVAR	1.41	1.02	**1.00**	**1.00**	1.01	1.01	1.21	1.01	1.00	**0.99**	1.00	1.00	1.26	0.96	0.96	**0.95**	0.96	0.96
AR	*1.01*						*1.03*						*0.94*					
							h=3											
DFM	1.12	1.13	1.25	1.06	**1.04**	1.16	1.06	1.13	1.29	1.08	**1.04**	**1.04**	1.06	1.12	1.35	**0.99**	1.26	1.14
Ridge	1.09	1.05	1.03	1.04	1.04	**1.01**	1.16	1.02	**0.97**	0.98	1.03	1.03	1.11	**0.99**	1.03	1.00	1.06	1.16
LARS	1.01	1.00	1.01	1.05	1.02	**0.98**	1.05	1.00	1.02	1.00	**0.99**	1.00	0.99	1.02	1.01	0.99	0.98	**0.97**
BLAR	1.05	1.03	1.04	1.04	**1.00**	**1.00**	1.01	1.01	**0.98**	0.99	1.00	0.99	**0.95**	0.96	1.00	0.97	0.99	0.96
BVAR	1.33	1.01	**1.00**	1.00	**1.00**	**1.00**	1.20	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	1.19	1.00	1.00	**0.99**	1.00	1.00
AR	*1.01*						*1.01*						*1.07*					
							h=4											
DFM	1.13	1.15	1.21	1.14	**1.07**	1.13	1.10	1.07	1.24	1.06	1.02	**1.00**	1.05	1.10	1.22	**1.04**	1.21	1.17
Ridge	1.05	**1.04**	**1.04**	1.05	**1.04**	**1.04**	1.07	1.00	**0.98**	**0.98**	1.02	1.01	1.10	0.98	0.99	**0.97**	1.03	1.09
LARS	1.00	1.00	1.02	1.00	1.01	**0.98**	1.01	1.01	1.01	1.01	0.99	**0.97**	0.99	1.00	1.01	0.99	**0.97**	0.99
BLAR	**1.00**	1.03	1.03	1.02	**1.00**	**1.00**	1.01	1.00	0.98	0.98	1.00	**0.97**	**0.95**	0.96	0.99	0.98	0.98	0.98
BVAR	1.29	1.00	**1.00**	**1.00**	**1.00**	**1.00**	1.29	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	1.25	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
AR	*1.01*						*1.03*						*1.10*					

qualitatively similar for both measures and therefore the discussion that follows refers to both sets of results.

Most entries in Table 1 are close to 1. This indicates that in general the competing forecasting approaches do not forecast the three target variables more accurately than the naïve approach. In most cases the competing methods at best match the naïve benchmark or only slightly outperform it. Hence, it seems that in particular with Australian GDP using a random walk with drift is sufficient.

All competing methods perform considerably better than the naïve benchmark in forecasting the IBR for at least $h = 1$ and for some cases 2-steps ahead. Interestingly the AR benchmark performs remarkably well for h =1-step ahead for both CPI inflation and IBR. For both these variables at least for very short horizon forecasting, information from the additional predictors does not seem to assist. Using only their own past information suffices.

In contrast to the general perception from forecasting US macroeconomic variables, the dynamic factor model performs poorly with forecasting Australian macroeconomic variables independent of the size of the information set and whether international variables are included or not. The DFM is considerably less accurate than the naïve benchmark and the other competing methods for both forecasting GDP growth and CPI inflation. In most cases it seems that its best performance comes from using the smallest possible information set of $K = 3$. We should note that beside the results we present here, for which the number of factors for the DFM is selected by the Ahn and Horenstein (2013) maximum eigenvalue ratio test and the number of lags selected using the BIC, as specified in Section 3.7, we also experimented with: using other model selection criteria such as the AIC and HQ in combination with the Ahn and Horenstein (2013) maximum eigenvalue ratio test; setting the number of factors to 1, 3, 5 and 8; and including the international variables with a smaller ($K = 13$) set of Australian variables. The results we present here are the best for the variations of the DFM we experimented with.

In an effort to investigate the effect of the information set sizes, we discover some interesting findings. The results for Ridge show that there are considerable improvements in accuracy going from $K = 3$ to $K = 13$, with minor improvements after that. For LARS there does not seem to be any differences stemming from the information set used. As expected, bagging LARS shows some improvements (although minor) in some cases. There is a substantial improvement in the accuracy of the BVAR by increasing the information set from $K = 3$ to $K = 13$, and some marginal improvements after that.

With regards to forecast stability we can draw a number of conclusions from the results of the Giacomini and Rossi (2009) test summarised in Table 3. First, for the forecasts from the naïve and AR benchmarks the null that forecasting performance is stable is rarely rejected. Of the regularisation methods, LARS in general seems to provide the most stable forecasts. This suggests that when a predictor loses its forecasting power after a structural change, LARS as a hard thresholding method will eventually drop this predictor as the rolling window moves forwards. Looking at the key variables, forecast stability is highest for the interbank rate, followed by GDP growth, followed by CPI inflation. This may be explained by changes in monetary and wages policy that ensure that good predictors of inflation change rapidly over time. Overall, the results do suggest that overfitting and a lack of forecast stability may be contributing factors to the failure to outperform a naïve benchmark.

Table 3: *Results from the forecast stability test of Giacomini and Rossi (2009). An asterisk denotes rejection of the null for a 1-sided test at a 5% level of significance. With the exception of the 1 step-ahead forecast from an AR model for inflation, the null was never rejected for the AR and NAIVE methods.*

	GDP growth						CPI inflation						IBR					
	$K=3$	13	23	43	151	336	3	13	23	43	151	336	3	13	23	43	151	336
							h=1											
DFM	*	*	*		*	*	*	*	*	*	*	*						
Ridge			*	*	*	*	*	*	*	*	*	*				*	*	*
LARS							*	*	*	*	*	*						
BLAR		*	*	*	*	*	*	*	*	*	*	*			*			
BVAR	*	*	*	*	*		*	*	*	*	*			*	*	*		
							h=2											
DFM	*		*			*		*	*	*	*	*			*			
Ridge			*	*	*	*	*	*	*	*	*	*			*	*	*	*
LARS							*		*	*	*	*						
BLAR			*	*	*	*	*	*	*	*	*	*					*	*
BVAR	*		*	*	*		*		*	*	*				*	*		
							h=3											
DFM			*				*	*	*	*					*		*	
Ridge					*	*	*	*	*	*	*	*				*	*	*
LARS							*		*	*	*	*						
BLAR							*	*	*	*	*	*						
BVAR	*		*		*		*		*	*	*				*	*		
							h=4											
DFM							*	*	*	*								
Ridge							*	*	*	*	*	*					*	*
LARS									*	*	*	*						
BLAR								*	*	*	*	*						
BVAR	*		*		*		*		*		*							

To further investigate the issue of forecast stability we compare the performance of all algorithms between two subperiods: a pre-GFC period (defined as 1997Q1-2008Q3) and a post-GFC period (defined as 2008Q4 to the end of the sample). For brevity we focus on RMSE for one-step ahead forecasts reported in Table 4, although results for multi-step ahead forecasts led to similar conclusions. In general, we find that the performance of all methods, relative to naïve forecasts, deteriorates during the post-GFC period, for all three variables of interest with very few exceptions mostly for IBR.

It is conventional in the literature to report the forecast accuracy for one measure of real economic activity (usually the growth rate of GDP), one measure of inflation (usually the CPI inflation) and one interest rate. This is what we do in Tables 1–2. However, the data set contains

Table 4: *One-step ahead forecast accuracy for pre- and post-GFC subperiods. Each entry shows RMSE relative to the naïve benchmark. K denotes the number of predictors in the information set used. BagL denotes Bagging-LARS. Bold entries indicate the lowest error measure achieved by the competing approaches for the variable of interest across each row, i.e., using an increasing number of predictors.*

	$K = 3$	13	23	43	151	336	3	13	23	43	151	336	3	13	23	43	151	336
	GDP growth						CPI inflation						IBR					
	Pre-GFC (1997Q4-2008Q3)																	
DFM	1.11	1.12	1.10	1.06	1.09	1.12	0.85	1.05	1.14	1.03	1.04	1.06	0.90	0.83	0.95	0.91	0.93	1.11
Ridge	1.00	0.99	1.00	1.00	1.03	1.01	0.96	0.99	0.97	0.96	0.92	1.01	0.90	0.81	0.85	0.73	0.81	0.89
LARS	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.01	1.01	0.99	1.01	1.02	0.86	0.81	0.85	0.66	0.69	0.74
BLAR	1.01	1.01	1.01	1.01	1.00	1.00	0.87	0.98	0.95	0.94	0.97	0.99	0.82	0.75	0.78	0.67	0.71	0.72
BVAR	1.24	1.01	1.00	1.00	1.01	0.99	0.74	0.99	1.00	0.98	0.97	1.00	1.04	0.74	0.84	0.79	0.87	0.84
AR	*1.07*						*0.87*						*0.78*					
	Post-GFC (2008Q4-2016Q1)																	
DFM	1.12	1.20	1.31	1.11	1.33	1.79	1.42	1.08	1.08	1.02	1.16	1.13	0.74	0.72	0.74	0.71	0.73	0.83
Ridge	1.08	1.02	1.04	1.05	1.09	1.11	1.37	1.01	1.09	1.09	1.08	1.07	0.76	0.86	0.83	0.79	0.77	0.72
LARS	1.07	1.00	1.16	1.00	1.01	1.01	1.12	1.00	1.02	1.06	0.97	0.96	0.95	0.98	0.96	0.92	0.93	0.94
BLAR	1.10	1.04	1.07	1.04	1.06	1.03	1.08	1.00	1.02	1.03	0.99	0.97	0.82	0.85	0.84	0.76	0.80	0.77
BVAR	1.57	1.05	1.03	1.03	1.03	1.03	1.39	0.96	1.01	1.01	1.02	1.00	0.93	0.85	0.87	0.86	0.88	0.79
AR	*1.04*						*0.96*						*0.76*					

data on all GDP components, several measures of the price level and many interest rates. In order to get a better understanding of predictability of the Australian key economic indicators, we check if our conclusions were specific to the economic indicators that we chose or the results would be qualitatively the same for alternative selections in each of the three categories, namely GDP components, prices and interest rates. We dig deeper into the forecastability of individual variables within each category with the aid of some bespoke scatter plots. We believe that this "data visualization" (see Lindquist, 2011 for a recent survey) provides useful insights into macroeconomic forecasting as we explain below. (For interested readers we present similar plots for other variable categories in Appendix B of the online supplement).

Figure 1 presents the results for the MASE [1]. For each point, the value on the vertical axis denotes the percentage deviation of the error measure of the competing approach relative to the error measure of the naïve benchmark for that particular variable. The corresponding value on the horizontal axis denotes the error measure for the naïve benchmark. Hence a point below the horizontal axis shows the percentage reduction in the error measure achieved by the forecasting approach relative to the naïve benchmark. The further to the right the point, the larger the error measure for the naïve benchmark; i.e., the harder the variable is to forecast.

[1] RMSE results are similar hence we do not present them here to save space. All RMSE results are available upon request

The scatter plots confirm and generalise some of the conclusions we have drawn so far. For example, it seems very challenging to forecast Australian macroeconomic variables more accurately than a simple benchmark such as the naïve with large cloud of points gathering above the horizontal axis, especially for the GDP category and for $h \geq 2$. From these, the points associated to the DFM (cyan solid circles) seem to be mostly identified as the ones with the largest loss compared to the naïve clustering well above the horizontal axis.

Despite the cloud of points above the horizontal axis there are also clouds of points that gather below the horizontal axis for each of the three categories of interest. An interesting question is whether concentrating on these "forecastable" variables, for example components of GDP growth or disaggregate variables of prices or interest rates can help in more accurately forecasting the aggregates.

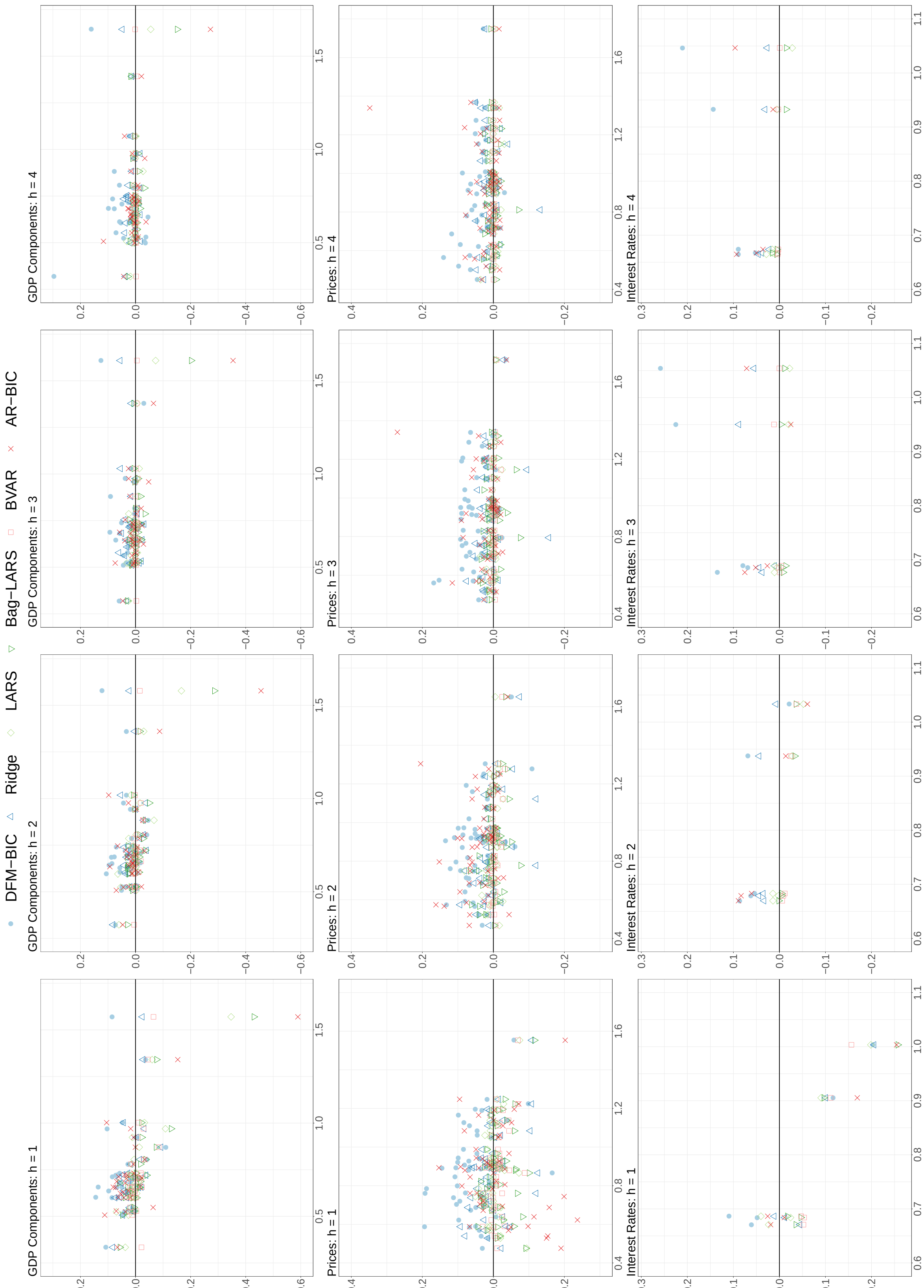


Figure 1: *Comparing the h = 1 to 4-steps ahead MASE between the alternative forecasting approaches and the naïve benchmark for all variables in the categories the key variables of interest belong to when K = 151. The colors indicate the 12 categories the variables belong to and the shapes identify the competing forecast approaches implemented. The vertical axis denotes the percentage deviation in RMSE for the competing approaches relative to the naïve benchmark. The horizontal axis denotes the MASE of the naïve benchmark.*

6 Discussion and Conclusion

The dataset comprising a large number of Australian macroeconomic variables provides an alternative empirical platform for research on macroeconomic forecasting to the oft-analysed US data of Stock and Watson (2002). Our results point to an important feature of this data set that distinguishes it from its US and European counterparts.

We find that for forecasting Australian key macroeconomic indicators simple methods that ignore information in the predictor set such as the naïve sample mean or the univariate autoregressive model compete well with, or in most cases do better than, alternative more complex methods that deliver forecasts as linear combinations of large sets of predictors. The alternatives we explore include methods that select a subset of predictors, such as LARS, or methods that use all predictors, such as ridge regression, VARs or dynamic factor models. This leads us to conclude that the signal in what are supposedly related macroeconomic variables used for forecasting key indicators is very weak. Moreover, it also possible that the relationship between the target variables and these predictors are extremely non-linear or unstable. Hence, this data set provides a good and challenging laboratory for future research on forecasting when signals are weak or relationship between variables is highly non-linear and unstable.

From an Australian perspective, forecast stability tests show that the reduced form relationships between the key macroeconomic variables and domestic macro variables have been too unstable to lead to useful forecasts. The sample mean is the best forecast for the GDP growth rate and forecasts from univariate autoregressive models are best for CPI inflation and inter-bank rate. Moreover, the addition of a judiciously chosen set of macroeconomic variables from Australia's major trading partners and data related to Australia's major exports to the set of predictors does not improve the forecasting performance over the naïve benchmarks. This is in sharp contrast to Eickmeier and Ng (2011) results for New Zealand, where the addition of international predictors produces significantly better forecasts than univariate benchmarks. This may be due to difference in the main export commodities in two countries (minerals in Australia versus agricultural products in New Zealand) coupled with relatively lower degree of penetration of New Zealand exports in the international export markets, which makes New Zealand exports more responsive to economic conditions in a small number of countries. A reflection of these differences was that Australia did not experience a recession during the global financial crisis whereas New Zealand did. There is also a possibility that the univariate benchmark in Eickmeier and Ng (2011) was particularly unstable, which might have exaggerated the performance of the "many predictor" models, since Bjørnland et al. (2017) find that international data do not help predict GDP growth rate for either Australia or New Zealand.

A significant result for economists interested in forecasting macroeconomic variables with many predictors is that, in contrast to the US data, the dynamic factor model does not retain its good forecast performance for the Australian economy. This result holds for different target variables, different sizes of information sets, and for different forecast horizons. Furthermore, this general conclusion is also robust to including either fewer or more dynamic factors.

Leaving aside the fact that simple univariate benchmarks outperformed most of the multivariate forecasts, our results show that adding extra predictors can improve the forecast accuracy over small models, especially for the shorter forecast horizons of one or two quarters ahead. In particular, we find gains in the accuracy of forecasts of the key macroeconomic variables of interest after increasing the information set from 3 to 13 predictors. However, the benefits from using conjunctural information (mostly disaggregate variables) beyond the main aggregate variables are found to be minor. Not considering the naïve sample mean and autoregressive benchmarks, the most accurate forecasts for the key macroeconomic variables are largely obtained with no more than 23 predictors, which are aggregates that characterize important aspects of the Australian economy. This finding is in line with Bańbura et al. (2010) and Koop (2013) who find little gain in expanding the information set beyond 20 important aggregates for the US data when forecasting with Bayesian VARs. We find that this is a general result, and robust to the different approaches to forecasting that we consider in the paper.

A Data Appendix

The complete data set as used in the paper can be downloaded the Australian Macro Database from http://ausmacrodata.org/research.php. An up-to-date complete data set can also be downloaded from this page.

Table 5: *Abbreviations used for each series and their Australian Bureau of Statistics or Reserve Bank of Australia Series ID. Data on the AllOrds were obtained from Yahoo Finance*

Name	Series ID	Name	Series ID	Name	Series ID
RGDP	A2304402X	IP_NMMP	A2716605L	HCE-Post	A3604720V
Cons_Food	A2303246R	IP_MP	A2716603J	HCE-TelEqu	A3604721W
Cons_CigTob	A2303248V	IP_ME	A2716604K	HCE-AVCE	A3604738T
Cons_Alc	A2303250F	RetSal	h03hist	HCE-DomTra	A3604739V
Cons_CloFoo	A2303252K	JobVac	A590698F	HCE-IntTra	A3604740C
Cons_RenDwe	A2303254R	Emp_LFPer	h05hist	HCE-Pet	A3604719K
Cons_EGF	A2303256V	Emp_HoursFtPer	A3346482L	PEXP	f15hist
Cons_FurEqu	A2303258X	Emp_HoursPtPer	A3346483R	PIMP	f15hist
Cons_Hea	A2303260K	Emp_HoursPer	A3346481K	COMMP	i02hist
Cons_PurVeh	A2303262R	Emp_FtPer	A181513R	RHDI	h02hist
Cons_OpeVeh	A2303264V	Emp_PtPer	A181514T	TotalComp	A2302607T
Cons_TraSer	A2303266X	Emp_TotalPer	A181515V	AveComp	A2302608V
Cons_Com	A2303268C	URate_OutofLF	h05hist	IBR	f01hist
Cons_RecCul	A2303270R	URate_LookforFtPer	A181526A	90 days Bk bills	f01dhist
Cons_Edu	A2303272V	URate_Person	A181525X	5 yr T-bond	f02histhist
Cons_HCR	A2303274X	UNum_LookforFtPer	A181516W	10 yr T-bond	f02histhist
Cons_InsFin	A2303276C	UNum_LookforPtPer	A181517X	10 yr NSWT-bond	f02hist
Cons_Other	A2303278J	UNum_Person	A181518A	Currency	d03hist
Cons_Final	A2303280V	HSTotalexfinNum	A2412508V	M1	d03hist
FixInv	A2304051J	HSTotalexfinVal	A2412509W	M3	d03hist
ResInv	A2304054R	HStarts: NSW	A2412632C	BM	d03hist
NResInv-Equip	A2304041C	HStarts: VIC	A2412636L	Mbase	d03hist
NResInv-CBR	A2716097C	HStarts: QLD	A2412644L	Credit_Person	d02hist
NResInv-lPP	A2716583K	HStarts: SA	A2412648W	Credit_Bus	d02hist
Exports	A2304114F	HStarts: WA	A2412656W	Credit_Total	d02hist
Imports	A2304115J	HStarts: TAS	A2412662T	Credit_Nar	d02hist
Gov	A2304080V	HStarts: NT	A2412668F	LoaAdv	d02hist
Gov Nat	A2304078J	HStarts: ACT	A2412672W	Ex rate: JPY	f11hist
Gov Nat/Loc	A2304079K	HStarts: Total	A2412624C	Ex rate: USD	f11hist
DomSales	A2302599C	Hstarts_PDA	h03hist	EX rate: KRW	f11hist
IP_Mining	A2716600A	InvLevel	A2302598A	Ex rate: NZD	f11hist
IP_Man	A2716601C	InvtoSales	A2302601C	Ex rate: CNY	f11hist
IP_EGWWS	A2716610F	CPI-ALL	A2325846C	Ex rate: GBP	f11hist
IP_TotalInd	A2298671X	HCE-UTF	A3604727K	Ex rate: SGD	f11hist
IP_FBT	A2716602F	HCE-MV	A3604722X	EX rate: IDR	f11hist
IP_TCO	A2716608V	HCE-ParAcc	A3604725F	Ex rate: HKD	f11hist
IP_WPP	A2716609W	HCE-Fuel	A3604723A	Ex rate: MYR	f11hist
IP_PRM	A2716607T	HCE-MaiRep	A3604726J	Ex rate: avg	f11hist
IP_PCCRP	A2716606R	HCE-OthMot	A3604724C	SP ASX AllOrds	Yahoo Finance
EPI_LA	A2295549R	EPI_TFW	A2295588F	EPI_PPA	A2295645R
EPI_Meat	A2295570J	EPI_CFCM	A2295591V	EPI_IS	A2295654T
EPI_DPBE	A2295573R	EPI_MOMS	A2295594A	EPI_NFM	A2295651K
EPI_FCMAI	A2295552C	EPI_CCB	A2295606X	EPI_PGME	A2295612V
EPI_Cer	A2295555K	EPI_PPRM	A2295600K	EPI_TESEM	A2295615A
EPI_VF	A2295558T	EPI_GNM	A2295603T	EPI_RV	A2295618J
EPI_SH	A2295561F	EPI_AOF	A2295609F	EPI_OTE	A2295621W
EPI_CTCSM	A2295576W	EPI_MPP	A2295663V	EPI_PSCIA	A2295627K
EPI_FSA	A2295564L	EPI_PNPF	A2295669J	EPI_PAESO	A2295630X
EPI_HSFR	A2295582T	EPI_CMP	A2295675C	EPI_MMA	A2295633F
EPI_CW	A2295585X	EPI_LLMDF	A2295639V	EPI_Gold	A2295636L
TermsTrade	A2304200A				

Table 6: *Categories of variables in the Australian macroeconomic data set*

Category (C)	Description	Number of Variables
1	GDP components	30
2	Prices	50
3	Interest rates	5
4	Industrial Production	13
5	Employment	9
6	Unemployment rate	5
7	Housing	12
8	Inventories	2
9	Wages	3
10	Money	10
11	Exchange rates	11
12	ASX S& P All Ordinaries index	1
13	International variables	185

Table 7: *w_t denotes an observed variable in levels. Transformation (T) denotes the transformation implemented to achieve stationarity: 1 = no transformation; 2 = first difference; 3 = second difference; 4 = log; 5 = first difference of logged variables; and 6 = second difference of logged variables.*

Transformation (T)	
1	w_t
2	$w_t - w_{t-1}$
3	$(w_t - w_{t-1}) - (w_{t-1} - w_{t-2})$
4	$\ln(w_t)$
5	$\ln(w_t/w_{t-1})$
6	$\ln(w_t/w_{t-1}) - \ln(w_{t-1}/w_{t-2})$

Table 8: *The three key macroeconomic variables in $\mathcal{I}_3$. These are used for forecasting in all settings.*

Name	T	C	Description
GDP growth	5	1	Gross domestic product: Chain volume measures
CPI inflation	6	2	Index Numbers; All groups CPI
IBR	2	3	Interbank overnight cash rate in Australia

Table 9: *Variables in $\mathcal{I}_{13} \backslash \mathcal{I}_3$ where $A \backslash B$ denotes the elements of A that are not also elements of B.*

Name	T	C	Description
Exports	5	1	Exports of goods and services
Imports	5	1	Imports of goods and services
COMMP	6	2	Index of commodity prices; All items; AUD, Index, 2013/14=100
TermsTrade	5	2	Terms of Trade; Index
IP_TotalInd	5	4	Total industrial industries; Index
Emp_TotalPer	5	5	Employed – total; Persons
Hstarts_PDA	5	7	Private dwelling approvals
M1	6	10	M1
Credit_Total	6	10	Credit; Total
SP ASX AllOrds	5	12	S& P ASX AllOrds adjusted closing prices

Table 10: *Variables in $\mathcal{I}_{23} \backslash \mathcal{I}_{13}$.*

Name	T	C	Description
Cons_Final	5	1	Household Final Consumption Expenditure: Chain volume measures
10 yr T-bond	2	3	10 yrs Australian Government
Urate_Per	3	6	Unemployment rate; Persons
AveComp	5	9	Average non-farm compensation per employee: Current prices
M3	6	10	M3
BM	6	10	Broad money
Mbase	6	10	Money base
Credit_Per	6	10	Credit; Other personal
Credit_Bus	6	10	Credit; Business
Ex rate: avg	5	11	Australian Dollar Trade-weighted Index

Table 11: *Variables in* $\mathcal{I}_{43} \backslash \mathcal{I}_{23}$.

Name	T	C	Description
Gov	5	1	General government; Final consumption expenditure
DomSales	5	1	Domestic sales: Current prices
PEXP	5	2	Real export-weighted index; Original
PIMP	5	2	Real import-weighted index; Original
90 days Bk bills	2	3	90 days Bank accepted bills
5 yr T-bond	2	3	5 yrs Australian Government
10 yr NSWT-bond	2	3	10 yrs NSW Treasury Corporation
RetSal	2	4	Retail sales; All industries; Current price
Emp_LFPer	5	5	Labour Force; Persons
Emp_HoursPer	5	5	Aggregate Monthly Hours Worked; Persons
HSTotalexfinNum	5	7	Total excluding refinancing of established dwellings – No.
HSTotalexfinVal	5	7	Total excluding refinancing of established dwellings – Value
HStarts: Total	5	7	Total (State); Number of Commitments
InvLevel	5	8	Private non-farm inventory levels; book values; Current prices
InvtoSales	2	8	Inventories to total sales; Ratio
RHDI	5	9	Real household disposable income
Currency	6	10	Currency: Seasonally adjusted
Credit_Nar	6	10	Narrow credit including loans and advances by AFIs plus Bills on issue
LoaAdv	6	10	Loans and advances; Banks

Table 12: *Variables in $\mathcal{I}_{151} \backslash \mathcal{I}_{43}$.*

Name	T	C	Description
Cons_Food	5	1	CVM (Chain Volume Measure) Household Cons Food
Cons_CigTob	5	1	CVM Household Cons Cigarettes and tobacco
Cons_Alc	5	1	CVM Household Cons Alcoholic beverages
Cons_CloFoo	5	1	CVM Household Cons Clothing and footwear
Cons_RenDwe	5	1	CVM Household Cons Rent and other dwelling services
Cons_EGF	5	1	CVM Household Cons Electricity, gas and other fuel
Cons_FurEqu	5	1	CVM Household Cons Furnishings and household equipment
Cons_Hea	5	1	CVM Household Cons Health
Cons_PurVeh	5	1	CVM Household Cons Purchase of vehicles
Cons_OpeVeh	5	1	CVM Household Cons Operation of vehicles
Cons_TraSer	5	1	CVM Household Cons Transport services
Cons_Com	5	1	CVM Household Cons Communications
Cons_RecCul	5	1	CVM Household Cons Recreation and culture
Cons_Edu	5	1	CVM Household Cons Education services
Cons_HCR	5	1	CVM Household Cons Hotels, cafes and restaurants
Cons_InsFin	5	1	CVM Household Cons Insurance and other financial services
Cons_Other	5	1	CVM Household Cons Other goods and services
ResInv	5	1	Gross fixed capital formation-Dwellings
NResInv-Equip	5	1	Gross fixed capital formation-Machinery and equipment
NResInv-CBR	5	1	Gross fixed capital formation-Cultivated biological resources
NResInv-IPP	5	1	Gross fixed capital formation-Intellectual property products
Gov Nat	5	1	Government-National; Final Cons. expenditure
Gov Nat/Loc	5	1	Government-State and local; Final Cons. expenditure
HCE-UTF	6	2	Index; Urban transport fares
HCE-MV	6	2	Index; Motor vehicles
HCE-ParAcc	6	2	Index; Spare parts and accessories for motor vehicles
HCE-Fuel	6	2	Index; Automotive fuel
HCE-MaiRep	6	2	Index; Maintenance and repair of motor vehicles
HCE-OthMot	6	2	Index; Other services in respect of motor vehicles
HCE-Post	6	2	Index; Postal services
HCE-TelEqu	6	2	Index; Telecommunication equipment and services
HCE-AVCE	6	2	Index; Audio, visual and computing equipment
HCE-DomTra	6	2	Index; Domestic holiday travel and accommodation
HCE-IntTra	6	2	Index; International holiday travel and accommodation
HCE-Pet	6	2	Index; Pets and related products
EPI_LA	5	2	Index Numbers; 00 Live animals other than division 03
EPI_Meat	5	2	Index Numbers; 01 Meat and meat preparations
EPI_DPBE	5	2	Index Numbers; 02 Dairy products and birds' eggs
EPI_FCMAI	5	2	Index Numbers; 03 Fish, crustaceans, molluscs and aquatic invertebrates and preparations thereof
EPI_ Cer	5	2	Index Numbers;04 Cereals and cereal preparations

Continued on next page

Table 12: *continued from previous page*

Name	T	C	Description
EPI_VF	5	2	Index Numbers; 05 Vegetables and fruit
EPI_SH	5	2	Index Numbers; 06 Sugars, sugar preparations and honey
EPI_CTCSM	5	2	Index Numbers; 07 Coffee, tea, cocoa, spices and manuf. thereof
EPI_FSA	5	2	Index Numbers; 08 Feeding stuff for animals (not including unmilled cereals)
EPI_HSFR	5	2	Index Numbers; 21 Hides, skins and furskins, raw
EPI_CW	5	2	Index Numbers; 24 Cork and wood
EPI_TFW	5	2	Index Numbers; 26 Textile fibres and their wastes
EPI_CFCM	5	2	Index Numbers; 27 Crude fertilizers, other than those of division 56, and crude minerals (excluding coal, petroleum)
EPI_MOMS	5	2	Index Numbers; 28 Metalliferous ores and metal scrap
EPI_CCB	5	2	Index Numbers; 32 Coal, coke and briquettes
EPI_PPRM	5	2	Index Numbers; 33 Petroleum, petroleum products and related materials
EPI_GNM	5	2	Index Numbers; 34 Gas, natural and manufactured
EPI_AOF	5	2	Index Numbers; 41 Animal oils and fats
EPI_MPP	5	2	Index Numbers; 54 Medical and pharmaceutical products
EPI_PNPF	5	2	Index Numbers; 58 Plastics in non-primary forms
EPI_CMP	5	2	Index Numbers; 59 Chemical materials and products, n.e.s.
EPI_LLMDF	5	2	Index Numbers; 61 Leather, leather manufactures, n.e.s., and dressed furskins
EPI_PPA	5	2	Index Numbers; 64 Paper, paperboard, and articles of paper pulp, of paper or of paperboard
EPI_IS	5	2	Index Numbers; 67 Iron and steel
EPI_NFM	5	2	Index Numbers; 68 Non-ferrous metals
EPI_PGME	5	2	Index Numbers; 71–75 Power generating, general industrial and other specialised machinery and equipment
EPI_TESEM	5	2	Index Numbers; 76–77 Telecommunications equipment, sound recording apparatus and electrical machinery, n.e.s.
EPI_RV	5	2	Index Numbers; 78 Road vehicles (incl. air-cushion vehicles)
EPI_OTE	5	2	Index Numbers; 79 Other transport equipment
EPI_PSCIA	5	2	Index Numbers; 87 Professional, scientific and controlling instruments and apparatus, n.e.s.
EPI_PAESO	5	2	Index Numbers; 88 Photographic apparatus, equipment and supplies and optical goods, n.e.s.
EPI_MMA	5	2	Index Numbers; 89 Miscellaneous manufactured articles, n.e.s.
EPI_Gold	5	2	Index Numbers; 97 Gold, non-monetary (excluding gold ores and concentrates)
IP_Mining	5	4	Mining excluding exploration and mining support services
IP_Man	5	4	Manufacturing
IP_EGWWS	5	4	Electricity, gas, water and waste services
IP_FBT	5	4	Food, beverage and tobacco products

Continued on next page

Table 12: *continued from previous page*

Name	T	C	Description
IP_TCO	5	4	Textile, clothing and other manufacturing
IP_WPP	5	4	Wood and paper products
IP_PRM	5	4	Printing and recorded media
IP_PCCRP	5	4	Petroleum, coal, chemical and rubber products
IP_NMMP	5	4	Non-metallic mineral products
IP_MP	5	4	Metal products
IP_ME	5	4	Machinery and equipment
JobVac	5	5	Job Vacancies; Australia
Emp_HoursFtPer	5	5	Aggregate Monthly Hours Worked (Emp f/t); Persons
Emp_HoursPtPer	5	5	Aggregate Monthly Hours Worked (Emp p/t); Persons
Emp_FtPer	5	5	Employed – full-time; Persons
Emp_PtPer	5	5	Employed – part-time; Persons
URate_OutofLF	3	6	Unemployed persons as percentage of labour force
URate_LookforFtPer	3	6	Unemployment rate – looking for full-time work; Persons
UNum_LookforFtPer	5	6	Unemployed – looking for full-time work; Persons
UNum_LookforPtPer	5	6	Unemployed – looking for part-time work; Persons
UNum_Person	5	6	Unemployed – total; Persons
HStarts: NSW	5	7	New South Wales; Number of Commitments
HStarts: VIC	5	7	Victoria; Number of Commitments
HStarts: QLD	5	7	Queensland; Number of Commitments
HStarts: SA	5	7	South Australia; Number of Commitments
HStarts: WA	5	7	Western Australia; Number of Commitments
HStarts: TAS	5	7	Tasmania; Number of Commitments
HStarts: NT	5	7	Northern Territory; Number of Commitments
HStarts: ACT	5	7	Australian Capital Territory; Number of Commitments
TotalComp	5	9	Non-farm; Total compensation of employees: Current prices
Ex rate: JPY	5	11	AUD/JPY Exchange Rate
Ex rate: USD	5	11	AUD/USD Exchange Rate
EX rate: KRW	5	11	AUD/KRW Exchange Rate
Ex rate: NZD	5	11	AUD/NZD Exchange Rate
Ex rate: CNY	5	11	AUD/CNY Exchange Rate
Ex rate: GBP	5	11	AUD/GBP Exchange Rate
Ex rate: SGD	5	11	AUD/SGD Exchange Rate
EX rate: IDR	5	11	AUD/IDR Exchange Rate
Ex rate: HKD	5	11	AUD/HKD Exchange Rate
Ex rate: MYR	5	11	AUD/MYR Exchange Rate

Table 13: *International Variables.*

Name	T	Description
		Commodities
CRUDE_PETRO	5	Crude oil, average ($/bbl)
CRUDE_DUBAI	5	Crude oil, Dubai ($/bbl)
NGAS_US	5	Natural gas, US ($/mmbtu)
NGAS_EUR	5	Natural gas, Europe ($/mmbtu)
INATGAS	5	Natural gas index (2010=100)
COCOA	5	Cocoa ($/kg)
COFFEE_ARABIC	5	Coffee, arabica ($/kg)
COFFEE_ROBUS	5	Coffee, robusta ($/kg)
TEA_AVG	5	Tea, avg 3 auctions ($/kg)
TEA_COLOMBO	5	Tea, Colombo ($/kg)
TEA_KOLKATA	5	Tea, Kolkata ($/kg)
TEA_MOMBASA	5	Tea, Mombasa ($/kg)
COCONUT_OIL	5	Coconut oil ($/mt)
COPRA	5	Copra ($/mt)
GRNUT_OIL	5	Groundnut oil ($/mt)
PALM_OIL	5	Palm oil ($/mt)
SOYBEANS	5	Soybeans ($/mt)
SOYBEAN_OIL	5	Soybean oil ($/mt)
SOYBEAN_MEAL	5	Soybean meal ($/mt)
BARLEY	5	Barley ($/mt)
MAIZE	5	Maize ($/mt)
SORGHUM	5	Sorghum ($/mt)
RICE_05	5	Rice, Thai 5% ($/mt)
WHEAT_US_HRW	5	Wheat, US HRW ($/mt)
BANANA_US	5	Banana, US ($/kg)
ORANGE	5	Orange ($/kg)
BEEF	5	Beef ($/kg)
CHICKEN	5	Meat, chicken ($/kg)
SUGAR_EU	5	Sugar, EU ($/kg)
SUGAR_US	5	Sugar, US ($/kg)
SUGAR_WLD	5	Sugar, world ($/kg)
TOBAC_US	5	Tobacco, US import u.v. ($/mt)
LOGS_MYS	5	Logs, Malaysian ($/cubic meter)
SAWNWD_MYS	5	Sawnwood, Malaysian ($/cubic meter)
COTTON_A_INDX	5	Cotton, A Index ($/kg)
RUBBER1_MYSG	5	Rubber, SGP/MYS ($/kg)
PHOSROCK	5	Phosphate rock ($/mt)
DAP	5	DAP ($/mt)
TSP	5	TSP ($/mt)
UREA_EE_BULK	5	Urea ($/mt)

Continued on next page

Table 13: *continued from previous page*

Name	T	Description
POTASH	5	Potassium chloride ($/mt)
ALUMINUM	5	Aluminum ($/mt)
IRON_ORE	5	Iron ore, cfr spot ($/dmtu)
COPPER	5	Copper ($/mt)
LEAD	5	Lead ($/mt)
TIN	5	Tin ($/mt)
NICKEL	5	Nickel ($/mt)
ZINC	5	Zinc ($/mt)
GOLD	5	Gold ($/troy oz)
PLATINUM	5	Platinum ($/troy oz)
SILVER	5	Silver ($/troy oz)
		China
FAIPriceInd	6	Fixed asset investment price index
GDPDeflator	2	Implicit price deflator for GDP by value added
NomGDPva	5	GDP by value added (RMB billion)
NomRetGoods	5	Retail sales of consumer goods (RMB billion)
NomFAI	5	Fixed asset investment (RMB bil) by eliminating the 1994Q4 outlier
NomGDPCH	5	GDP by expenditure (RMB billion)
NomNetExpCH	2	Net exports by expenditure (RMB billion)
NomHHC	5	Household consumption by expenditure (RMB billion)
NomGovtC	5	Government consumption by expenditure (RMB billion)
NomGCF	5	Nominal gross capital formation (RMB billion)
NomInvty	2	Changes in inventories (RMB billion)
AvgNomWage	5	Aggregate average nominal wages
logrealHHC	2	log(NominalHHC) - log(CPI)
CPICH	6	Consumer price index
GFCFPI	6	Price index for gross fixed capital formation
Price2CPI	2	Relative prices of investment goods (to CPI)
BankLoans	6	End-of-quarter financial institution loans outstanding: total
RealGDPva	5	Real GDP by value added (RMB billion)
RealGDPCH	5	Real GDP by expenditure (RMB billion)
		Euro area
GCD	2	General Government Final Consumption Deflator, Index, Index base year 1995 (1995 = 1)
GCR	5	General Government Final Consumption Expenditure, Mil of euros, Chain linked volume, Calendar and seas adjusted, Ref year 1995
XTR	5	Exports of Goods and Services, Mil of euros, Chain linked volume, Calendar and seasonally adjusted data, Reference year 1995
YED	2	GDP Deflator, Index, 1995 = 1
YER	5	GDP at market prices, Million Euro, Chain linked volume, Calendar and seasonally adjusted data, Reference year 1995
MTR	5	Imports of Goods and Services, Mil of euros, Chain linked volume,

Continued on next page

Table 13: *continued from previous page*

Name	T	Description
		Calendar and seasonally adjusted data, Reference year 1995
PCR	5	Individual Consumption Expenditure, Millions of euros,
		Chain linked volume, Calendar and seas adjusted, Ref year 1995
ITR	5	Gross Fixed Capital Formation, Mil of euros, Chain linked volume,
		Calendar and seasonally adjusted data, Reference year 1995
PCD	2	Individual Consumption Deflator, Index, 1995 = 1
ITD	2	Gross Fixed Capital Formation Deflator, 1995 = 1
XTD	2	Exports of Goods and Services Deflator, 1995 = 1
MTD	2	Imports of Goods and Services Deflator, 1995 = 1
YFD	2	GDP at Factor Costs Deflator, Index
YIN	5	GDP, Income Side, YIN = YFN + TIN.
WIN	5	Compensation of Employees, Mil of euros, Current prices
GON	5	Gross Operating Surplus, GON = YEN - WIN - TIN.
TIN	5	Taxes on Production and Imports Less Subsidies, Mil of euros
YFN	5	GDP at Factor Costs, YFN = WIN + GON.
HICP	6	Harmonised Index of Consumer Prices, Index, base 1996 = 100
CAN_YEN	2	Current Account Balance as a Share of GDP
NFN_YEN	1	Net Factor Income from Abroad as a Share of GDP
LFN	5	Labour Force, Thousands of persons
LNN	5	Total Employment, Thousands of persons
UNN	5	Number of Unemployed, Thousands of persons
URX	2	Unemployment Rate
LEN	5	Employees, Thousands of persons
STN	2	Nominal Short-Term Int Rate, Euribor 3-month
LTN	2	Nominal Long-Term Int Rate, Euro area 10-year
COMPR	5	Commodity Prices, US dollars
POILU	5	Oil Prices, UK, Petroleum: UK Brent, US dollars per barrel.
PCOMU	5	Non-oil Commodity Prices, ECB commodity price index US is dollars
YWD	2	"World" GDP Deflator, Index, Index base year 1995 (1995 = 1)
YWDX	2	"World" Demand Deflator, Composite Indicator
YWR	5	"World" GDP, Millions of US dollars
YWRX	5	"World" Demand, Composite Indicator
LPROD	2	Labour Productivity
ULC	5	Unit Labour Costs
WRN	5	Wage per Head
SAX	2	Gross Household Saving Rate, Percentage
EEN	5	Nom Effective Exchange Rate (NEER)
EXR	5	Euro-per-USD Exchange Rate
SPREURO	2	Euro area 10-yr Government bond yield minus Euribor 3-mth
		Japan
CPAA	5	Private final consumption expenditure
GDPVD	5	Gross domestic product, volume, at 2010 PPP, USD

Continued on next page

Table 13: *continued from previous page*

Name	T	Description
IRL	2	Long-term government bond yields: 10 years
ITV	5	Gross fixed capital formation, total, volume
MGSVD	5	Real Imports of goods and services, volume, USD, 2010 prices
PCP	2	Private final consumption expenditure, deflator, index
XGSVD	5	Real Exports of goods and services, volume, USD, 2010 prices, sa
YDRH	5	Net household disposable income, real, sa
SP	5	Total Share Prices for All Shares for Japan; Index; not sa
PROD	5	Production of Total industry excluding construction sa, Index
RetailTrade	5	Total retail trade, (Volume) sa, Index
CPIJPN	6	Consumer Price Index: Index 2010=100
HWMN03Q661S	2	Monthly Hours Worked: Manufacturing, Index 2010=1
BSQ160S	1	Business Tendency Surveys for Manufacturing
ULQ661S	5	Early Estimate of Quarterly ULC Indicators: Index 2010=1
LCQ661S	5	Hourly Earnings: Manufacturing for Japan, Index 2010=1
CC1Q661N	5	Real Eff Ex Rates Based on Manuf CPI, Index 2010=1
CC2Q661N	5	Real Eff Ex Rates Based on Manuf Unit Labor Cost, Index 2010=1
MAQ189S	6	M1, National Currency
LFAQ647S	5	Active Population: Aged 15 and Over, Persons
LFEQ647S	5	Employed Population: Aged 15 and Over, Persons
LRHQ156S	2	Harmonised Unemployment Rate: Total, Percent
ULQ661S	5	Early Estimate of Quarterly ULC Indicators: Index 2010=1
WSQ661S	5	Total Dwellings and Residential Buildings, index 2010 = 1
PRMNQ	5	Production in Total Manufacturing, Index 2010=100
PRMNVQ661S	5	Tot. Production of Investment Goods for Manufacturing, 2010=1
PRMNIQ661S	5	Tot. Production of Intermediate Goods for Manufacturing, 2010=1
IR3Q156N	2	3-Month Rates and Yields: Certificates of Deposit, Percent
M3JPN	6	M3, National Currency
SPR01	2	10-year gvt bond yields minus 3-month certificates of Deposit, Percent
SPR02	2	10-year gvt bond yields minus Central Bank Rates, Percent
		US
GDPC1	5	Real Gross Domestic Product, Billions of Chained 2009 Dollars
PFCEQDSMEI	5	Private Final Consumption Expenditure, Billions of Dollars
GFCFQDSMEI	5	Gross Fixed Capital Formation, Billions of Dollars
GFCEQDSMEI	5	Government Final Consumption Expenditure, Billions of Dollars
B020RA3Q086SBEA	5	Real exports of goods and services, Index 2009=100
RA3Q086SBEA	5	Real imports of goods and services, Index 2009=100
LFEMTQ647S	5	Employed Population: Aged 15 and Over: All Persons
C1Q027SBEA	5	Personal consumption excluding food and energy, Billions of Dollars
CUMFN	2	Capacity Utilization: Manufacturing (NAICS), Percent of Capacity
IPB50001SQ	5	Industrial Production: Total index, Index 2012=100
LFAC7Q647S	5	Active Population: Aged 15-74: Persons
SLRTTQ661S	5	Volume of Total Retail Trade sales, Index 2010=100

Continued on next page

Table 13: *continued from previous page*

Name	T	Description
WSCNDQ661S	5	Total Dwellings and Residential Buildings, Index 2010=1
HOHWMQ065S	2	Weekly Hours Worked: Manufacturing, Hours
IPG333SQ	5	Industrial Production: Durable manufacturing: Machinery, 2012=100
PRMNIQ661S	5	Total Production of Intermediate Goods for Manufacturing, 2010=1
IPB51200NQ	5	Industrial Production: Nondurable consumer goods, Index 2012=100
SLWHTQ189S	5	Value of Total Wholesale Trade sales, National Currency
A371RX1BEA	5	Real private inventories, Billions of Chained 2009 Dollars
LRHQ156S	2	Harmonised Unemployment Rate: Total: All Persons, Percent
CPIUS	6	Consumer Price Index: Total All Items, Index 2010=1
A829RD3	5	Gvt cons exp and gross inv: State and local, Index 2009=100
A006RD3	5	Gross private domestic investment, Index 2009=100
A011RD3	5	Gross private domestic fixed investment: Residential, 2009=100
A008RD3	5	Gross private domestic fixed investment: Nonresidential, 2009=100
ULCNFB	5	Nonfarm Business Sector: Unit Labor Cost, Index 2009=100
ULQEUL0	5	Early Estimate of Quarterly ULC Indicators: Index 2010=1
B020RG3	5	Exports of goods and services, Index 2009=100
B021RG3	5	Imports of goods and services, Index 2009=100
OPHNFB	5	Nonfarm Business Sector: Real Output Per Hour All Persons, 2009=100
HOUREARN	5	Hourly Earnings: Manufacturing, Index 2010=100
M3US	6	M3, National Currency
M1US	6	M1, National Currency
CCRETT	5	Real Effective Exchange Rates Based on Manufacturing CPI, 2010=1
IRSTFR	5	Immediate Rates: Less than 24 Hours: Federal Funds Rate, Percent
IR3TED	5	3-Month or 90-day Rates and Yields: Eurodollar Deposits, Percent
IR3TCD	5	3-Month or 90-day Rates and Yields: Certificates of Deposit, Percent
DPIC96	5	Real Disposable Personal Income, Billions of Chained 2009 Dollars
T5YFFM	2	5-Year Treasury Constant Maturity Minus Federal Funds Rate, Percent
T10Y2YM	2	10-Year Treasury Constant Maturity (TCM) Minus 2-Year TCM, Percent
T10Y3MM	2	10-Year TCM Minus 3-Month TCM, Percent
T10YFFM	2	10-Year TCM Minus Federal Funds Rate, Percent

B Online supplement: evaluating forecast accuracy of all variables

In this online supplement we complement the main results in the paper by evaluating the forecast performance of the methods in forecasting all $K = 151$ variables. The aim here is to investigate whether some methods produce more accurate forecasts for specific categories of Australian macroeconomic variables, as it is reasonable to expect that no single method will dominate all others.

Table 14 shows the average error measures relative to the naïve benchmark from forecasting all K variables within the different information sets. Hence, it is only appropriate to compare results within each panel where the number of variables forecast is K. The results send some very clear messages. Bagging LARS is the best performing method and the only one comparable to the AR benchmark, when using an information set of only $K = 3$ predictors, the variables we consider as the ones of main interest. As the information set increases beyond these three variables, ridge and BVAR catch up and provide qualitatively very similar forecasting performance to the LARS results. It is only for very few cases, for $K \geq 13$ and only for $h = 1$, that these four methods show any improvement over the naïve benchmark; however, this improvement is not substantial. The DFM seems to be in almost all cases, the least accurate.

The scatterplots that follow extend the results presented in Figure 1 for the rest of the twelve variable categories. As a reminder for each point on the scatterplot, the value on the vertical axis denotes the percentage deviation of the error measure of the competing approach relative to the error measure of the naïve benchmark for that particular variable. The corresponding value on the horizontal axis denotes the error measure for the naïve benchmark. Hence a point below the horizontal axis shows the percentage reduction in the error measure achieved by the forecasting approach relative to the naïve benchmark. The further to the right the point, the larger the error measure for the naïve benchmark; i.e., the harder the variable is to forecast.

Some very interesting observations can be made. In general the DFM seems to be the least accurate, and not a suitable method for forecasting Australian macroeconomic variables. For many variable categories we observe some sizeable improvements in forecast accuracy over the naïve benchmark especially for $h = 1$ and 2 quarters ahead. Examples include, industrial production, employment and unemployment, housing and wages. In summary, such a visualisation aided analysis can assist in identifying specific categories of variables where some gains in forecast accuracy over the naïve benchmark can be achieved.

Table 14: *Each entry shows the average error measure relative to the naïve benchmark from forecasting all K variables in the information set. Note that for K = 336 the international variables are included in the information set however the error measures reported are for forecasting the 151 Australian variables. BagL denotes Bagging-LARS. Bold entries indicate the lowest error measure achieved across the competing approaches for each forecast horizon.*

	Average RMSE											
	$h = 1$	2	3	4	$h = 1$	2	3	4	$h = 1$	2	3	4
	$K = 3$				$K = 13$				$K = 23$			
DFM	1.00	1.06	1.07	1.07	0.99	1.03	1.02	1.05	1.11	1.07	1.16	1.26
Ridge	0.99	1.09	1.09	1.05	0.97	**0.99**	**0.99**	**1.00**	**0.98**	1.00	**1.00**	**1.00**
LARS	1.00	1.03	1.02	**1.00**	0.99	1.00	1.00	**1.00**	1.00	1.01	**1.00**	**1.00**
BLAR	0.94	**1.01**	**1.01**	**1.00**	0.97	1.00	1.00	**1.00**	**0.98**	1.00	1.01	1.01
BVAR	1.08	1.20	1.18	1.21	**0.96**	**0.99**	1.00	**1.00**	**0.98**	**0.99**	**1.00**	**1.00**
AR	**0.93**	**1.01**	1.02	1.02	0.99	1.02	1.03	1.03	1.00	1.05	1.04	1.03
	$K = 43$				$K = 151$				$K = 336$			
DFM	0.99	1.01	1.02	1.06	1.03	1.03	1.04	1.04	1.06	1.05	1.05	1.06
Ridge	0.97	**0.99**	1.00	**1.00**	0.99	**1.00**	**1.00**	1.01	0.99	1.01	1.02	1.02
LARS	0.99	1.00	1.00	**1.00**	0.99	**1.00**	**1.00**	**1.00**	0.99	1.00	1.00	1.00
BLAR	**0.96**	**0.99**	**0.99**	**1.00**	**0.98**	**1.00**	**1.00**	**1.00**	**0.98**	1.00	1.00	1.00
BVAR	0.97	**0.99**	1.00	**1.00**	**0.98**	**1.00**	**1.00**	**1.00**	**0.98**	**1.00**	**1.00**	**1.00**
AR	0.99	1.04	1.03	1.02	1.00	1.05	1.05	1.06	1.00	1.05	1.05	1.06
	Average MASE											
	$K = 3$				$K = 13$				$K = 23$			
DFM	0.93	1.04	1.08	1.08	0.99	1.03	1.03	1.07	1.08	1.08	1.14	1.19
Ridge	0.97	1.10	1.12	1.08	0.96	**0.99**	**1.00**	**1.00**	0.98	1.00	1.01	**1.00**
LARS	0.95	1.01	1.01	1.00	0.98	1.00	**1.00**	**1.00**	1.00	1.00	**1.00**	1.01
BLAR	0.89	0.99	**0.99**	**0.98**	0.97	**0.99**	**1.00**	**1.00**	**0.97**	1.00	1.01	**1.00**
BVAR	1.11	1.29	1.23	1.27	**0.95**	**0.99**	**1.00**	**1.00**	**0.97**	**0.99**	**1.00**	**1.00**
AR	**0.87**	**0.98**	1.04	1.06	0.96	1.01	1.03	1.03	0.99	1.04	1.03	1.03
	$K = 43$				$K = 151$				$K = 336$			
DFM	0.99	1.02	1.02	1.06	1.03	1.04	1.05	1.05	1.04	1.04	1.05	1.07
Ridge	**0.96**	**0.99**	1.01	**1.00**	1.00	1.01	1.01	1.01	0.98	1.01	1.02	1.02
LARS	0.98	1.00	**1.00**	**1.00**	0.99	1.00	**1.00**	**1.00**	0.99	1.00	1.00	1.00
BLAR	**0.96**	**0.99**	**1.00**	**1.00**	**0.97**	**0.99**	**1.00**	**1.00**	**0.97**	0.99	1.00	1.00
BVAR	**0.96**	**0.99**	**1.00**	**1.00**	0.98	**0.99**	**1.00**	**1.00**	**0.98**	**0.99**	**1.00**	**1.00**
AR	0.99	1.03	1.02	1.02	0.99	1.03	1.02	1.02	0.99	1.03	1.02	1.02

Figure 2: *Comparing the $h = 1$ to 4-steps ahead MASE between the alternative forecasting approaches and the naïve benchmark for all variables in the categories the key variables of interest belong to when $K = 151$. The colors indicate the 12 categories the variables belong to and the shapes identify the competing forecast approaches implemented. The vertical axis denotes the percentage deviation in RMSE for the competing approaches relative to the naïve benchmark. The horizontal axis denotes the MASE of the naïve benchmark.*

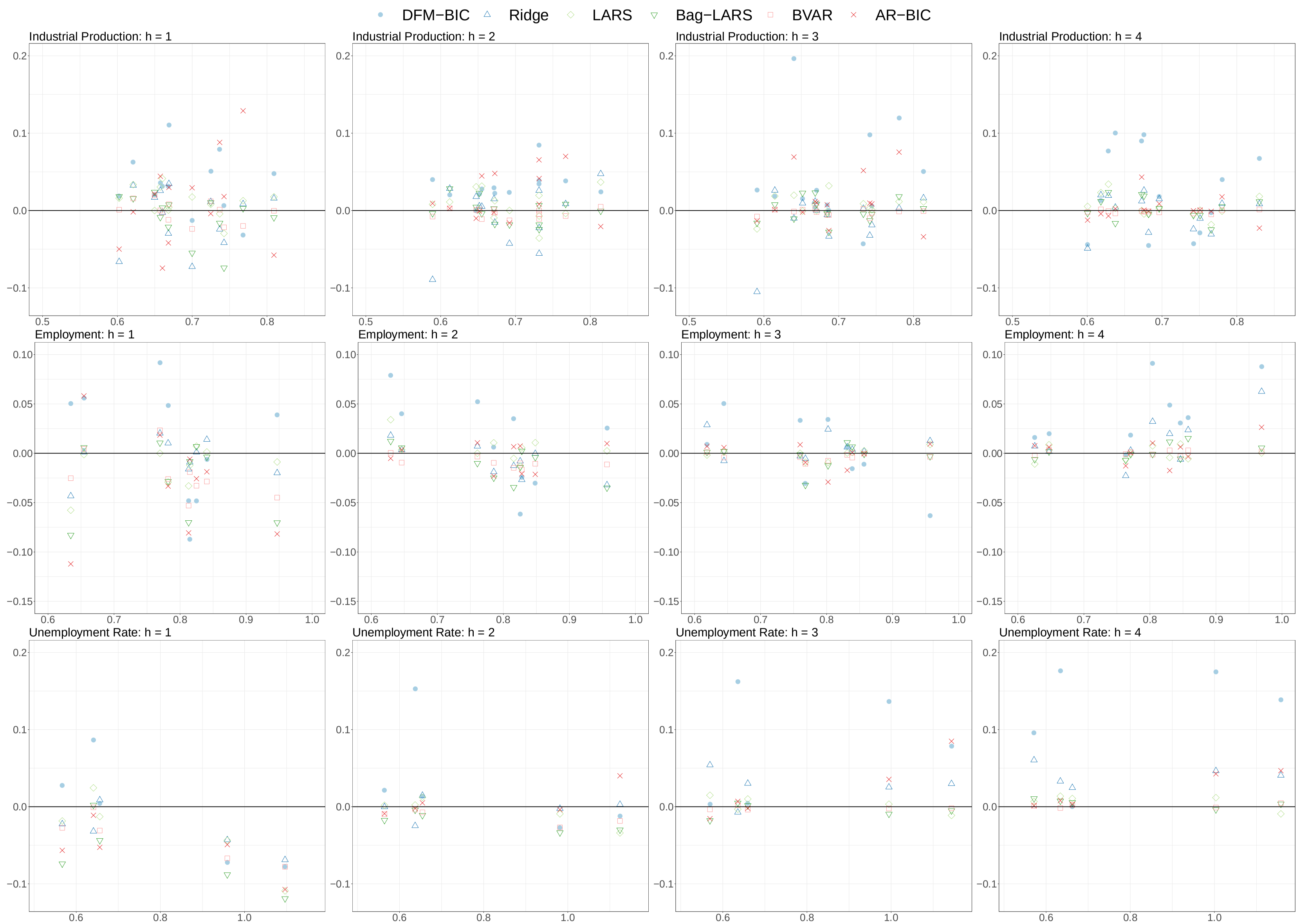
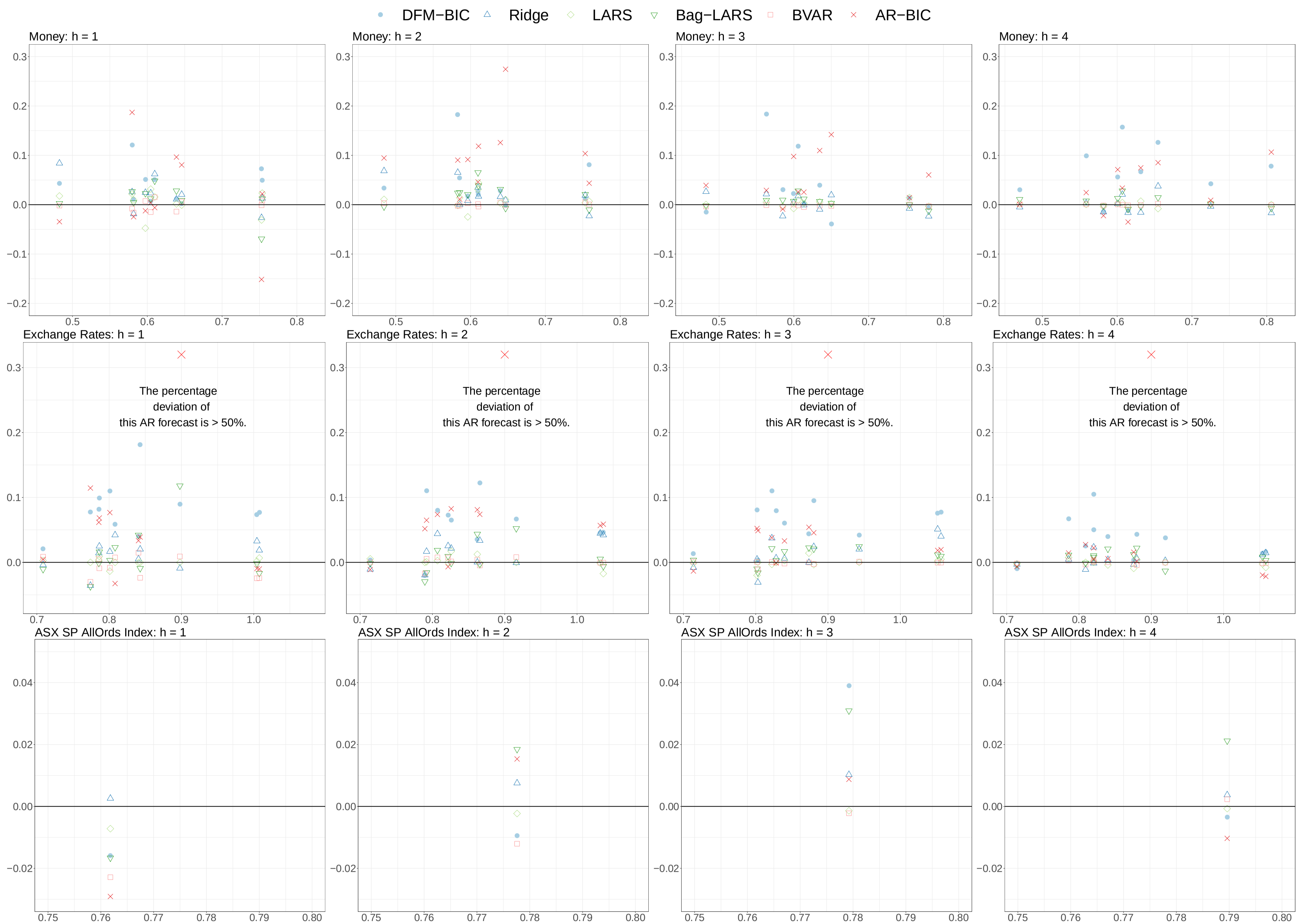


Figure 3: *Comparing the h = 1 to 4-steps ahead MASE between the alternative forecasting approaches and the naïve benchmark for all variables in the categories the key variables of interest belong to when K = 151. The colors indicate the 12 categories the variables belong to and the shapes identify the competing forecast approaches implemented. The vertical axis denotes the percentage deviation in RMSE for the competing approaches relative to the naïve benchmark. The horizontal axis denotes the MASE of the naïve benchmark.*

Figure 4: *Comparing the $h = 1$ to 4-steps ahead MASE between the alternative forecasting approaches and the naïve benchmark for all variables in the categories the key variables of interest belong to when $K = 151$. The colors indicate the 12 categories the variables belong to and the shapes identify the competing forecast approaches implemented. The vertical axis denotes the percentage deviation in RMSE for the competing approaches relative to the naïve benchmark. The horizontal axis denotes the MASE of the naïve benchmark.*



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