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LIEBERMANN, JOELLE

Universite Libre de Bruxelles, Central Bank of Ireland

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# Real-time forecasting in a data-rich environment

Joëlle Liebermann\*

Central Bank of Ireland and  
ECARES, Université Libre de Bruxelles

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## Abstract

This paper assesses the ability of different models to forecast key real and nominal U.S. monthly macroeconomic variables in a data-rich environment and from the perspective of a real-time forecaster, i.e. taking into account the real-time data revisions process and data flow. We find that for the real variables predictability is confined over the recent recession/crisis period. This is in line with the findings of D’Agostino and Giannone (2012) that gains in relative performance of models using large datasets over univariate models are driven by downturn periods which are characterized by higher comovements. Regarding inflation, results are stable across time, but predictability is mainly found at the very short-term horizons. Inflation is known to be hard to forecast, but by exploiting timely information one obtains gains at nowcasting and forecasting one-month ahead, especially with Bayesian VARs. Furthermore, for both real and nominal variables, the direct pooling of information using a high dimensional model (dynamic factor model or Bayesian VAR) which takes into account the cross-correlation between the variables and efficiently deals with the “ragged edge” structure of the dataset, yields more accurate forecasts than the indirect pooling of bi-variate forecasts/models.

*Keywords:* Real-time data, Nowcasting, Forecasting, Factor model, Bayesian VAR, Forecast pooling

*JEL Classification:* C11, C33 E52, C53,

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\*The views expressed in this paper are those of the author, and do not necessarily reflect those of the Central Bank of Ireland. Address for correspondence: jlieberm@ulb.ac.be

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# 1 Introduction

This paper evaluates the ability of different models to forecast key real and nominal U.S. monthly macroeconomic variables in a data-rich environment and from the perspective of a real-time forecaster, i.e. taking into account the real-time data revisions process and data flow. This is an issue which, to the best of our knowledge, has not yet been examined.

In the forecasting literature there is widespread empirical evidence on instabilities, whether attributed to changes in individual predictive content, in parameters and/or model, or over time. Many empirical studies evaluate different methods at forecasting key variables, using different datasets, periods and models, making the results and ranking of methods, difficult to compare. Furthermore, and importantly for a real-time forecaster and policymaker, no studies compare the different methods in a truly real-time setting.

This study contributes to the literature in a number of ways. Firstly, we run a forecasting horse race between the different methods used to forecast using many predictors. Since using all predictors at once in traditional time series models leads to the so-called curse of dimensionality problem<sup>1</sup>, specific methods have been developed that can overcome this problem. Broadly speaking, two approaches have been followed to forecast in a data-rich environment, namely pooling of bi-variate forecasts which is an indirect way to exploit large cross-section and directly pooling of information using a high-dimensional model.

The first approach, pooling over small models' forecasts, initially emerged as a response to the instabilities found in individual predictive content. Stock and Watson (2003a), using bi-variate models to forecast output growth and inflation from 1959 to 1999, find considerable instability over time and across countries of asset prices and leading indicators predictive content. More recently, Rossi and Sekhposyan (2010) re-assess the findings of Stock and Watson over the sample 1970 to 2005; they broadly confirmed the instability results of Stock and Watson and similarly to D'Agostino, Giannone and Surico (2006) found that most predictors lose their ability to forecast around the start of the great moderation or before.<sup>2</sup> As a more robust tool to produce forecasts in light of model uncertainty/instability, a number of studies have suggested using model averaging. Stock and Watson (2004), among others, show that using the simple (unweighted) average over individual predictor forecasts yields better and more stable results. Timmermann's (2006) survey put forth theoretical rationales in favor of forecast combinations such as model misspecification, structural breaks and, more generally, unknown instabilities. The combined forecast can be viewed as "integrating

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<sup>1</sup>That is, when the size of the information set ( $n$ ) is too large relative to the sample size ( $T$ ), then the loss of degrees of freedom results in poor or unfeasible (if  $n > T$ ) ordinary least squares (OLS) forecasts (see De Mol, Giannone and Reichlin, 2008).

<sup>2</sup>To be precise, for forecasting output, they find that financials were useful up to the mid-1970s, and that predictive content of the indicators for inflation break down around the start of the great moderation.

out” model (predictor) uncertainties, as highlighted in Bayesian model averaging. Aiolfi and Timmermann (2006), for instance, find that averaging over the top performing models (based on past forecasting performance) provides better forecasts than just relying on the first best model. This pooling/averaging over small models’ forecasts helps mitigate the issue of unstable predictors and exploits the information content from many predictors, yielding in general more accurate forecasts.

The second approach, which has in fact directly focused on the particular issue of forecasting with many predictors, pools information directly using a high-dimensional model that can overcome the curse of dimensionality problem. Dynamic factor models (DFM) (Forni, Hallin, Lippi and Reichlin (2000,2005); Stock and Watson (2002a,b)) have been the predominant tool used and have been found to perform well.<sup>3</sup> In such a framework, it is assumed that the first few factors, which capture the bulk of the comovement among the predictors, summarize all the relevant information in the dataset. Hence, the number of parameters to estimate in the forecasting equation is substantially reduced by replacing the large set of predictors by these first few factors. More recently, Bańbura, Giannone and Reichlin (2010) have considered Bayesian vector autoregression (BVAR) as an alternative for forecasting with many predictors. These authors found that by applying Bayesian shrinkage (i.e. shrinking the parameters via the imposition of priors) to deal with the curse of dimensionality problem, it is not only possible to forecast using large VAR but also that these forecasts compare favorably relative to those of the DFM. De Mol, Giannone and Reichlin (2008) further show that when variables comove, these models yield similar results. In both models, regressors used to construct the forecasts are linear combinations of all variables in the panel; factor model (principal components) forecasts put unit weight on the first dominant eigenvalues of the covariance matrix of the data and zero on the others, while Bayesian forecasts assign decreasing weights to all the ordered eigenvalues. Hence, difference in forecasting performance of these two models will inform us as to whether minor eigenvalues (factors) in the dataset contribute to forecasting performance.

Alternative methods to forecast using many predictors such as variables selection algorithms (e.g. Lasso and Bayesian model averaging) have not been found to yield any forecasting improvement over these two former methods and the variables selected have no clear economic interpretation as collinearity renders their weights unstable (see Stock and Watson (2011) and De Mol, Giannone and Reichlin (2008)). Hence among the methods enabling to directly forecast in a data-rich environment, we focus on the DFM and BVAR. We also retain the simple approach of pooling bi-variate forecasts as it has been reported to perform well by some authors, and it will serve as an additional benchmark against which to evaluate the

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<sup>3</sup>See Stock and Watson, 2002a,b; Bernanke and Boivin, 2003; Forni, Hallin, Lippi and Reichlin, 2005; Boivin and Ng, 2005; D’Agostino and Giannone, 2012.

former models.

Noteworthy is that in a real-time setting the models must also be able to deal with an unbalanced panel at the end of the sample (i.e. at the forecast origin), which is commonly referred to as a “ragged edge” structure. This arises because variables are released in a non-synchronous manner and with varying publication lags. Hence taking into account the real-time data flow implies that one must use econometric approaches that allow to deal with an unbalanced panel and that the marginal predictive ability of different variables also depends on their timeliness as found in the recent literature devoted to nowcasting GDP. Since both the DFM and the BVAR admit a state space representation, this issue can be dealt with efficiently using the Kalman filter and smoother. This leads us to our second contribution, that is to run the forecasting horse race in a truly real-time setting. That is, we replicate the situation faced by a real-time forecaster as we take into account the preliminary nature of the data as well as the real-time data flow. To do so we have constructed a real-time database<sup>4</sup> of vintages for a large panel of macroeconomic series. Most of the studies forecasting the key US monthly variables use ex-post revised datasets, which differ from the preliminary data available to a real-time forecaster and policy makers. Given that data revisions may be quite substantial, the use of revised data instead of real-time may not be innocuous for forecasting. Faust and Wright (2009), for example, argue that the practical relevance for forecasting of findings based on revised data is an open issue. Croushore (2011)<sup>5</sup> provides an extensive survey of the impact of using latest-available, i.e. revised, data instead of real-time on empirical results and shows that it can substantially affect findings. Among those studies using real-time data, such as Rossi and Sekhposyan (2010), Heij, van Dijk and Groenen (2011) and Banterghansa and McCracken (2011) among others, only balanced datasets are used; implying disregarding the most up to date information.<sup>6</sup>

Our third contribution is to use similar forecast combination schemes across models to overcome the choice of model specification faced by the practitioner, e.g. which (information) criteria to use to select the parametrization of the model, as we seek for evidence regarding the performance of a model that is robust across specifications/combination schemes. This should also help to insure against model/specification instability. For instance, Banterghansa and McCracken (2011) consider the real-time forecasting ability of different combining schemes to outperform information criterion based model selection for bi-variate VARs in

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<sup>4</sup>For most of the series (around 70%) real-time information was gathered from the Federal Reserve Bank of St. Louis ALFRED database (see Appendix A.1).

<sup>5</sup>See also, Croushore and Stark (2002a,b) and Bernanke and Boivin (2003) on this issue.

<sup>6</sup>Furthermore the two state-of-the art techniques, BVAR and DFM have been compared to each other using balanced revised panels (e.g. Bańbura, Giannone and Reichlin, 2010) or in a real-time setting for forecasting Euro-area inflation but benchmarked against simple univariate models (Lenza and Warmedinger, 2011; Giannone, Lenza, Momferatou and Onorante, 2010).

the light of instabilities in these models. Whereas, the Bank of England<sup>7</sup> and the Norges Bank<sup>8</sup> further combine over a suite of models to generate forecasts of key macroeconomic variables. Hence different forecast combination schemes are used to pool within and between models.

Finally, following the findings of D’Agostino and Giannone (2012) that gains from data-rich methods over univariate models mainly confine to downturn periods, we also investigate the sensitivity of the results over the (end of the) great moderation and recent recession.

We find that for the real variables, predictability is confined over the recent recession/crisis period. This in line with the findings of D’Agostino and Giannone (2012) over an earlier period, that gains in relative performance of models using large datasets over univariate models are driven by downturn periods which are characterized by higher comovements. These results are robust to the combination schemes or models used. Regarding inflation, results are stable across time, but predictability is mainly found at nowcasting and forecasting one-month ahead, with the BVAR standing out at nowcasting. The results show that the forecasting gains at these short horizons stem mainly from exploiting timely information. Furthermore, for both real and nominal variables, the direct pooling of information using a high dimensional model (DFM or BVAR) which takes into account the cross-correlation between the variables and efficiently deals with the “ragged edge” structure of the dataset, yields more accurate forecasts than the indirect pooling of bi-variate forecasts/models.

The paper is organized as follows. In Section 2 we describe the design of the real-time forecasting exercise, the dataset, models and combination schemes used to construct the forecasts. Section 3 presents the empirical results over the full sample period as well as over the pre-crisis and crisis sub-samples. This section also displays the results regarding the marginal predictive ability of the timely leading indicators variables. Section 4 concludes.

## 2 Real-time forecasting setting and dataset

The objective is to predict four key U.S. monthly macroeconomic variables, namely industrial production (IP) and the unemployment rate (UR) for the real-side of the economy and headline consumer price index (CPI) and personal consumption expenditures price index (PCE-P) for the nominal side.

The forecasting exercise is performed in a data-rich environment and fully real-time setting. To this end we use vintages<sup>9</sup> for a panel of 68 monthly U.S. macroeconomic indicators from

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<sup>7</sup>Kapetanios, Labhard and Price (2008).

<sup>8</sup>Aastveit, Gerdruo and Jore (2011) and Gerdrup, Jore, Smith and Thorsrud (2009).

<sup>9</sup>For most of the series real-time information was collected from the Federal Reserve Bank of ST.Louis ALFRED database (see Appendix 1).

December 2001 to December 2011, reproducing the exact information available to a real-time forecaster. The panel consists of hard data such as industrial production, employment, retail sales, housing and prices among others, and soft data which includes surveys and financials (e.g. term and credit spreads and stock market index). These variables are released in a non-synchronous manner and with varying publication lags. As a consequence the panel is unbalanced at the end of the sample, i.e. it has a “ragged edge” structure.

To fix ideas let  $V_t$  denote the vintage for the panel available at the end of a given month  $t$  which is the forecast origin:

$$V_t = \{Z_{i,t^*|t}, \quad i = 1 \dots n; \quad t^* = 1 \dots T_{i|t}^*\}$$

where  $Z_{i,t^*|t}$  is the month  $t^*$  value of a generic variable  $i$  available in month  $t$  and  $T_{i|t}^* \leq t$  because of publication lags. The bulk of the hard data are released in the month following the one they cover and a few are released with a two month delay, i.e.  $T_{i|t}^* = t - 2$  or  $t - 1$ . The financial data and commodity prices<sup>10</sup> and most of the surveys are very timely as they are already available at the end of the month they refer to. Hence,  $T_{i|t}^* = t$  for all the financials and commodity prices and  $T_{i|t}^* = t$  or  $t - 1$  for the surveys. A detailed description of the variables along with their publication lags and transformation applied to each series are reported in Appendix A.1.

Similar to a real-time forecaster constructing her forecasts at the end of each month, we generate forecasts for the series of interest for the  $h = 0, 1, 3, 6$  and 12 months horizon, conditional on the information available at that point in time, using a range of models. The nowcasts, i.e.  $h = 0$ , are also produced since all of the predicted series are released after the close of the month they refer to, hence are not available for the month considered as the forecast origin.

### 3 Forecasting models and combination schemes

#### 3.1 Forecasting models

To forecast the series of interest we consider four classes of models. Firstly, we use a random walk (RW) model. This *naive model* is the standard benchmark against which one evaluates more sophisticated models. Secondly, we consider autoregressive *univariate models* (AR), which only use past information on the targeted series to construct the forecasts. Within this class,  $h$ -steps ahead forecasts can be generated by either iterating

<sup>10</sup>These data are in fact observed at the daily frequency and are converted to the monthly frequency by aggregating daily price changes over the month.

forward a one-step ahead model (iterated or indirect approach) or by estimating a multistep model (direct approach). Since both approaches are used in the literature and that the issue of which one works better is an empirical one (see Marcellino, Stock and Watson, 2006), we construct forecasts using both approaches under the AR model.

The third and fourth classes of models make use of numerous additional predictors to generate the forecasts, i.e. they aim at forecasting in a *data-rich environment*. But, using all predictors at once in traditional time series models leads to the so-called curse of dimensionality problem. That is, when the size of the information set ( $n$ ) is too large relative to the sample size ( $T$ ), then the loss of degrees of freedom results in poor or unfeasible (if  $n > T$ ) ordinary least squares (OLS) forecasts (see De Mol, Giannone and Reichlin, 2008).

One way to circumvent this problem is to pool *bi-variate model* forecasts. Under this approach a model is estimated using each candidate predictor one at a time in addition to the targeted series to construct the forecasts. Then, to make use of all the information, the individual predictor forecasts are combined to provide a single forecast. Similar to the AR model, these bi-variate predictions can be constructed using a direct or iterated (indirect) forecasting model. The former method entails using a standard regression model, while the latter entails the use of a VAR model; both are considered within the bi-variate (BIV) class of models.

The alternative approach is to pool information directly using a *high-dimensional multivariate model* that overcomes the curse of dimensionality problem. The standard model used for that purpose which has been found to forecast well is the DFM. Recently, Bańbura, Giannone and Reichlin (2010) have considered BVAR as an alternative for forecasting with large panels. VARs are flexible models as they can accommodate rich cross-correlation and autocorrelation among variables, but as such, are heavily parametrized and run into the curse of dimension problem quickly with an increasing number of series. These authors found that by applying Bayesian shrinkage (i.e. shrinking the parameters via the imposition of priors) it is not only possible to forecast using large VARs but also that these forecasts compare favorably to those obtained by the factor model.

An important issue, governing the choice of the models (as mentioned in the introduction), is that since the forecasts are generated in a real-time setting, they all need to be able to deal with the “ragged-edge” structure of the dataset. For the univariate models (RW and AR-direct) this is straightforward as a one month publication lag translates directly into a one month increase in the forecast horizon. The standard regression model can also directly be modified to account for publication lags. For all the other models, since they admit a state space representation, the Kalman filter and smoother algorithm with a time-



varying dimension observation equation<sup>11</sup> can be used to compute recursively the forecasts conditional on the available information, i.e the unbalanced panel.

With the exception of the BVAR, in all the models series are transformed to obtain stationarity. For most of the series we take the first (i.e. month-over-month) difference of the level or log level; interest rates spreads and some of the surveys are un-transformed.<sup>12</sup> Thus all models, except the BVAR, produce forecasts for the month-over-month growth rate or change of the key series, whereas the BVAR for the level. These forecasts are then used to construct the target being predicted which is the cumulative growth or change over the forecast horizon for the real variables and the h-month ahead level of yearly inflation<sup>13</sup> for the nominal variables. Note that due to publication lags, the level of the key series are unknown for the forecast origin month  $t$  and the last available value for these series relates to  $t - 1$ <sup>14</sup> (i.e.  $Z_{i,T^*|t} = Z_{i,t-1|t}$ ), hence for a h-step ahead forecast one needs in fact to forecast h+1-months.

To further set notations, let  $Z_t = (Z_{1,t} \dots Z_{n,t})'$  denote the  $n \times 1$  vector of un-transformed (in level) variables, and  $X_t = (X_{1,t} \dots X_{n,t})'$  its transformed to stationary counterpart. We aim at forecasting some elements of  $Z_t$  ( $X_t$ ) which will be subscripted by  $j$  and a candidate predictor will be subscripted by  $i^*$ , whereas the subscript  $i$  will be used to refer to a generic variable in the vector  $Z_t$  ( $X_t$ ).

Then the target being forecasted at origin  $t$  for horizon  $h$  is defined as follows:

- $100 * (\log Z_{j,t+h} - \log Z_{j,t-1})$  for IP;
- $Z_{j,t+h} - Z_{j,t-1}$  for the UR;
- $100 * (\log Z_{j,t+h} - \log Z_{j,t+h-12})$  for CPI and PCE-P.

### Naive model (RW)

At each forecast origin, the forecasts are simply set to a constant which is the recursively computed historical mean of the series of interest. For all horizons the model is defined as follows:

$$X_{j,t+h} = \alpha_j + \varepsilon_{j,t+h}^h \quad (1)$$

Given the transformations used to obtain stationarity, this naive model corresponds to a random walk (RW) with drift for the level or log level of the series.

<sup>11</sup>In practice this is implemented by using a selection matrix applied to the measurement equation (see Koopman and Durbin (2001), §4.8).

<sup>12</sup>See Appendix A.1 for a description of the transformation applied to each variable.

<sup>13</sup>This is the standard target forecasted in the literature for price indices.

<sup>14</sup>Note that for PCE-P inflation, in approximatively 30% of the cases it is released with two months publication lags, hence we also need to backcast its value for  $t - 1$ .

## Univariate models (AR)

The direct AR model entails projecting a dated  $t + h$  variable on dated  $t$  available information. Hence for each horizon  $h$  one needs to estimate a different model as defined by equation (2):

$$X_{j,t+h} = \alpha_j^h + \sum_{l=1}^p \gamma_{j,l}^h X_{j,t-l} + \varepsilon_{j,t+h}^h \quad (2)$$

Note that the index in the summation in (2) starts at one and not at zero as due to publication lags, at the end of month  $t$  the available information regarding the past of the series of interest pertains only to month  $t - 1$  and earlier. In the indirect approach, a single one-step ahead model is used:

$$X_{j,t} = \alpha_j + \sum_{l=1}^p \gamma_{j,l} X_{j,t-l} + \varepsilon_{j,t} \quad (3)$$

Then, given the estimated parameters, h-step ahead forecasts are constructed recursively by iterating on equation (3).

## Bi-variate models (BIV)

For a given targeted series  $j$  and forecast horizon  $h$ , forecasts using each candidate predictor  $i^*$  one at a time will be constructed as defined by equations (4) and (5) below.

Under the direct approach, forecasts are based on a h-step ahead regression model defined as:

$$X_{j,t+h} = \alpha_{ji^*}^h + \sum_{l=1}^p \gamma_{ji^*,l}^h X_{j,t-l} + \sum_{q=q_i^*}^{p+q_i^*} \beta_{ji^*,q}^h X_{i^*,t-q} + \varepsilon_{j,t+h}^h \quad (4)$$

This equation is the direct AR model augmented by a candidate predictor taking into account the real-time availability of the latter as  $q_i$  takes values 0, 1 or 2 according to its publication lag.

In the case of iterated forecasts, let  $X_{ji^*,t} = (X_{j,t} \ X_{i^*,t})'$  denote the  $2 \times 1$  vector of the targeted series and a candidate predictor, then the bi-VAR is defined as:

$$X_{ji^*,t} = A_{ji^*,0} + \sum_{l=1}^p A_{ji^*,l} X_{ji^*,t-l} + \varepsilon_{j,t} \quad (5)$$

The model parameters are estimated on a balanced panel, i.e. truncating the panel at the last month for which both series are available. Next the model is put in the state space form and the Kalman filter and smoother are used to compute recursively the forecasts conditional on the unbalanced panel.

The parameters of equations (2) to (5) are estimated by OLS and the maximum lag length  $p$  and  $q$  are set to 6.<sup>15</sup>

## Multivariate models (MULT)

### • *Dynamic factor model (DFM)*

The DFM framework used here relies on the Giannone, Reichlin and Small (2008) framework that can deal with large and unbalanced datasets. The model can be consistently estimated by either the two-step estimator of Doz, Giannone and Reichlin (2011a) or by maximum likelihood using the Expectation-Maximisation (EM) algorithm as shown in Doz, Giannone and Reichlin (2011b). The latter approach is followed in this paper and will be explained further on.

In the DFM model, the  $n \times 1$  vector of stationary standardized monthly variables,  $x_t$ <sup>16</sup>, is represented as the sum of two orthogonal unobserved components: a common component which is driven by a small number of factors that account for most of the comovement among the variables and an idiosyncratic component which is driven by variable-specific shocks. This model is given by:

$$x_t = \Lambda f_t + \xi_t \quad (6)$$

where  $f_t$  is a  $r \times 1$  vector of common factors,  $\Lambda$  is the  $n \times r$  matrix of the factor loadings, and  $\xi_t$  is a  $n \times 1$  vector of idiosyncratic components.

The factors are modeled as a stationary VAR(p):

$$f_t = A_1 f_{t-1} + \dots + A_p f_{t-p} + u_t; \quad u_t \sim i.i.d.N(0, Q) \quad (7)$$

where  $A_1, \dots, A_p$  are  $r \times r$  matrices of autoregressive coefficients. The idiosyncratic components,  $\xi_t$ , are orthogonal to the common shocks  $u_t$ , and are modeled as independent stationary AR(1) processes:

$$\xi_t = \psi \xi_{t-1} + e_t; \quad e_t \sim i.i.d.N(0, R) \quad (8)$$

where  $\psi = \text{diag}(\psi_1, \dots, \psi_n)$  and  $R = \text{diag}(\sigma_1^2, \dots, \sigma_n^2)$ . Modelling the serial correlation in the idiosyncratic component<sup>17</sup> can be helpful to forecast variables with strong non-common

<sup>15</sup>Note that for equation (4), for a given value of  $q_i^*$  forecasts are constructed using  $l = 0, 1, \dots, 6$ . Hence forecasts are also constructed without using lags of the targeted series.

<sup>16</sup>We use lowercase letters to denote the standardized version of the  $n \times 1$  vector  $X_t$

<sup>17</sup>To obtain optimal estimates of the unobserved state vector using the Kalman filter and smoother, the observation equation errors must be white noises. For the DFM (6)-(8), one can either first transform the model into one with non-autocorrelated errors (equation (9)) then put the transformed model into the state space form (10)-(11) or one can augment the state vector with the  $\xi_t$ . Reis and Watson (2010) have followed the first formulation while Bańbura and Modugno (2010) have adopted the second. The latter authors have

dynamics (see Bańbura and Modugno (2010) and Bańbura, Giannone and Reichlin (2011)). Substituting (8) into (6), one obtains a DFM with non-autocorrelated errors in the transformed variables  $\tilde{x}_t$ :

$$\tilde{x}_t = x_t - \psi x_{t-1} = \Lambda f_t - \psi \Lambda f_{t-1} + e_t \quad \forall t \geq 2 \quad (9)$$

The DFM (6)-(8) can be written in the state space form as:

$$\tilde{x}_t = \tilde{\Lambda} z_t + e_t \quad (10)$$

$$z_t = \tilde{A} z_{t-1} + \tilde{u}_t \quad (11)$$

where if  $p \geq 2$ ,  $\tilde{\Lambda} = [\Lambda \quad -\psi\Lambda \quad 0_{n \times r(p-2)}]$ ,  $\tilde{A} = \begin{bmatrix} A_1 \dots A_{p-1} & A_p \\ I_{r(p-1)} & 0_{r(p-1) \times r} \end{bmatrix}$ ,  $\tilde{u}_t = \begin{bmatrix} u_t \\ 0_{r(p-1) \times 1} \end{bmatrix}$  and  $z_t = \begin{bmatrix} f_t \\ f_{t-1} \\ \dots \\ f_{t-p+1} \end{bmatrix}$  is the state vector. In the case  $p = 1$ ,  $\tilde{\Lambda} = [\Lambda \quad -\psi\Lambda]$ ,  $\tilde{A} = \begin{bmatrix} A_1 & 0_{r \times r} \\ I_r & 0_{r \times r} \end{bmatrix}$ ,  $\tilde{u}_t = \begin{bmatrix} u_t \\ 0_{r \times 1} \end{bmatrix}$  and  $z_t = \begin{bmatrix} f_t \\ f_{t-1} \end{bmatrix}$ .

The observation equation (10) holds  $\forall t \geq 2$  and for the initial observation, since  $\xi_1$  is  $N(0, (I - \psi^2)^{-1}R)$  the observation equation is:

$$x_1 = \Lambda f_1 + \xi_1 \quad \text{where} \quad \xi_1 = e_1 \quad (12)$$

The model parameters  $\phi = \{\Lambda, A_1, \dots, A_p, \psi, R, Q\}$  and the factors are estimated by maximum likelihood following Doz, Giannone and Reichlin (2011b). These authors have proved that maximum likelihood estimation of large DFM is not only consistent, as  $n, T \rightarrow \infty$  along any path, but also computationally feasible as the likelihood can be maximized via the EM<sup>18</sup> algorithm. Note that the DFM (6)-(8) is an exact factor model as it is assumed

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adapted the EM algorithm to deal with arbitrary pattern of missing observations and in such a case the first formulation is not valid. Since we estimate the parameters on a balanced panel and that the second formulation is computationally less efficient, as the dimension of the state vector increases a lot, we use the first formulation. More recently, Jungbacker, Koopman and van der Wel (2011) have accelerated Bańbura and Modugno's (2010) estimation procedure.

<sup>18</sup>The EM algorithm of Dempster, Laird and Rubin (1977) is a well-known approach to maximize the Gaussian likelihood function in the presence of missing data, which here are the unobserved factors. One computes the expected value of the complete data  $(x_t, f_t)$  log-likelihood and then iterate between the expectation (E) and maximization (M) steps. The procedure continues until convergence of the likelihood. In practice to speed up the computation we use the computational device of Jungbacker and Koopman (2008) and apply the Kalman filter and smoother algorithm to the collapsed observation vector.

that there is no cross-correlation in the idiosyncratic components which might not hold in large cross-sections. However, Doz, Giannone and Reichlin (2011b) show that this estimator based on a possibly mis-specified, i.e. exact, factor model is consistent for an approximate factor model. In such a case, the estimation method is quasi maximum likelihood.

The parameters are estimated for all combinations over the range  $r = 1, \dots, 10$  and  $p = 1, 2$  using a balanced panel as is the standard practice in the real-time forecasting literature since the unbalanced part of the panel is only at the end of the sample and concerns at most two months. Then, given the parameters estimates, the forecasts are generated by running the Kalman filter and smoother on the unbalanced part of the panel. Note that Bańbura and Modugno (2010) adapt the EM algorithm to deal with arbitrary pattern of missing observations<sup>19</sup> and their procedure has been further accelerated by Jungbacker, Koopman and van der Wel (2011).

• **Bayesian VAR (BVAR)**

Bańbura, Giannone and Reichlin (2010) found that by applying Bayesian shrinkage, large VAR works well at forecasting. Bayesian estimation combines sample information with priors to yield a posterior estimate, as such shrinkage is incorporated through the priors which take the form of imposing restrictions on parameters. The standard BVAR in the forecasting literature, and used by Bańbura, Giannone and Reichlin (2010), is based on the Minnesota prior of Litterman (1986) and Doan, Litterman and Sims (1984) with the modifications proposed by Kadiyala and Karlsson (1997) and Sims and Zha (1998).

This model is defined as follow<sup>20</sup>:

$$z_t = A_0 + \sum_{l=1}^p A_l z_{t-l} + \varepsilon_t; \quad \varepsilon_t \sim i.i.d.N(0, \Sigma) \quad (13)$$

where  $z_t = (z_{1,t} \dots z_{n,t})'$  denotes the  $n \times 1$  vector of variables in log-level or level for those series that are expressed in rates,  $A_0$  is an  $n \times 1$  vector of constants,  $A_1, \dots, A_p$  are an  $n \times n$  matrices of autoregressive coefficients. The coefficients  $A_1, \dots, A_p$  are assumed to be a priori independent and normally distributed random variables with mean and variances:

$$E[(A_l)_{iu}] = \begin{cases} \delta_i, & u = i, l = 1 \\ 0, & otherwise \end{cases} \quad and \quad V[(A_l)_{iu}] = \begin{cases} \frac{\lambda^2}{l^2} & \\ \frac{\lambda^2}{l^2} \frac{\sigma_i^2}{\sigma_u^2} & \end{cases} \quad (14)$$

where  $\delta_i = 1$  for non-stationary variables and  $\delta_i = 0$  for stationary ones.<sup>21</sup> The hyperpa-

<sup>19</sup>e.g. in a mixed frequency framework or in cases where some series have a shorter history such as for the euro area.

<sup>20</sup>For details see Bańbura, Giannone and Reichlin (2010).

<sup>21</sup>This corresponds to a random walk and white noise prior respectively. Note that in the original Minnesota

parameter  $\lambda$  controls the overall tightness of the prior distribution around  $\delta_i$ <sup>22</sup>: if  $\lambda = 0$  the prior is imposed exactly and the data do not influence the estimate, whereas if  $\lambda = \infty$  the posterior estimates are the OLS estimates. The prior on the intercept is diffuse and the covariance matrix of the residuals  $\Sigma$  is assumed to follow an inverse Wishart distribution.<sup>23</sup> Furthermore, a sum of coefficients prior is also imposed which constrains  $A_1 + \dots + A_p$ . This prior shrinks  $I_n - A_1 - \dots - A_p$  towards zero and is imposed exactly if this sum is zero which amounts to a VAR in first difference. A hyperparameter  $\mu$  governs the degree of shrinkage of this prior.<sup>24</sup>

In practice, the priors are implemented by adding dummy observations. The specification ranges over which the model is estimated are:  $p = 1, \dots, 6$ ,  $\lambda = 0.01:0.01:0.2$  and  $\mu = 0.1\lambda, \lambda, 10\lambda$ . The median of the posterior distribution of the parameters is used to compute point forecasts. Similar to the VAR, these forecasts are computed recursively using the Kalman filter and smoother to take into account the unbalanced part of the panel.

### 3.2 Forecast combination schemes

Out-of-sample forecasts are computed recursively conditional on the real-time information available at the end of each month over the period December 2001 to December 2011 and the estimation sample starts in January 1992. For each targeted variable  $j$  and each forecast horizon  $h$  we have a set of forecasts computed from the suite of models. With the exception of the RW, each model is estimated over a range of specifications as described in the previous subsection, and thereby generates multiple forecasts. To overcome the choice of model specification faced by the practitioner, e.g. which (information) criteria to use to select the parametrization of the model, different forecasts combination schemes<sup>25</sup> are used to produce a single forecast for each model. These schemes are chosen in such a way that as they are the same for each model, by which we mean that they are available for each model. Indeed, we seek for evidence regarding the performance of a model that is robust across specifications/combination schemes; this should also help to insure against specification instability.

The first three combination schemes assign time-varying and horizon specific weights based

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prior  $\delta_i = 1$  for all  $i$ , reflecting the belief that all the variables are highly persistent. In practice the random walk prior is set according to the transformations applied to the series to obtain stationarity as needed in the other models. Hence a white noise prior is used for those series which are untransformed in the  $X_t$  vector (interest spreads and some of the surveys) and a random prior is used for the other series (see Appendix 1).

<sup>22</sup>The decay factor  $1/l^2$  is the rate at which prior variance decreases with the lag length and  $\sigma_i^2 \setminus \sigma_u^2$  accounts for the different scale and variability of the series. The parameters  $\sigma_i^2$  is set to the estimate of the residuals variance from a univariate AR(p).

<sup>23</sup>for details see Kadiyala and Karlsson (1997) and Sims and Zha (1998).

<sup>24</sup>as  $\mu \rightarrow 0$  the prior is more tightly imposed, whereas as  $\mu \rightarrow \infty$  it is looser.

<sup>25</sup>Standard ones used in the forecasting literature.

on past out-of-sample forecasting performance, as measured by the mean square forecast errors (MSFEs) statistic. A burning in phase of two-years starting in December 2001 is used to determine the initial weights. Firstly, we follow Aiolfi and Timmermann (2006) and average over the 10% first best specifications up to that point. Then we consider the MSFEs (*av.msfe*) and discounted-MSFEs (*av.d-msfe*) weighting schemes following Stock and Watson (2004) in which weights are inversely proportional to past forecasting performance. The discounted-MSFEs scheme, with discount factor equal to .9, further assigns a higher weight to the more recent forecasting performance. Lastly, the equally-weighted average (*av.all*) which assigns a constant weight to all specifications over time and across horizons is used; this simple average has been found to work well in practice.<sup>26</sup> These weighting schemes are used to produce a single forecast from combining over all the specifications for a given model (AR, BIV, DFM, BVAR). Furthermore, pooling over all specifications from all models (ALL) and all multivariate models (MULT) using the aforementioned schemes is also considered.<sup>27</sup>

## 4 Empirical results

This section presents the forecasting results for the key series. The root mean square forecast errors (RMSFEs) statistic is used as a metric for evaluating the forecasts and the first release of the series of interest is used as actual. Since our goal is to assess the predictability at different horizons of real and nominal variables, as well as the ability of several models/combination schemes to exploit such predictability, (relative) predictability<sup>28</sup> is defined as the forecasting ability of a given model/combination scheme relative to that of the RW model, i.e. the ratio between the RMSFEs of a given model/combination scheme and the naive RW model.

Figure 1 reports the relative predictive ability of the different forecasting models over the full evaluation period, which runs from December 2003 to December 2011. Since this period includes the two rather distinct sub-periods, namely the so-called (end of the) great moderation (pre-crisis) and the great recession (crisis), Figures 2 and 3 further investigate the stability/instability of the results over these two sub-samples. In each figure forecast horizons are displayed in columns and targeted series in rows; and in each sub-figure the four consecutive same coloured bars for a given model display the results for the different combination schemes, i.e. *av.10%*, *av.msfe*, *av.d-msfe* and *av.all*. A bar below the solid

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<sup>26</sup>cf. Stock and Watson, 2004.

<sup>27</sup>Note that when we pool over more than one model (univariate, bi-variate, multivariate and all), to take into account the different number of specifications across models, the equally-weighted average forecast is constructed by first averaging over all specifications for a given model, then averaging over all models average.

<sup>28</sup>see D'Agostino, Giannone and Surico, 2006.

black line (drawn at one), indicates a forecast that is more precise, on average, than the RW benchmark. To further compare the data-rich forecasting performance to those of the AR model, the dashed blue line shows the relative RMSFEs of the best performing combination scheme for the AR model. Tables A.2.1 and A.2.2 in Appendix 2 reports the actual numbers. First from the results for the **full sample period** (Figure 1) the following comments are made:

- For the **real variables** there is considerable predictability as nearly all relative RMSFEs are smaller than one. For the UR all data-rich forecasts, irrespective of the model, combination schemes and forecast horizon, are always more accurate than the RW and AR models. The DFM is the most accurate at nowcasting ( $h = 0$ ) and for pure forecasting ( $h > 0$ ) both the DFM and the BVAR perform best. For IP this also holds true up to the six-month horizon, whereas for one-year ahead forecasts it holds only for the BVAR and for pooling over all multivariate (MULT) or all (ALL) models.
- Regarding **inflation**, only at the very short-term horizons ( $h = 0$  and  $h = 1$ ) do all the data-rich forecasts beat the naive RW benchmark but do not always improve upon the best AR model for  $h = 1$ . This is not surprising since inflation is known to be hard to forecast over the recent sample (see, among others, Stock and Watson, 2011 and D’Agostino, Giannone and Surico, 2006). The BVAR clearly stands out for both inflation series as it performs much better than the other models with reductions in RMSFEs of the order of 25% for nowcasts and 10% for one-month ahead forecasts. This is in line with the findings of Giannone, Lenza, Momferatou and Onorante (2010) who forecast euro area inflation over the period 2000 to 2009 with a real-time and “ragged-edge” dataset and also found strong improvement of the BVAR over the RW at the short-term horizons.

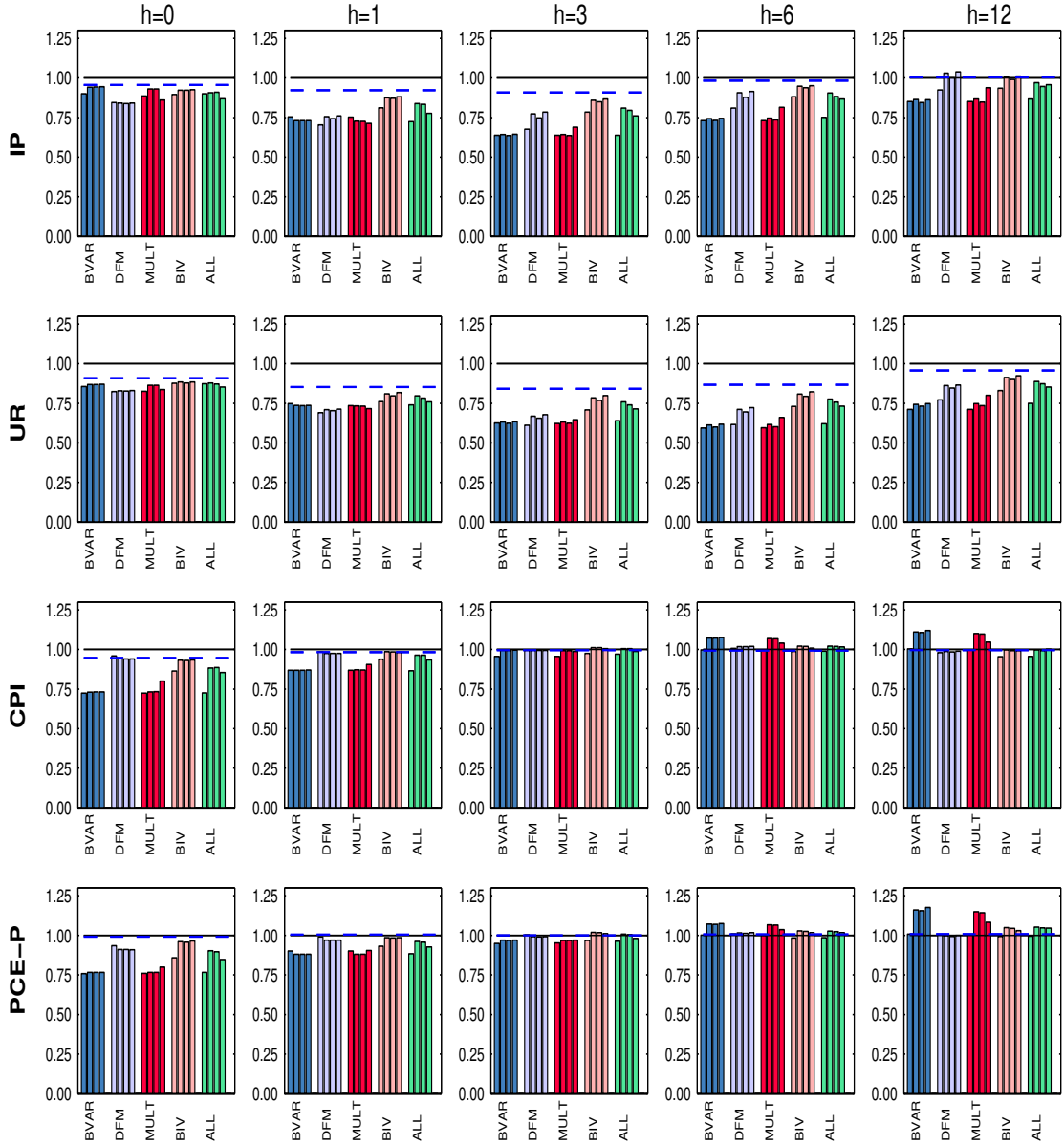
Let us now investigate the stability/instability of the results over the **pre-crisis** and **crisis** sub-samples. This is motivated by the findings of D’Agostino, Giannone and Surico (2006) that relative forecasting performance is related to macroeconomic volatility. These authors find that there is a sizable decline in the predictive accuracy of forecasts based on large datasets relative to univariate models in the post 1985 (great moderation) period, compared to the 70s and early 80s, which also coincides with a marked fall in macroeconomic volatility. D’Agostino and Giannone (2012) further show that most of the forecasting gains of the data-rich models over the univariate ones for the sample 1970 to 1998 are confined to recession/downturn periods which are known to be characterized by higher volatility and comovements, especially among the real variables.

The sub-sample results for the real variables are displayed in Figure 2 and in Figure 3 for the nominal variables; the following comments are made:



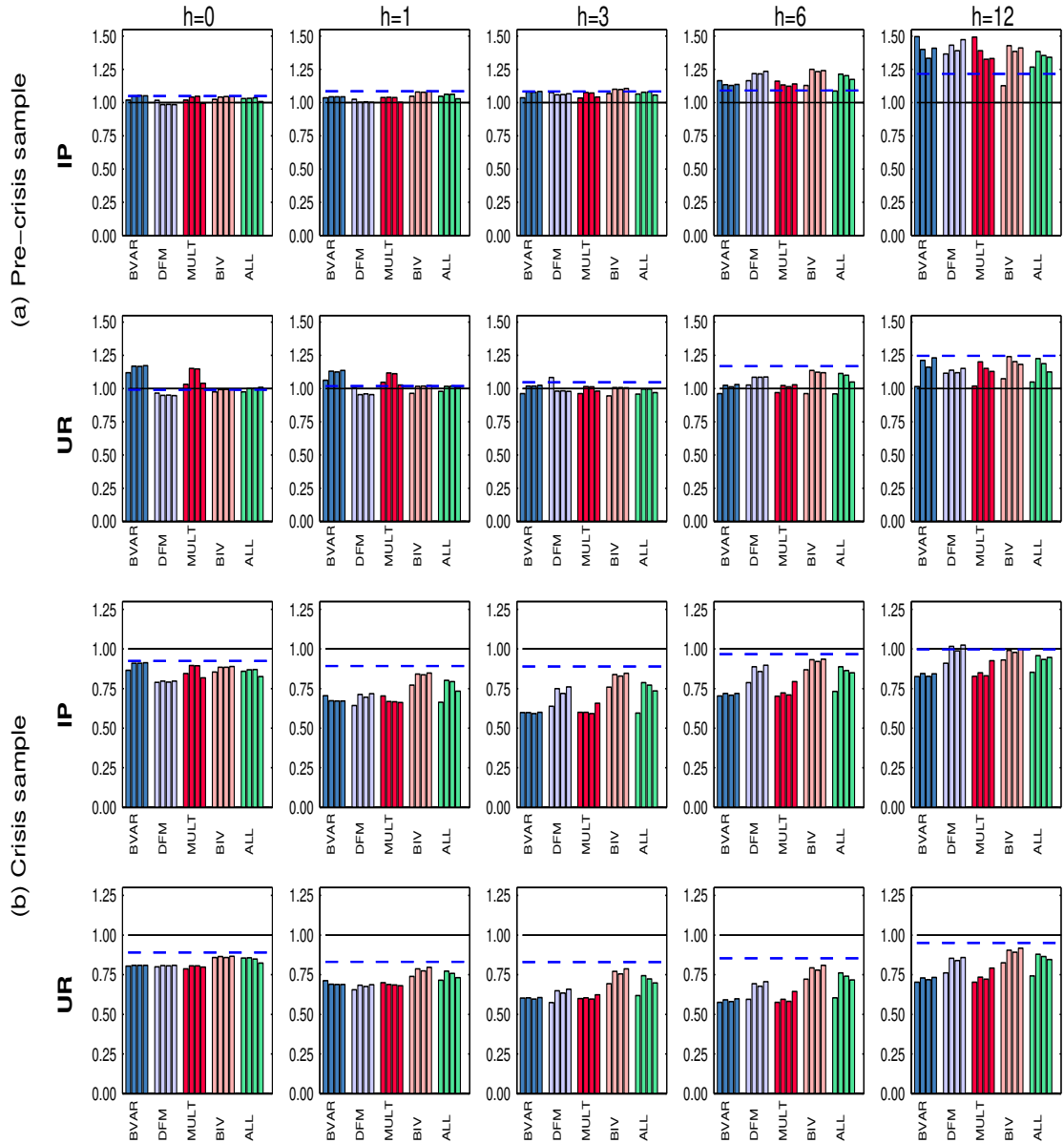
- The striking feature is that for the **real variables** indeed most of the full-sample predictability comes from the great recession period. Over the pre-crisis sample (upper panel), there are only very marginal improvements over the univariate AR and RW models at nowcasting for IP and up to  $h = 3$  for the UR. The picture that emerges when looking at the results over the crisis/great recession period (lower panel) is quite different as evidenced by the fact that nearly all relative RMSFEs are much smaller than one. The comments that can be made for the results over this period are in fact very similar to those made previously over the full sample period. Broadly speaking, there is substantial predictability of the real variables, with this finding being robust across models and combination schemes and multivariate models yield more accurate forecasts than pooling of bi-variate models.
- For **inflation**, on the other hand, the results are quite stable across sub-periods. Faust and Wright (2011), similarly find that forecasting results for inflation are not affected by inclusion or exclusion of the recent crisis, as inflation behavior has not been as extreme as that of the real variables. There is considerable predictability at horizon  $h = 0$  and the BVAR stands out by far as the most precise nowcasting model for both inflation series. Also over both sub-samples, all models beat the RW at horizon  $h = 1$  and for longer horizons results are more mixed across models and combination schemes.

Figure 1: Relative RMSFEs - full sample



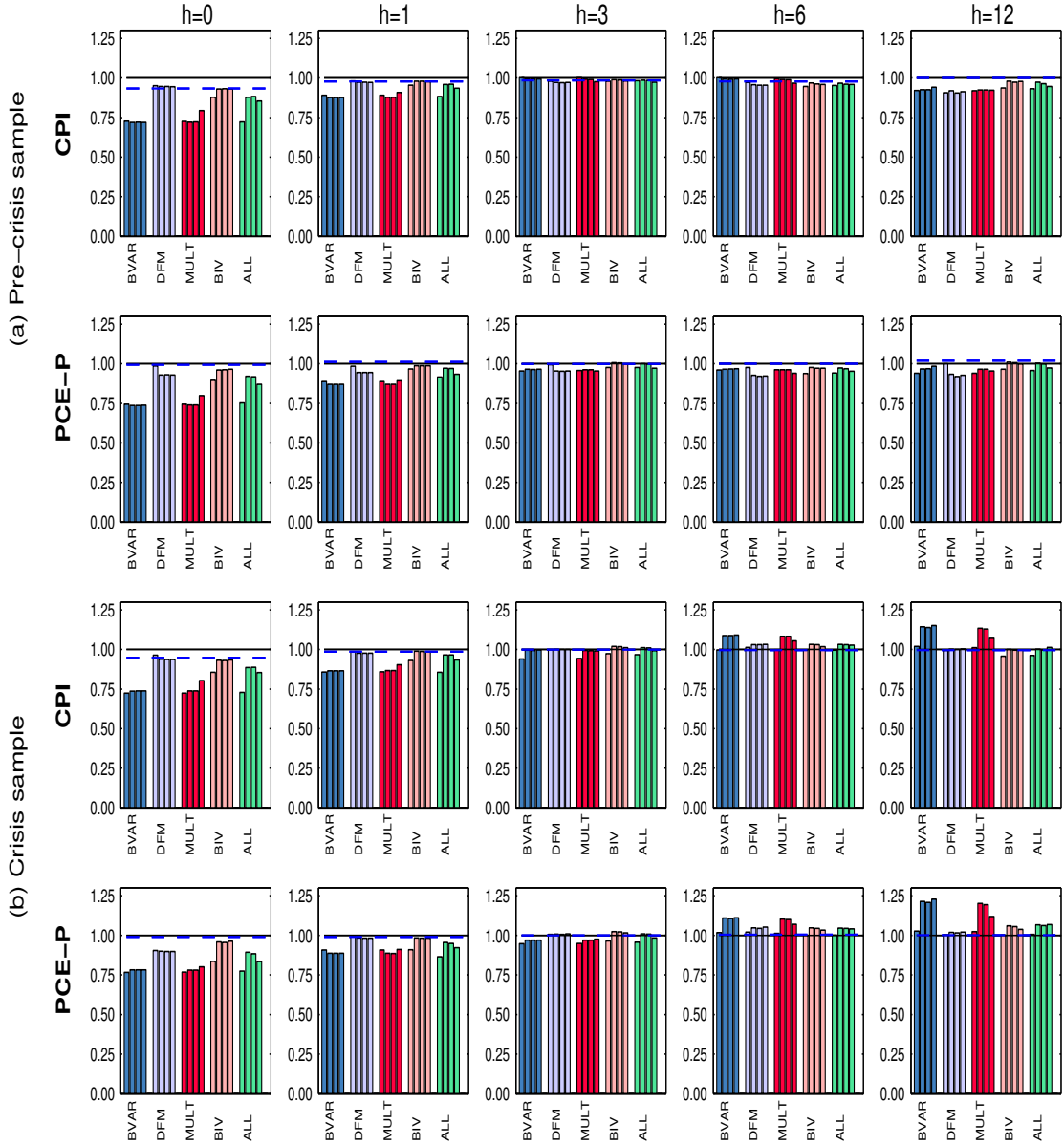
**Notes:** The Figure shows the relative (versus the RW) RMSFEs for each model over the full sample evaluation period which runs from December 2003 to December 2011. In each sub-figure the four consecutive (same coloured) bars for a given model display the results for the forecasts combination schemes used, i.e. av.10%, av.msfe, av.d.msfe and av.all. The dashed blue line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

Figure 2: Relative RMSFEs - real variables - sub-samples



**Notes:** The figure shows the relative (versus the RW) RMSFEs for each model over the pre-crisis period December 2003–November 2007 (top panel) and crisis period December 2007–December 2011 (lower panel). In each sub-figure the four consecutive (same coloured) bars for a given model display the results for the forecasts combination schemes used, i.e. av.10%, av.msfe, av.d.msfe and av.all. The dashed blue line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

Figure 3: Relative RMSFEs - nominal variables - sub-samples



**Notes:** The figure shows the relative (versus the RW) RMSFEs for each model over the pre-crisis period December 2003–November 2007 (top panel) and crisis period December 2007–December 2011 (lower panel). In each sub-figure the four consecutive (same coloured) bars for a given model display the results for the forecasts combination schemes used, i.e. av.10%, av.msfe, av.d-msfe and av.all. The dashed blue line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

To sum up, the results show that, when there is predictability, also in real-time does cross-sectional information helps at forecasting since data-rich forecasts not only beat the RW but also the AR model.

For the real variables, predictability is confined over the recent recession/crisis period. This in line with the findings of D’Agostino and Giannone (2012) over an earlier period, that gains in relative performance of models using large datasets over univariate models are driven by downturn periods which are characterized by higher volatility and comovements. To further gauge the link between comovement and predictability, the upper part of Table 1 reports the percentage of the total panel variance accounted for by the first ten static and dynamic principal components whereas the lower part of the table displays the fraction of predictors that have information content for the targeted series.<sup>29</sup> Results show that over the crisis sample, when the forecasting gains of data-rich models is high, comovement is higher as well as the proportion of indicator which has information content for the targeted series.

Table 1: Comovement and predictability

<i>Comovement:</i>										
period / no. of PCs:	1	2	3	4	5	6	7	8	9	10
	<i>Static PCs</i>									
pre-crisis	0.16	0.28	0.38	0.45	0.51	0.56	0.61	0.65	0.69	0.73
crisis	0.31	0.45	0.53	0.60	0.67	0.71	0.75	0.78	0.81	0.84
	<i>Dynamic PCs</i>									
pre-crisis	0.38	0.59	0.73	0.83	0.89	0.93	0.95	0.96	0.97	0.98
crisis	0.48	0.69	0.80	0.88	0.93	0.95	0.97	0.98	0.99	0.99
<i>Individual predictive content:</i>										
period / for.hor.:	h=0	h=1	h=3	h=6	h=12	h=0	h=1	h=3	h=6	h=12
	<i>IP</i>					<i>UR</i>				
pre-crisis	0.10	0.13	0.13	0.13	0.06	0.10	0.10	0.06	0.04	0.03
crisis	0.67	0.73	0.72	0.58	0.57	0.69	0.67	0.70	0.70	0.67
	<i>CPI</i>					<i>PCE-P</i>				
pre-crisis	0.34	0.37	0.34	0.22	0.24	0.42	0.49	0.39	0.34	0.13
crisis	0.45	0.30	0.13	0.09	0.27	0.24	0.25	0.15	0.07	0.12

**Notes:** The upper part of the Table shows the percentage of total panel variance explained by the first ten static and dynamic principal components (PCs). The lower part of the Table shows the fraction of variables for each target series that have individual predictive content at a given horizon. The results are based on forecasts constructed using equation (4) without lags of the targeted series. A variable is considered to have predictive content if its RMSFEs are smaller than those of the RW model for all the forecasting combination schemes. All results are displayed over the pre-crisis (Dec.2003-Nov.2007) and crisis (Dec.2007-Dec.20011) samples

In such a situation when faced with many informative predictors that are highly collinear, i.e. admit a (approximate) factor structure, a forecaster is better off using all the information. Furthermore the direct pooling of information using a high dimensional model (DFM or

<sup>29</sup>For each targeted series, using each candidate predictor we generate forecasts at a given horizon with equation (4) but without lags of the targeted series over both sub-samples. The lower part of Table 1 reports the % of predictors which are found to have information content at a given horizon. This is the % of predictors that yield more accurate forecasts than the RW model, with a predictor being considered to be helpful if results are robust across combination schemes.

BVAR) which takes into account the cross-correlation between the variables, yields more accurate forecasts than pooling of bi-variate models. These multivariate models perform better than the simple average (*av.all*) combination scheme of the bi-variate models, which Timmermann (2004) and Stock and Watson (2004), using a balanced datasets, report as a difficult benchmark to beat. This holds true for real and nominal variables. A further reason put forward for the better performance of direct pooling of information is that in a real-time setting the missing months at the forecast origin (or before), due to publication lags, are efficiently estimated taking into account all the available information via the Kalman filter and smoother.

De Mol, Giannone and Reichlin (2008) further show that in such a case (high comovement and predictive content), factor model (principal components) forecasts and Bayesian forecasts under normal prior (with the degree of shrinkage chosen in relation to the cross-sectional dimension) yield similar results. Although not reported here, we find similarly to these authors that the DFM and BVAR forecasts are highly correlated when they both perform well. In both models, regressors used to construct the forecasts are a linear combination of all variables (i.e. linear shrinkage) in the panel<sup>30</sup>; principal components forecasts put unit weight on the first ( $r$ ) dominant eigenvalues of the covariance matrix of the data and zero on the others, while Bayesian forecasts assign decreasing weight to all the ordered eigenvalues.

The fact that the BVAR assigns non-zero weights to less important eigenvalues whereas the DFM gives them a zero weight also helps explain why the former model stands out for nowcasting inflation in real-time. Our conjecture is that an oil price component, which is the main driver of short-run inflation dynamics, is captured by these minor eigenvalues as commodity prices and prices survey data for the reference month are known at the forecast origin. We will come back to this point in the sequel by looking at the marginal predictive ability of these timely indicators.

Lastly, our results also show that results are robust to forecasts combination schemes (i.e. model specification) and that pooling over different models works. In instances when the BVAR or DFM performs less well, the pooling over these models always ranks among the best. The same can be said about pooling over all models as even if it only seldom gives the lowest RMSFEs for a given forecast horizon, it never ranks last. Although, when there are big differences between the different models RMSFEs, then generally it is only the combination scheme (*av.10%*) which stands out as it assigns weights only to the top 10%

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<sup>30</sup> An alternative method is to use non-linear shrinkage such as Lasso regression, which simultaneously does shrinkage and variable selection. However, when variables are highly collinear, these forecasts should produce similar results to those obtained with DFM and Bayesian regression under normal prior, and the weights attached to individual predictors would be unstable. See De Mol, Giannone and Reichlin (2008). Stock and Watson (2011) further find that these alternative shrinkage estimators do not perform better than DFM.

best past performers. These results suggest that pooling across models is useful from a real-time forecaster perspective who does not know ex-ante which model to choose among the competing ones.

### ***Marginal predictive ability of surveys, financials and commodity prices***

A related although distinct issue that we further investigate over these two periods is the predictive content of the timely blocks of variables, i.e. the surveys, financials and commodity prices.

The standard balanced panel literature includes mixed results regarding the predictive ability of these variables, in particular of the financials which are commonly thought of as leading indicators, using different approaches and over different samples.<sup>31</sup> From a real-time forecaster perspective, these blocks of data have additional value because of their timeliness. Since they are released ahead of the hard data, and are for the bulk of them already available at the end of the month they refer to, one would expect them to be helpful at forecasting, especially at the short-term horizon. This has been extensively emphasized in the recent GDP nowcasting literature which finds that surveys help nowcasting growth especially at the beginning of the quarter when they are the only source of information on the current quarter. Their contribution to nowcasting mainly derives from their timeliness, as they are generally found to carry no information beyond and above hard data once the later have been released.<sup>32</sup>

To assess the marginal predictive ability for targeted series of these timely blocks, taking into account the real-time data flow, we revisit the results of the previous sub-section by comparing the forecasts generated with the following datasets:

- all variables;
- all variables excluding the surveys, financials and commodity prices;
- all variables excluding the surveys;
- all variables excluding the financials;
- all variables excluding the commodity prices.

Firstly we examine whether the overall results regarding the relative forecasting performance of models using large data over the univariate models, are dependent upon the type of information included. These results are reported in Figures A.2.1 to A.2.8 in Appendix A.2 to ease readability. Each figure shows the results for a given targeted series and sub-period; the sub-figures report the results using the different datasets for a given model and forecast

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<sup>31</sup>See among others, Stock and Watson, 2003a; Forni, Hallin, Lippi and Reichlin, 2003.

<sup>32</sup>See, among others, Giannone, Reichlin and Small, 2008; Liebermann, 2011; Bańbura and Runstler, 2011. Whereas, Andreou, Ghysels and Kourtellos, 2010, using the MIDAS framework, find that the use of timely daily financials data improves GDP nowcasts significantly.

horizon. At a glance, one can see that the overall finding of considerable predictability, in size and across models, for the real variables in the great-recession sub-period holds true irrespective of the data set used to construct the forecasts. Whereas for inflation a worth mentioning pattern across both sub-samples is that forecasting performance of the BVAR in particular at the short-term horizons, deteriorates considerably across models when excluding the soft data altogether.

To further assess the marginal predictive content, above and beyond the hard data, of the timely blocks, Figures 4 and 5 report the percentage change in RMSFEs due inclusion of all the soft data <sup>33</sup> in the panel, whereas the conditional (on the other blocks) marginal contribution of a given block are shown in Figures A.2.9 to A.2.12 in Appendix A.2. A bar below zero, means that the inclusion of all the soft data (a block) in the dataset decreases RMSFEs relative to those obtained from a dataset without them. A first overall observation, which helps to explain the mixed results found in the literature, is that for none of the key series, soft data (taken as a whole or looking at a specific block) uniformly, over both sub-samples and for all models (and combination schemes), have marginal predictive content over all horizons.

For the real variables, these timely blocks help more during the crisis period, and as such are also only really helpful when the hard data are. Over this later period, for the UR the inclusion of the soft data always improves the forecasting performance of the multivariate models across all horizons; the impact on the bi-variate models is more modest but it never deteriorates the performance. For IP the same holds true only for pure forecasting, and at  $h = 0$  the DFM and BVAR shows conflicting results. Further evidence in Appendix A.2 shows that it is the surveys and financial block which have an impact on the real variables; and that surveys, conditional on the financials (and commodity prices) are helpful and vice versa. For both inflation series and across both sub-samples, the inclusion of the soft data block (driven by surveys and commodity prices) only helps to considerably improve the performance of the BVAR at  $h = 0$  and  $h = 1$ . This empirically supports our conjecture made previously about the factor behind its better performance over the DFM for the nominal variables.

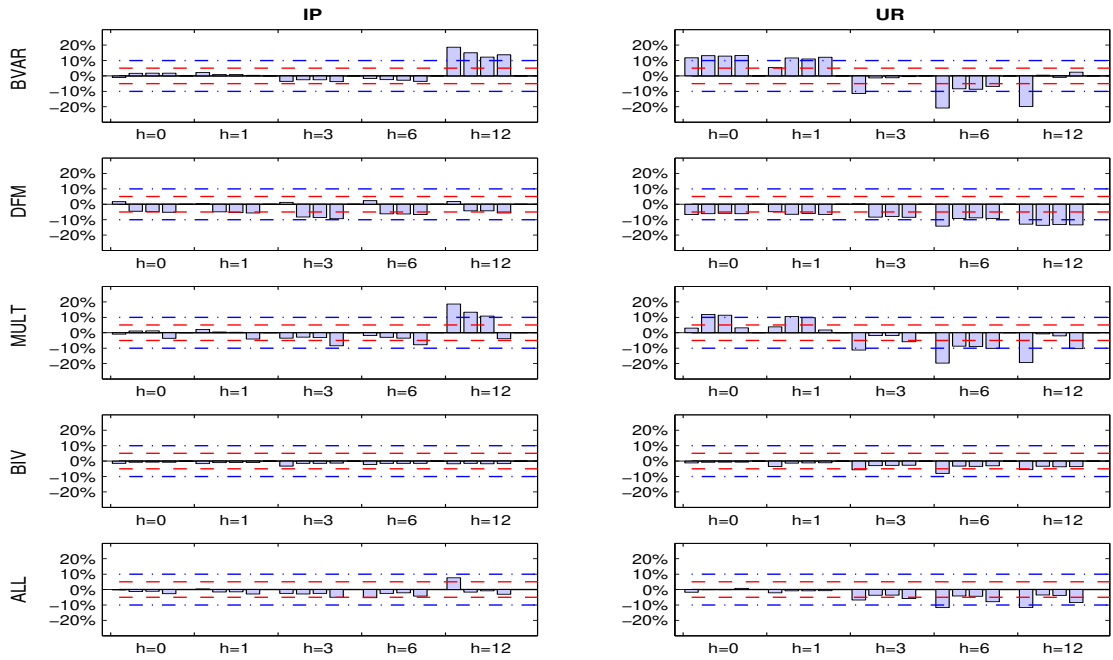
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<sup>33</sup>For simplicity we classify the three blocks of timely variables as soft data.

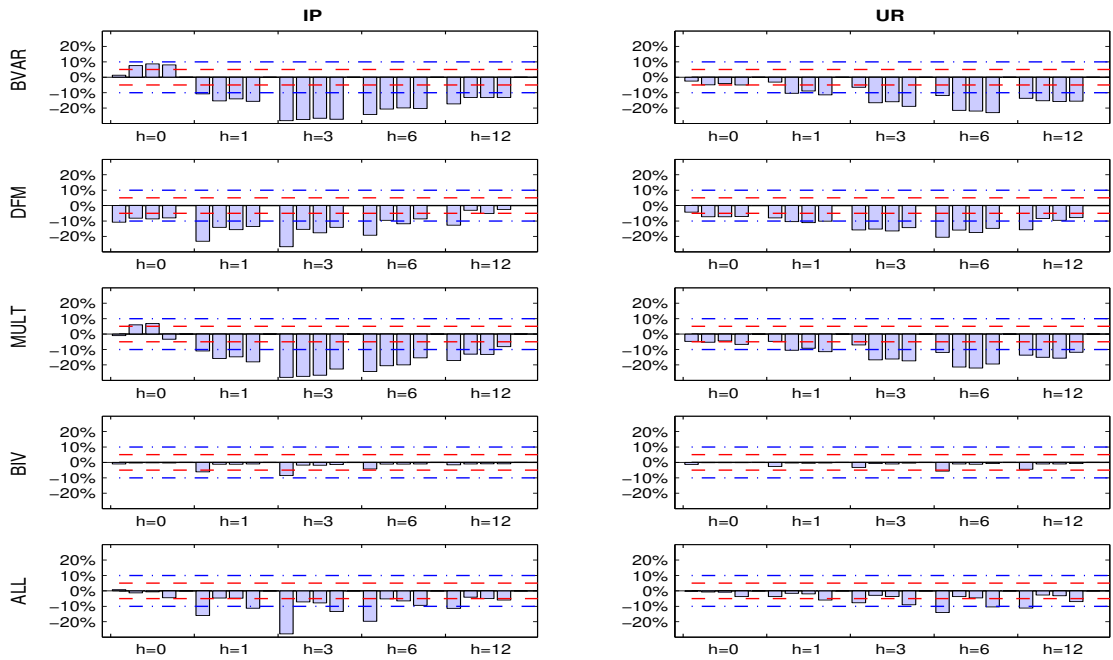


Figure 4: Marginal predictive ability of soft data for the real variables

(a) Pre-crisis sample



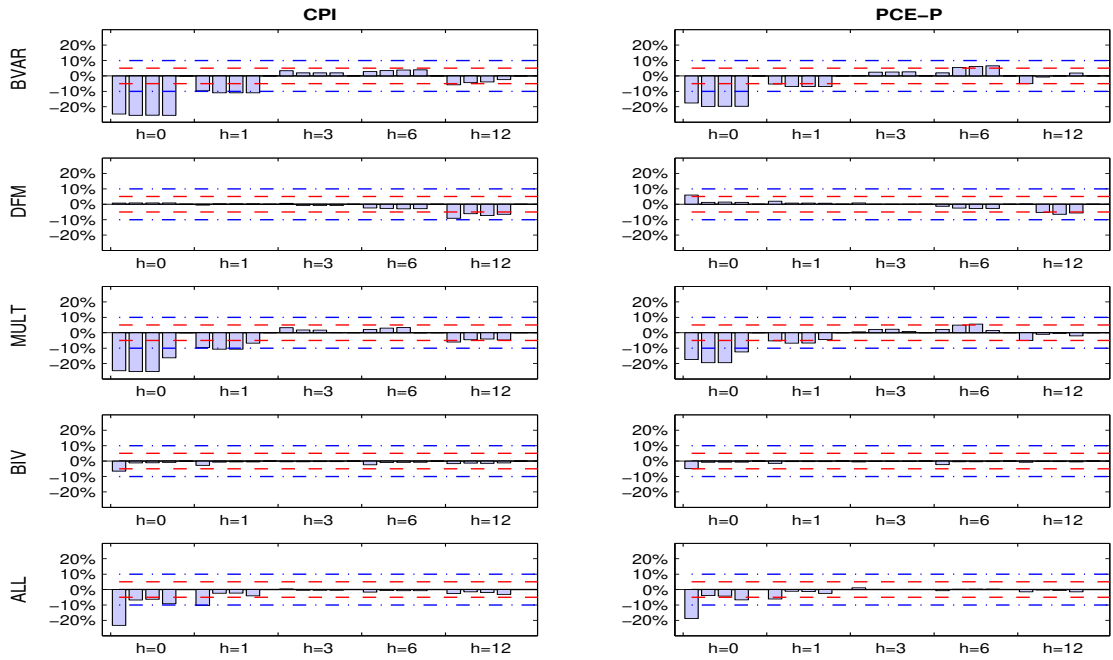
(b) Crisis sample



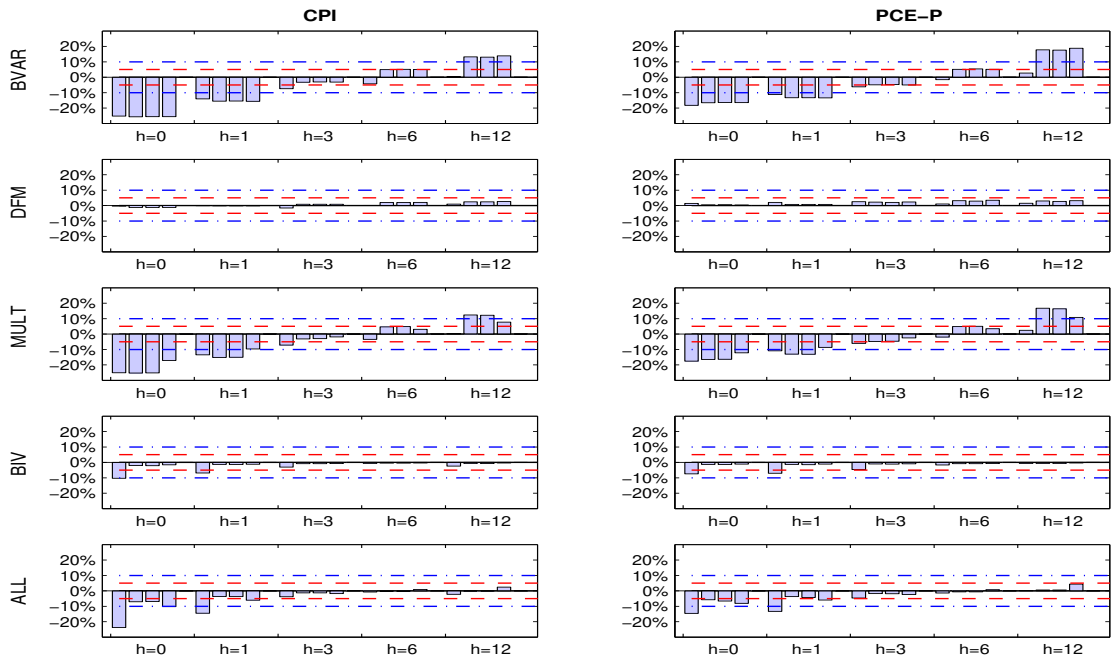
**Notes:** The figure shows for each model the percentage change in RMSFEs from including the different respective block(s) of soft data. In each sub-figure the four consecutive bars for a given horizon displays the results for the four forecasts combination schemes used, i.e. av.10%, av.mse, av.d-mse and av.all. The dashed and dashed dotted lines are drawn at the  $\pm 5\%$  and  $\pm 10\%$  threshold respectively.

Figure 5: Marginal predictive ability of soft data for the nominal variables

(a) Pre-crisis sample



(b) Crisis sample



**Notes:** The figure shows for each model the percentage change in RMSFEs from including the different respective block(s) of soft data. In each sub-figure the four consecutive bars for a given horizon displays the results for the four forecasts combination schemes used, i.e. av.10%, av.mse, av.d-mse and av.all. The dashed and dashed dotted lines are drawn at the  $\pm 5\%$  and  $\pm 10\%$  threshold respectively.

## 5 Conclusion

This paper evaluates the ability of different models to forecast key real and nominal U.S. monthly macroeconomic variables in a data-rich environment and from the perspective of a real-time forecaster, i.e. taking into account the real-time data revisions process and data flow.

Our findings show that predictability of the real variables is confined over the recent recession/crisis period. This is in line with the findings of D’Agostino and Giannone (2012) over an earlier period, that gains in relative performance of models using large datasets over univariate models are driven by downturn periods which are characterized by higher comovements. These results are robust to the combination schemes or models used. Regarding inflation, results are stable across time, but predictability is mainly found at nowcasting and forecasting one-month ahead, with the BVAR standing out at nowcasting. The results show that the forecasting gains at these short horizons stem mainly from exploiting timely information.

For both real and nominal variables, the direct pooling of information using a high dimensional model (DFM or BVAR) which takes into account the cross-correlation between the variables and efficiently deals with the “ragged-edge” structure of the dataset, yields more accurate forecasts than the indirect pooling of bi-variate forecasts/models. The fact that the DFM and the BVAR yield similar results (forecasts with comparable RMSFEs and highly correlated) when there is comovement has been shown by De Mol, Giannone and Reichlin (2008). In both models, regressors used to construct the forecasts are linear combinations of all variables in the panel; factor model forecasts put unit weight on the first dominant eigenvalues of the covariance matrix of the data and zero on the others, while Bayesian forecasts assign decreasing weights to all the ordered eigenvalues. The fact that the BVAR assigns non-zero weights to less important eigenvalues whereas the DFM gives them a zero weight also helps to explain why the former model stands out for nowcasting inflation in real-time. Presumably, an oil price component, which is the main driver of short-run inflation dynamics, is captured by these minor eigenvalues as commodity prices and prices survey data for the reference month are known at the forecast origin.

## Appendix A.1: Data description

Releases/reports	Sources	Series	Publication lag (in months)	Transformation code		
Business Outlook Survey	(1)(b)	diffusion index of current activity	0	0		
		diffusion index of current employment	0	0		
		diffusion index of current price paid	0	0		
		diffusion index of current price received	0	0		
Manufacturing ISM Report on Business	(2)(a)(b)	ISM manufacturing: PMI composite index	1	0		
NFIB Small Business Optimism index	(10)(c)	Small Business Optimism index	1	0		
The Conference Board Consumer's index	(3)(d)	Index of consumer confidence	0	1		
University of Michigan Consumer Sentiment index	(4)(b)(c)	Index of consumer sentiment (preliminary (4)(d), final (4)(a))	0	1		
University of Michigan Inflation expectation	(4)(b)(c)	Index of consumer sentiment	0 or 1	1		
The Employment Situation	(5)(a)	Employees on nonfarm payrolls: total	1	2		
		Employees on nonfarm payrolls: manufacturing	1	2		
		Employees on nonfarm payrolls: construction	1	2		
		Employees on nonfarm payrolls: financial activities	1	2		
		Employees on nonfarm payrolls: government	1	2		
		Employees on nonfarm payrolls: goods-producing industries	1	2		
		Employees on nonfarm payrolls: other services	1	2		
		Employees on nonfarm payrolls: service-providing industries	1	2		
		Employees on nonfarm payrolls: retail trade	1	2		
		Employees on nonfarm payrolls: wholesale trade	1	2		
		Employees on nonfarm payrolls: total private industries	1	2		
		Average hourly earnings: total private industries	1	3		
		Average weekly hours: total private industries	1	2		
		Average weekly hours: manufacturing	1	2		
		Average weekly hours: overtime - manuf.	1	2		
		Civilian unemployment rate	1	1		
		Civilian participation rate	1	1		
		Mean duration of unemployment	1	2		
		G.17 Industrial Production and Capacity Utilization	(6)(a)	Industrial production : total	1	2
				Capacity utilization: total	1	1
Advance Monthly Sales for Retail and Food Services	(7)(a)	Retail and food services sales	1	2		
Manufacturing and Trade Inventories and Sales	(7)(a)	Inventories: total business	2	2		
		Inventories to sales ratio: total business	2	2		
Manufacturer's Shipments, Inventories, and Orders (M3)	(7)(a)	Manufacturer's new orders: durable goods	1	2		
		Manufacturer's new orders: non defense capital goods excluding aircraft	2	2		
Supplemental Estimates, Motor Vehicles	(8)(a)	Light weight vehicle sales: autos & light trucks	1	2		
New Residential Construction	(7)(a)	Housing starts: total	1	2		
		Housing starts: 1-unit structure	1	2		
		New private housing units authorized by building permit	1	2		
New Residential Sales	(7)(a)	New one family houses sold: U.S.	1	2		
Personal Income and Outlays	(8)(a)	Real disposable personal income	1 or 2	2		
		Real personal consumption expenditures	1 or 2	2		
		Real personal consumption expenditures: durable goods	1 or 2	2		
		Real personal consumption expenditures: nondurable goods	1 or 2	2		
		Real personal consumption expenditures: services	1 or 2	2		
		Personal saving rate	1 or 2	1		
		Personal consumption expenditures: chain-type price index	1 or 2	2		
		Personal consumption expenditures: chain-type price index less food & energy	1 or 2	2		

Releases/reports	Sources	Series	Publication lag (in months)	Transformation code
Consumer Price Index	(5)(a)	Consumer price index for all urban consumers: all items	1	2
		Consumer price index for all urban consumers: all items less food & energy	1	2
		Consumer price index for all urban consumers: food	1	2
		Consumer price index for all urban consumers: energy	1	2
Producer Price Index	(5)(a)	Produce price index: finished goods	1	2
		Produce price index: finished goods less food & energy	1	2
		Produce price index: finished consumer goods excluding foods	1	2
		Produce price index: finished energy goods	1	2
		Produce price index: crude materials for further processing	1	2
		Produce price index: intermediate materials: supplies & components	1	2
G.19. Consumer Credit	(6)(a)	Total consumer credit outstanding	2	2
H.6. Money Stock Measures	(6)(a)	M2 money stock	1	2
H.8. Assets and Liabilities of Comm. Banks in the U.S.	(6)(a)	Consumer (Individual) Loans at all commercial banks	1	2
		Commercial and Industrial Loans at all commercial banks	1	2
Selected Interest Rates	(6)	Federal funds rate	0	1
		spread of 10-year U.S. Treasury yield (constant maturity) over the Federal funds rate	0	0
		spread of Moody's BAA Corporate bonds yield over 10-year U.S. Treasury yield (constant maturity)	0	0
		Usd versus weighted average of foreign currencies (broad)	0	2
Exchange rate	(6)	Usd versus weighted average of foreign currencies (broad)	0	2
S&P	(c)	S&P500 Composite	0	2
Commodity price index	(c)	Commodity price index	0	2
WTI Oil price	(c)	Oil price	0	2

**Notes:**

The second column refers to the following sources:

- |  |   |
|--|---|
| (1) The Federal Reserve Bank of Philadelphia                                   | (a) The Federal Reserve Bank of St.Louis, ALFRED database |
| (2) The Institute for Supply Management  | (b) Bloomberg   |
| (3) The Conference Board   | (c) Datastream  |
| (4) The University of Michigan   |   |
| (5) U.S. Department of Labor: Bureau of Labor Statistics                       |   |
| (6) Board of Governors of the Federal Reserve System                           |   |
| (7) U.S. Department of Commerce: Census Bureau                                 |   |
| (8) U.S. Department of Commerce: Bureau of Economic Analysis                   |   |
| (9) U.S. Department of Commerce: Bureau of Economic Analysis and Census Bureau |   |
| (10) NFIB Research Foundation  |   |

The last column refers to the following transformation codes:

code:	transformation to stationary:	transformation used in the BVAR in level:	prior $\delta_i$ :
0	$X_{it} = Z_{it}$	$z_{it} = Z_{it}$	0
1	$X_{it} = (1 - L)Z_{it}$	$z_{it} = Z_{it}$	1
2	$X_{it} = 100 \times (1 - L)\log(Z_{it})$	$z_{it} = \log(Z_{it})$	1

## Appendix A.2: Tables and figures

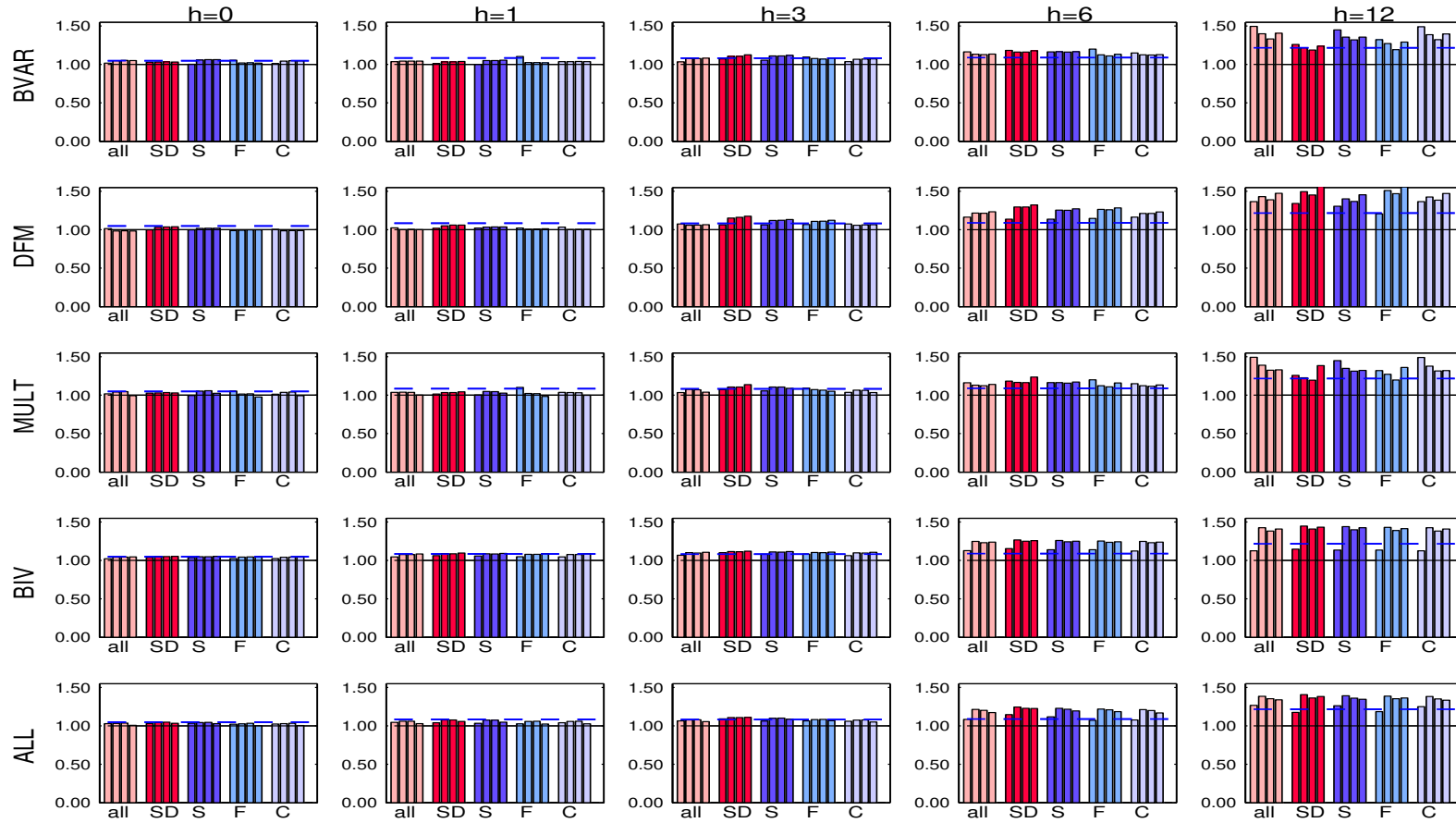
Table A.2.1: Relative RMSFEs - full sample

hor.:	h=0				h=1				h=3				h=6				h=12			
comb. scheme:	av. 10%	av. mse	av. d-mse	av. all	av. 10%	av. mse	av. d-mse	av. all	av. 10%	av. mse	av. d-mse	av. all	av. 10%	av. mse	av. d-mse	av. all	av. 10%	av. mse	av. d-mse	av. all
<i>Industrial production</i>																				
AR	0.98	0.96	0.96	0.96	0.97	0.92	0.92	0.92	0.95	0.91	0.91	0.91	0.99	0.99	0.98	0.99	1.00	1.04	1.03	1.04
BVAR	0.90	0.94	0.94	0.94	0.75	0.73	0.73	0.73	0.64	0.64	0.64	0.64	0.73	0.74	0.73	0.74	0.85	0.86	0.84	0.86
DFM	0.84	0.84	0.84	0.84	0.70	0.76	0.74	0.76	0.68	0.77	0.75	0.78	0.81	0.91	0.88	0.92	0.92	1.03	1.00	1.04
MULT	0.89	0.93	0.93	0.86	0.75	0.73	0.73	0.71	0.64	0.64	0.64	0.69	0.73	0.75	0.73	0.81	0.85	0.87	0.85	0.94
BIV	0.90	0.92	0.92	0.93	0.81	0.88	0.87	0.88	0.78	0.86	0.85	0.87	0.88	0.95	0.94	0.95	0.94	1.01	0.99	1.01
ALL	0.90	0.91	0.91	0.87	0.72	0.84	0.83	0.78	0.64	0.81	0.80	0.76	0.75	0.91	0.88	0.87	0.87	0.97	0.95	0.96
<i>Unemployment rate</i>																				
AR	0.95	0.91	0.91	0.91	0.90	0.86	0.85	0.86	0.86	0.85	0.84	0.85	0.92	0.87	0.87	0.87	0.99	0.96	0.96	0.96
BVAR	0.86	0.87	0.87	0.87	0.75	0.74	0.73	0.74	0.63	0.63	0.62	0.63	0.59	0.61	0.60	0.62	0.71	0.74	0.73	0.75
DFM	0.82	0.83	0.83	0.83	0.69	0.71	0.70	0.71	0.61	0.67	0.66	0.68	0.62	0.71	0.70	0.72	0.77	0.86	0.85	0.87
MULT	0.83	0.86	0.86	0.84	0.73	0.73	0.73	0.72	0.62	0.63	0.62	0.65	0.59	0.62	0.60	0.66	0.71	0.75	0.73	0.80
BIV	0.88	0.88	0.88	0.88	0.76	0.81	0.80	0.82	0.71	0.78	0.77	0.80	0.73	0.81	0.79	0.82	0.83	0.91	0.90	0.92
ALL	0.87	0.88	0.87	0.85	0.74	0.80	0.78	0.76	0.64	0.76	0.74	0.71	0.62	0.78	0.76	0.73	0.75	0.89	0.87	0.85
<i>Consumer price index</i>																				
AR	0.95	0.95	0.95	0.95	0.98	1.00	1.00	1.00	1.00	1.01	1.01	1.01	0.99	1.01	1.01	1.01	1.00	1.00	1.00	1.01
BVAR	0.72	0.73	0.73	0.73	0.87	0.87	0.87	0.87	0.96	0.99	0.99	1.00	1.00	1.07	1.07	1.07	1.00	1.11	1.11	1.12
DFM	0.96	0.94	0.94	0.94	0.98	0.98	0.98	0.98	0.99	0.99	0.99	0.99	1.01	1.02	1.02	1.02	0.98	0.99	0.99	0.99
MULT	0.72	0.73	0.73	0.80	0.87	0.87	0.87	0.91	0.96	0.99	0.99	0.99	1.00	1.07	1.07	1.04	1.00	1.10	1.10	1.05
BIV	0.86	0.93	0.93	0.93	0.94	0.99	0.98	0.98	0.98	1.01	1.01	1.00	0.99	1.02	1.02	1.01	0.95	1.00	0.99	0.99
ALL	0.73	0.88	0.89	0.85	0.87	0.96	0.96	0.93	0.97	1.01	1.00	0.99	0.99	1.02	1.02	1.02	0.96	1.00	0.99	1.00
<i>Personal consumption expenditures price index</i>																				
AR	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.02	1.02	1.02	1.01	1.02	1.02	1.02	1.01	1.03	1.03	1.03
BVAR	0.76	0.77	0.77	0.77	0.90	0.88	0.88	0.88	0.95	0.97	0.97	0.97	1.00	1.07	1.07	1.07	1.01	1.16	1.15	1.17
DFM	0.93	0.91	0.91	0.91	0.99	0.97	0.97	0.97	1.00	0.99	0.99	0.99	1.01	1.02	1.01	1.02	1.00	1.00	0.99	1.00
MULT	0.76	0.77	0.77	0.80	0.90	0.88	0.88	0.90	0.95	0.97	0.97	0.97	1.00	1.07	1.06	1.04	1.00	1.15	1.14	1.08
BIV	0.86	0.96	0.96	0.96	0.93	0.99	0.98	0.98	0.97	1.02	1.02	1.01	0.98	1.03	1.02	1.02	0.99	1.05	1.04	1.03
ALL	0.77	0.90	0.90	0.85	0.88	0.96	0.96	0.93	0.96	1.01	1.00	0.98	0.99	1.03	1.02	1.02	0.99	1.05	1.05	1.05

Notes: The table displays the relative RMSFEs for each model and combination scheme over the RW benchmark. The full evaluation sample runs from December 2003 to December 2011. Numbers below one are put in bold and are further shaded if the relative RMSFE is lower than that of the best AR model for the corresponding forecast horizon.



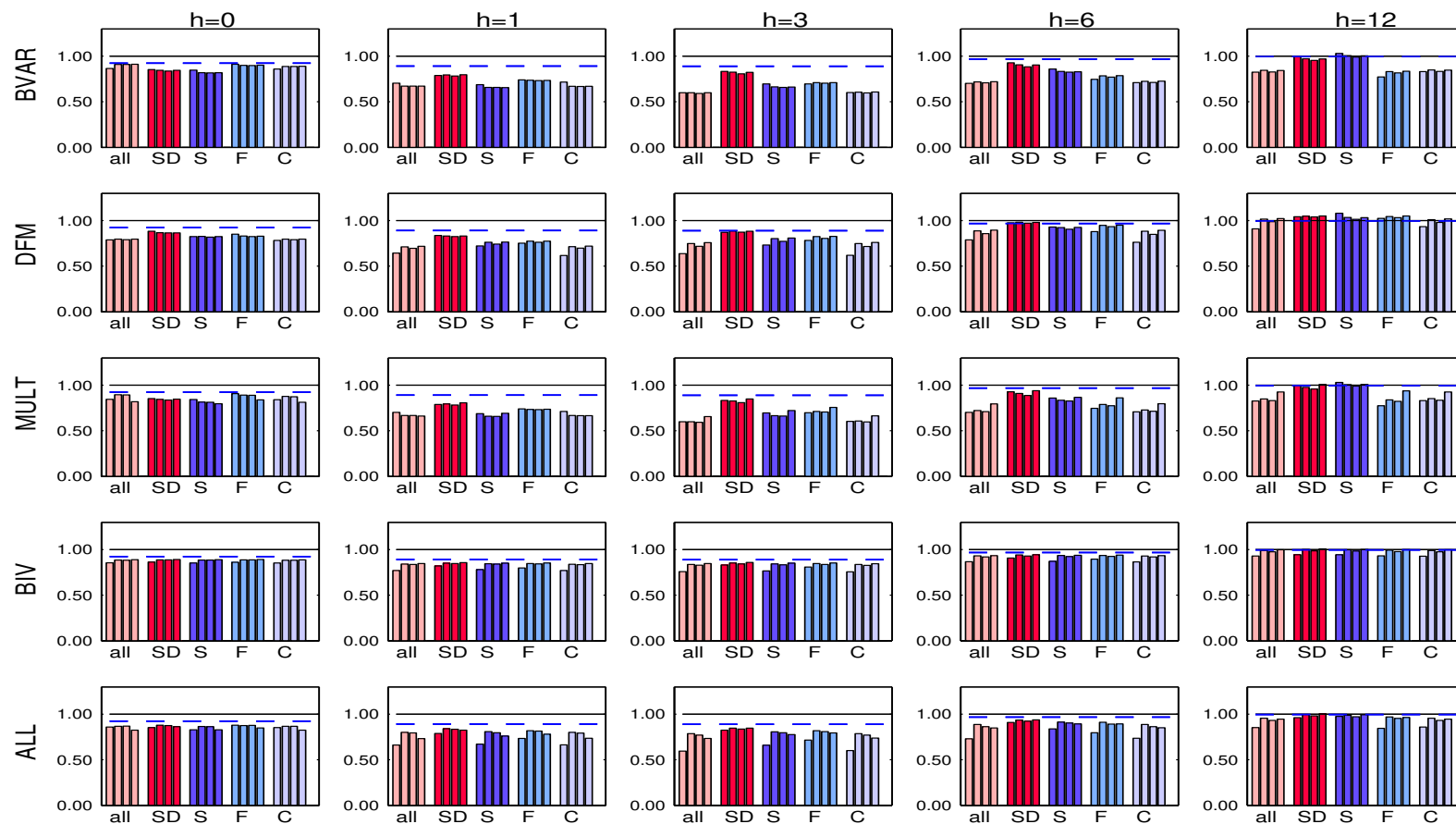
Figure A.2.1: Relative RMSFEs of the different panels for **industrial production** - Pre-crisis sample



**Notes:** The Figure shows the relative (versus the RW) RMSFEs for each model over the pre-crisis sample (Dec. 2003 - Nov. 2007). For each model, the forecasts are computed using five different data sets as displayed on the x-axis: **all** is the full data set, whereas **SD**, **S**, **F** and **C** are the data sets obtained by excluding all the soft data, the surveys, the financials and the commodity prices respectively. In each sub-figure the four consecutive (same coloured) bars for a given model and data set display the results for the forecasts combination schemes used, i.e. *av.10%*, *av.msfe*, *av.d-msfe* and *av.all*. The dashed red line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

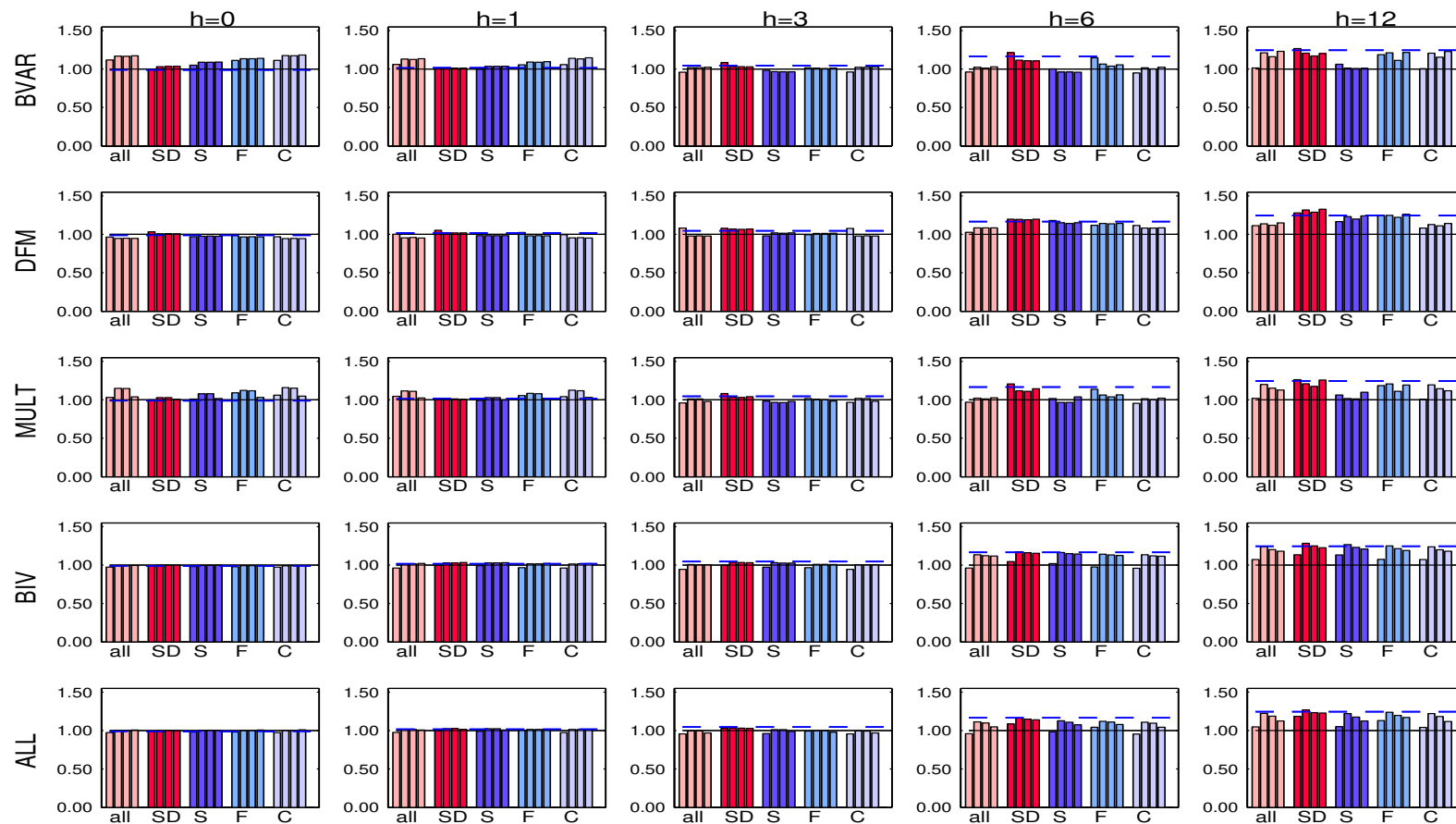


Figure A.2.2: Relative RMSFEs of the different panels for **industrial production** - Crisis sample



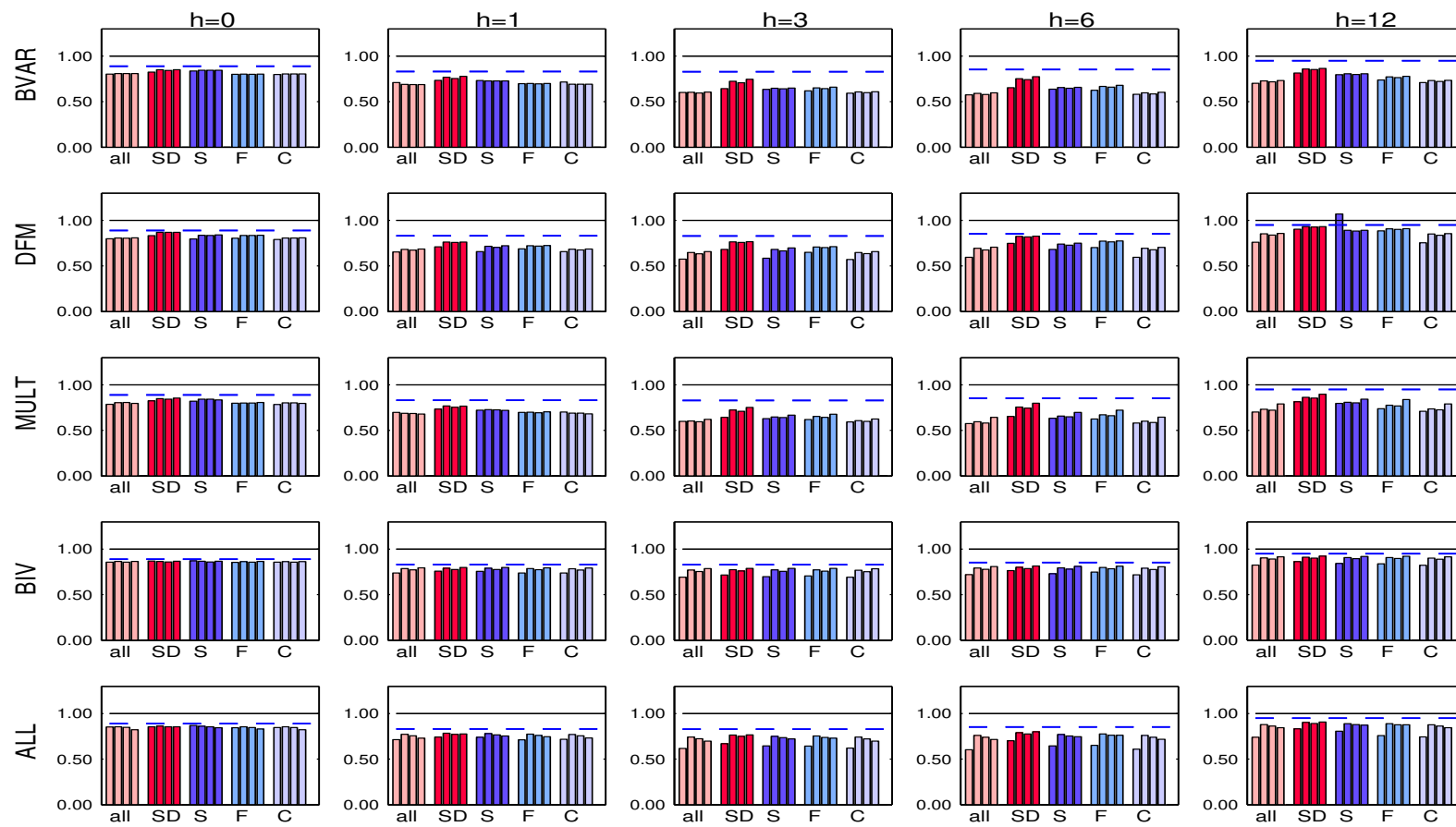
**Notes:** The Figure shows the relative (versus the RW) RMSFEs for each model over the pre-crisis sample (Dec. 2007 - Dec. 2011). For each model, the forecasts are computed using five different data sets as displayed on the x-axis: **all** is the full data set, whereas **SD**, **S**, **F** and **C** are the data sets obtained by excluding all the soft data, the surveys, the financials and the commodity prices respectively. In each sub-figure the four consecutive (same coloured) bars for a given model and data set display the results for the forecasts combination schemes used, i.e. *av.10%*, *av.msfe*, *av.d-msfe* and *av.all*. The dashed red line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

Figure A.2.3: Relative RMSFEs of the different panels for the **unemployment rate** - Pre-crisis sample



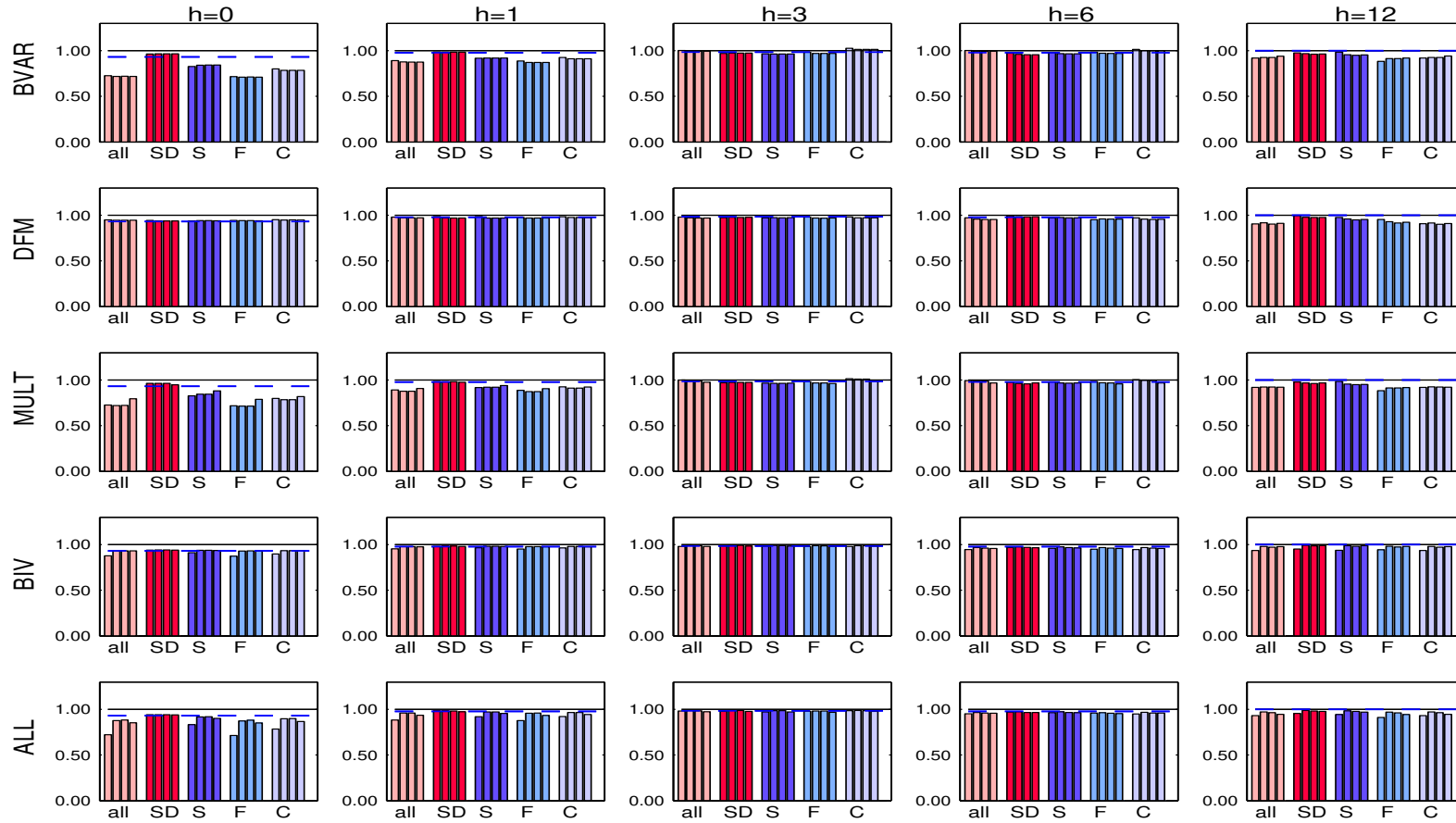
**Notes:** The Figure shows the relative (versus the RW) RMSFEs for each model over the pre-crisis sample (Dec. 2003 - Nov. 2007). For each model, the forecasts are computed using five different data sets as displayed on the x-axis: **all** is the full data set, whereas **SD**, **S**, **F** and **C** are the data sets obtained by excluding all the soft data, the surveys, the financials and the commodity prices respectively. In each sub-figure the four consecutive (same coloured) bars for a given model and data set display the results for the forecasts combination schemes used, i.e. *av.10%*, *av.msfe*, *av.d-msfe* and *av.all*. The dashed red line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

Figure A.2.4: Relative RMSFEs of the different panels for the **unemployment rate** - Crisis sample



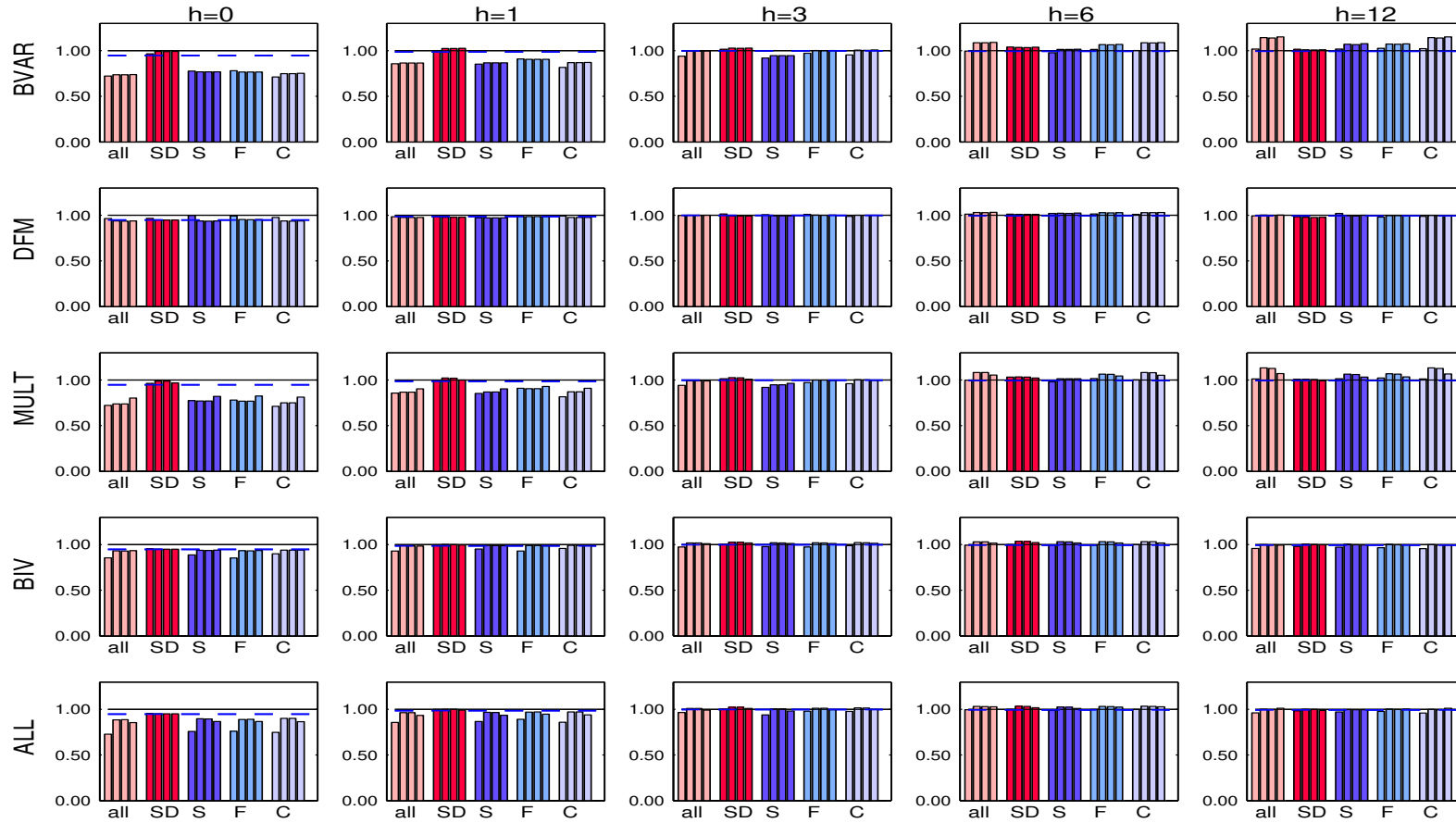
**Notes:** The Figure shows the relative (versus the RW) RMSFEs for each model over the pre-crisis sample (Dec. 2007 - Dec. 2011). For each model, the forecasts are computed using five different data sets as displayed on the x-axis: **all** is the full data set, whereas **SD**, **S**, **F** and **C** are the data sets obtained by excluding all the soft data, the surveys, the financials and the commodity prices respectively. In each sub-figure the four consecutive (same coloured) bars for a given model and data set display the results for the forecasts combination schemes used, i.e. *av.10%*, *av.msfe*, *av.d-msfe* and *av.all*. The dashed red line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

Figure A.2.5: Relative RMSFEs of the different panels for the **consumer price index** - Pre-crisis sample



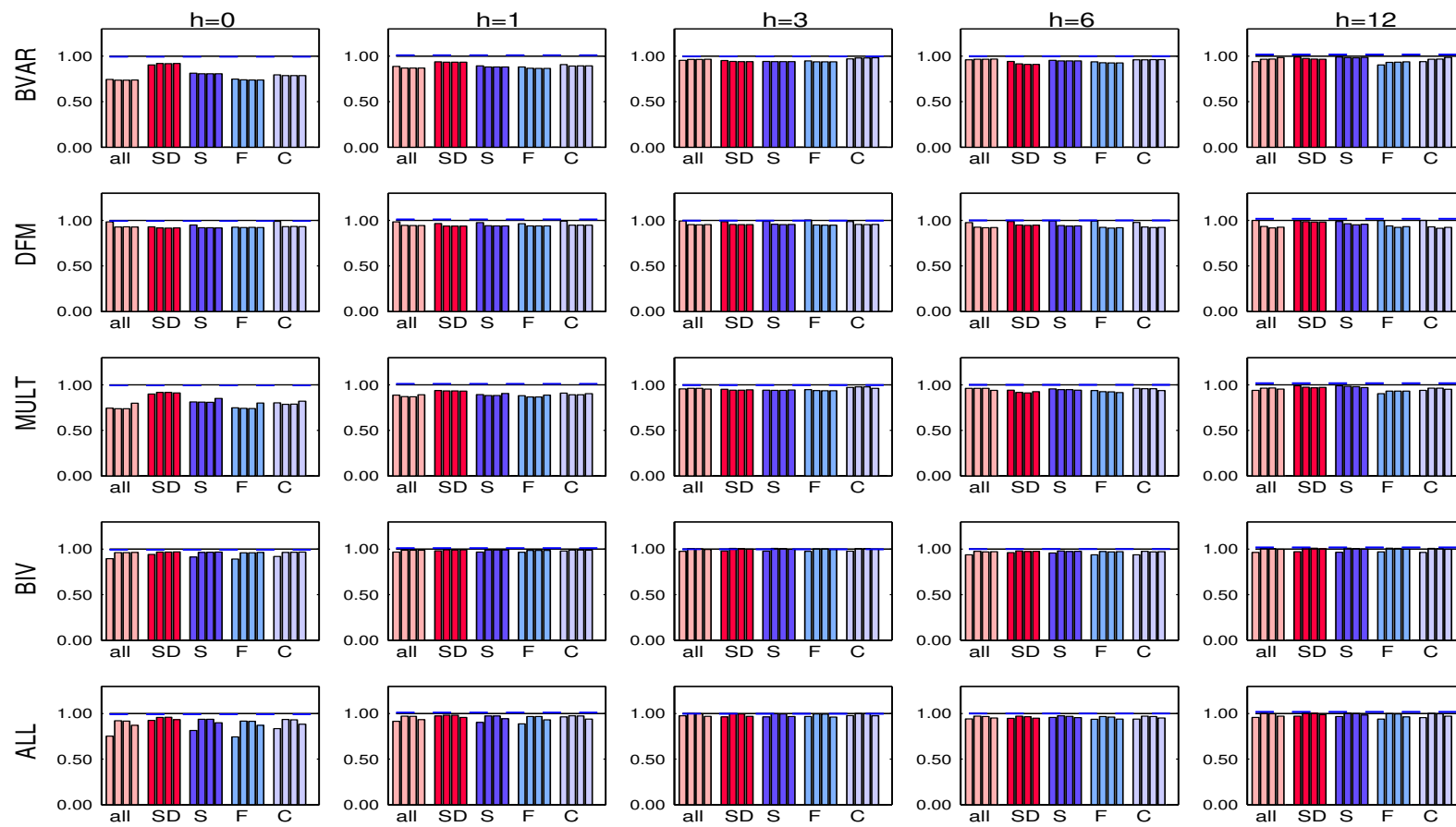
**Notes:** The Figure shows the relative (versus the RW) RMSFEs for each model over the pre-crisis sample (Dec. 2003 - Nov. 2007). For each model, the forecasts are computed using five different data sets as displayed on the x-axis: **all** is the full data set, whereas **SD**, **S**, **F** and **C** are the data sets obtained by excluding all the soft data, the surveys, the financials and the commodity prices respectively. In each sub-figure the four consecutive (same coloured) bars for a given model and data set display the results for the forecasts combination schemes used, i.e. *av.10%*, *av.msfe*, *av.d-msfe* and *av.all*. The dashed red line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

Figure A.2.6: Relative RMSFEs of the different panels for the **consumer price index** - Crisis sample



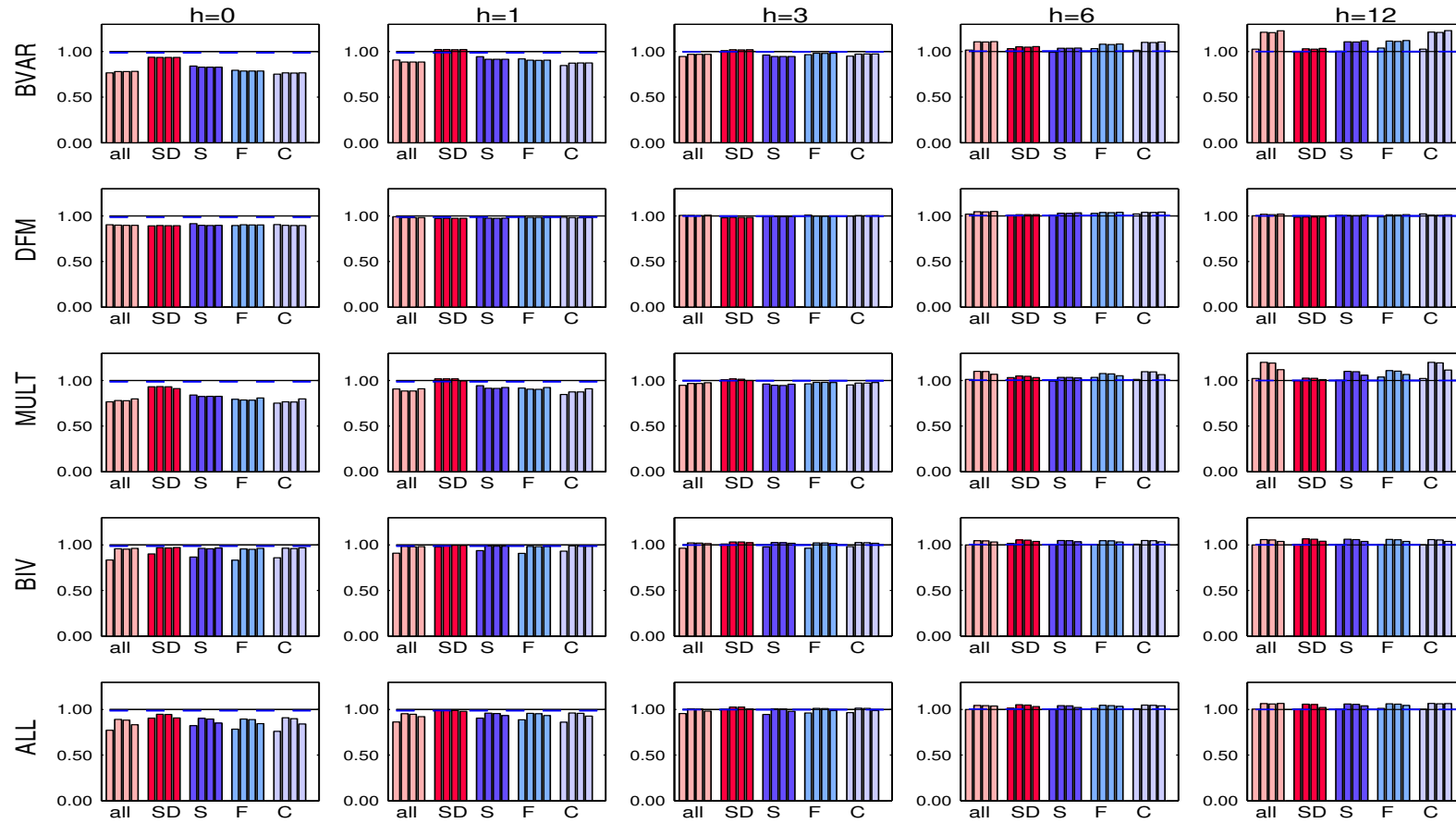
**Notes:** The Figure shows the relative (versus the RW) RMSFEs for each model over the pre-crisis sample (Dec. 2007 - Dec. 2011). For each model, the forecasts are computed using five different data sets as displayed on the x-axis: **all** is the full data set, whereas **SD**, **S**, **F** and **C** are the data sets obtained by excluding all the soft data, the surveys, the financials and the commodity prices respectively. In each sub-figure the four consecutive (same coloured) bars for a given model and data set display the results for the forecasts combination schemes used, i.e. *av.10%*, *av.msfe*, *av.d-msfe* and *av.all*. The dashed red line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

Figure A.2.7: Relative RMSFEs of the different panels for the **pers. cons. expend. price index** - Pre-crisis sample



**Notes:** The Figure shows the relative (versus the RW) RMSFEs for each model over the pre-crisis sample (Dec. 2003 - Nov. 2007). For each model, the forecasts are computed using five different data sets as displayed on the x-axis: **all** is the full data set, whereas **SD**, **S**, **F** and **C** are the data sets obtained by excluding all the soft data, the surveys, the financials and the commodity prices respectively. In each sub-figure the four consecutive (same coloured) bars for a given model and data set display the results for the forecasts combination schemes used, i.e. *av.10%*, *av.msfe*, *av.d-msfe* and *av.all*. The dashed red line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

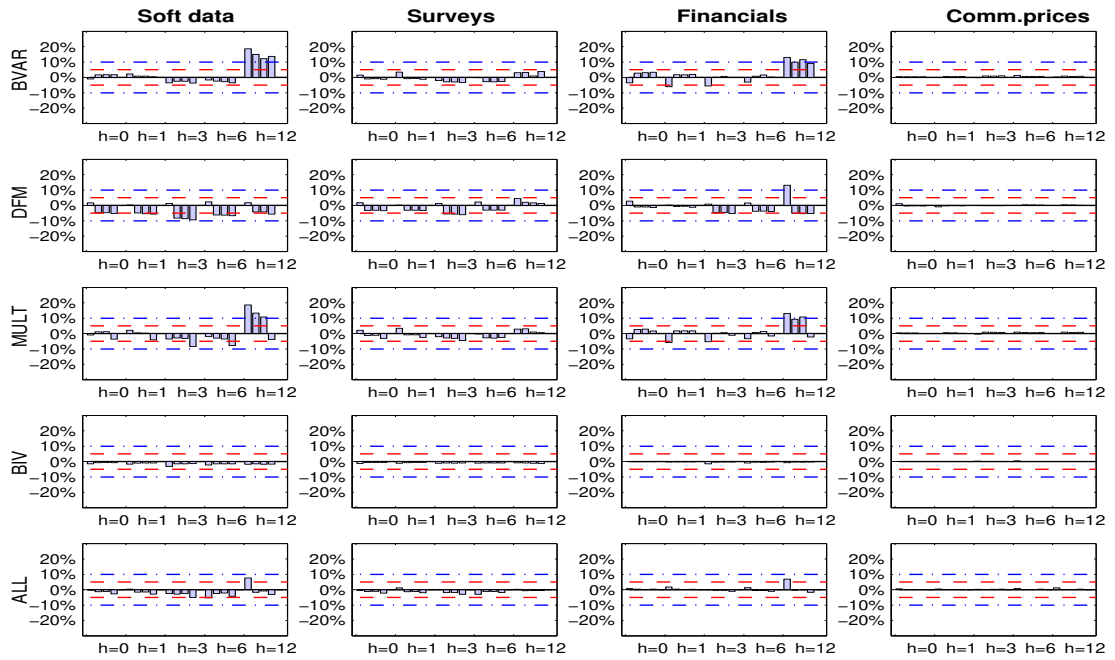
Figure A.2.8: Relative RMSFEs of the different panels for the **pers. cons. expend. price index** - Crisis sample



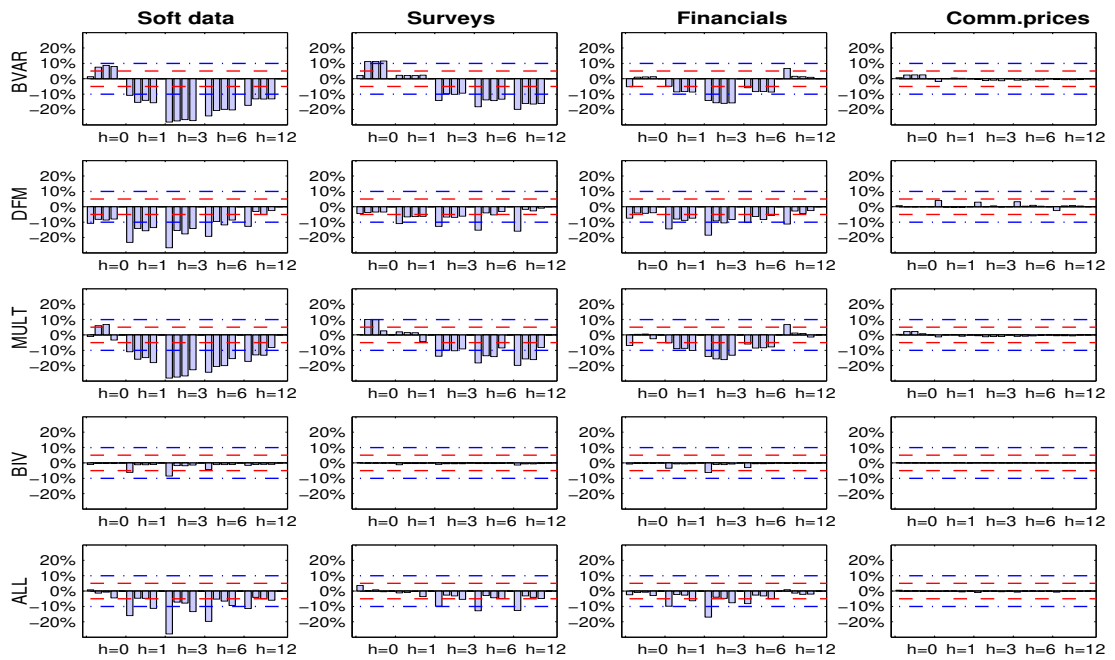
**Notes:** The Figure shows the relative (versus the RW) RMSFEs for each model over the crisis sample (Dec. 2007 - Dec. 2011). For each model, the forecasts are computed using five different data sets as displayed on the x-axis: **all** is the full data set, whereas **SD**, **S**, **F** and **C** are the data sets obtained by excluding all the soft data, the surveys, the financials and the commodity prices respectively. In each sub-figure the four consecutive (same coloured) bars for a given model and data set display the results for the forecasts combination schemes used, i.e. av.10%, av.msfe, av.d-msfe and av.all. The dashed red line is the relative RMSFEs of the best AR model for the corresponding horizon and the black line is drawn at one (relative RMSFEs of RW).

Figure A.2.9: Marginal predictive ability of soft data for industrial production

(a) Pre-crisis sample



(b) Crisis sample

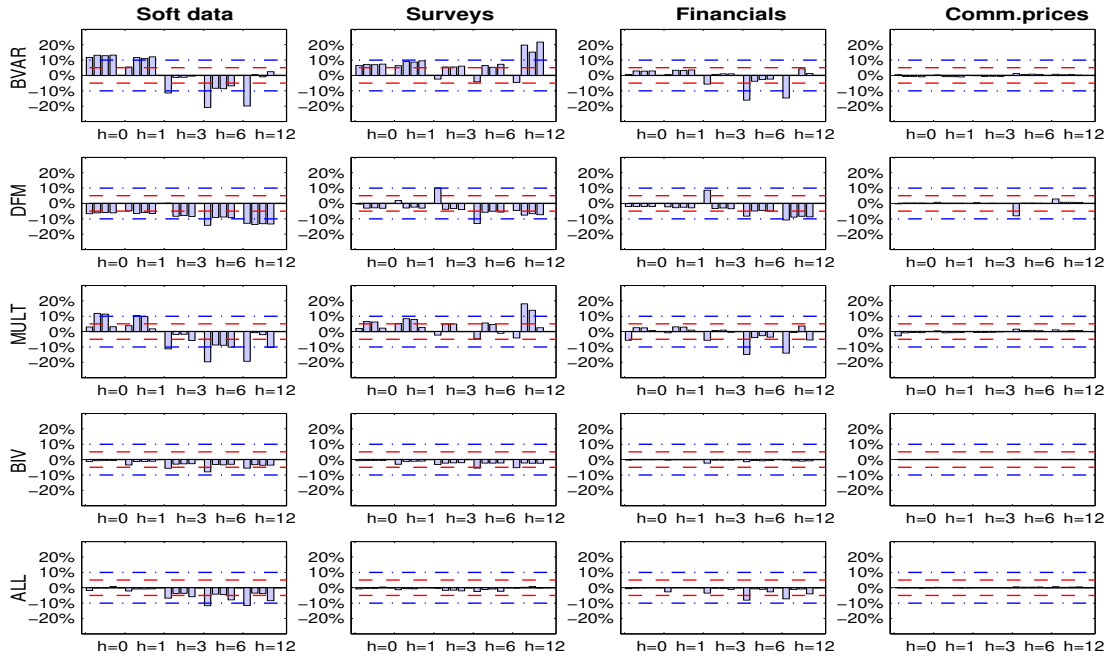


**Notes:** The figure shows for each model the percentage change in RMSFEs from including the different respective block(s) of soft data. In each sub-figure the four consecutive bars for a given horizon displays the results for the forecasts combination schemes used, i.e. av.10%, av.mse, av.d-mse and av.all. The dashed and dashed dotted lines are drawn at the  $\pm 5\%$  and  $\pm 10\%$  threshold respectively.

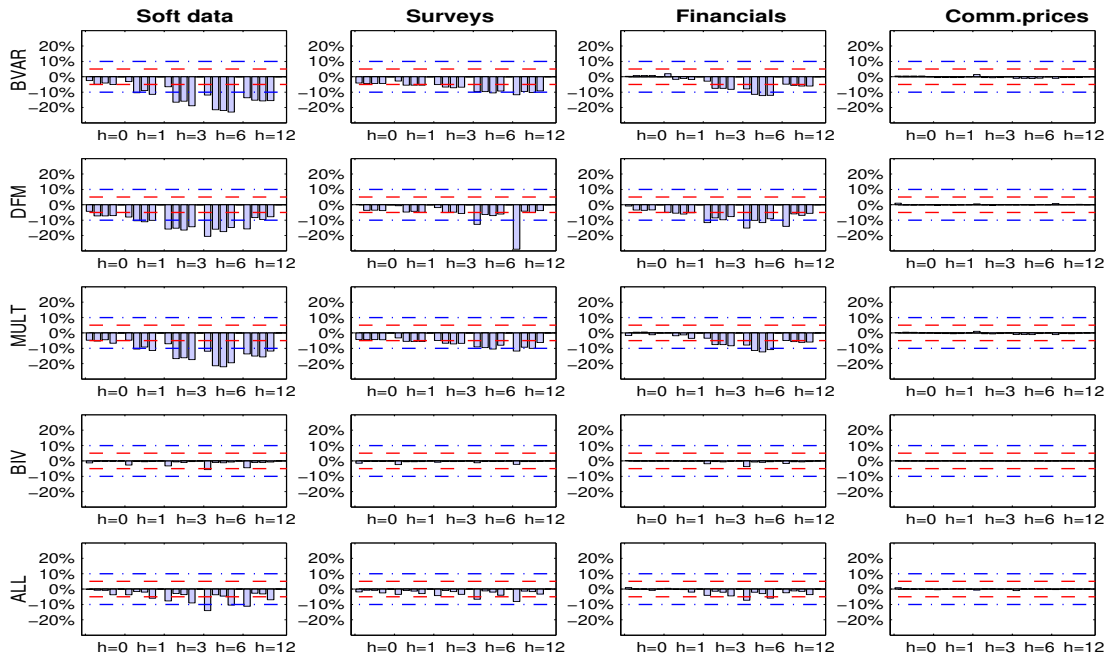


Figure A.2.10: Marginal predictive ability of soft data for the unemployment rate

(a) Pre-crisis sample



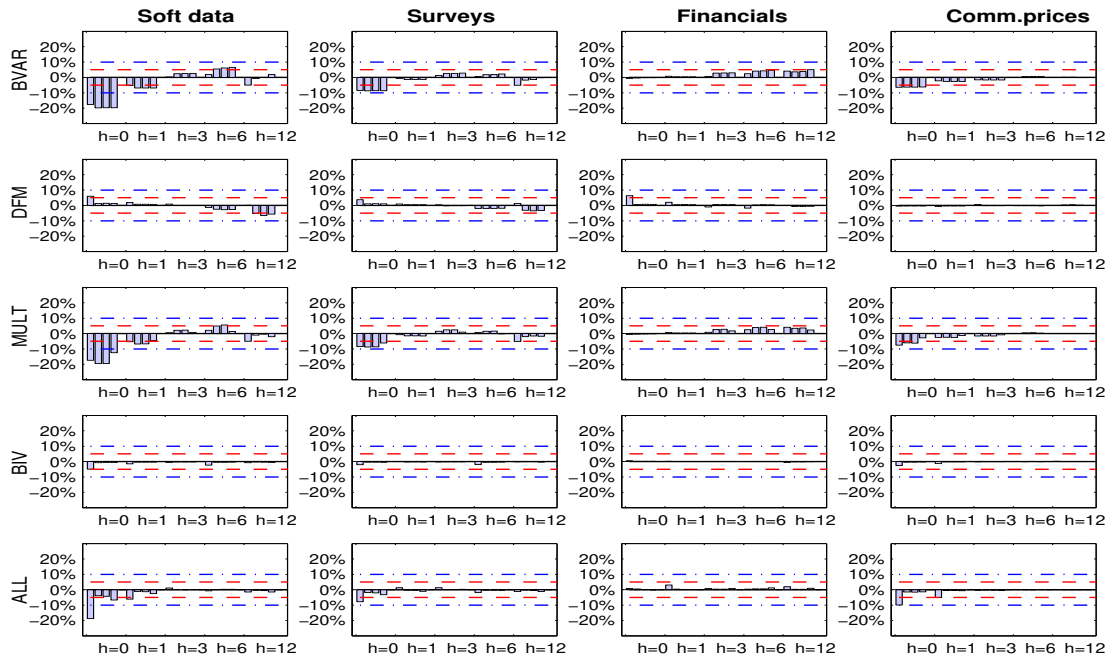
(b) Crisis sample



**Notes:** The figure shows for each model the percentage change in RMSFEs from including the different respective block(s) of soft data. In each sub-figure the four consecutive bars for a given horizon displays the results for the forecasts combination schemes used, i.e. av.10%, av.mse, av.d-mse and av.all. The dashed and dashed dotted lines are drawn at the  $\pm 5\%$  and  $\pm 10\%$  threshold respectively.

Figure A.2.11: Marginal predictive ability of soft data for the consumer price index

(a) Pre-crisis sample



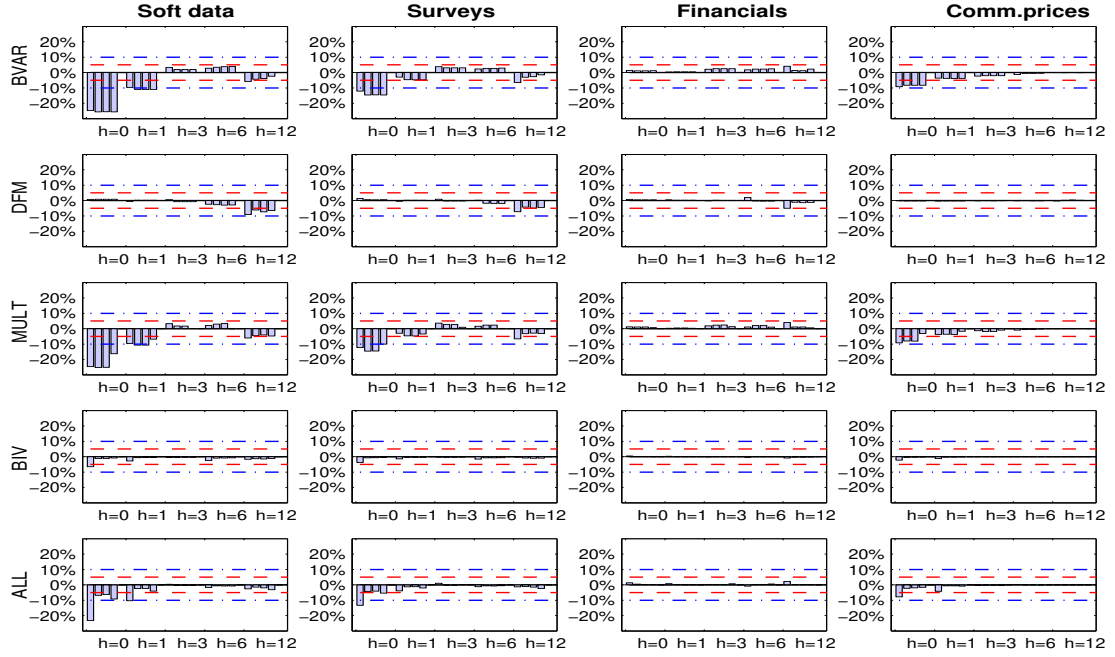
(b) Crisis sample



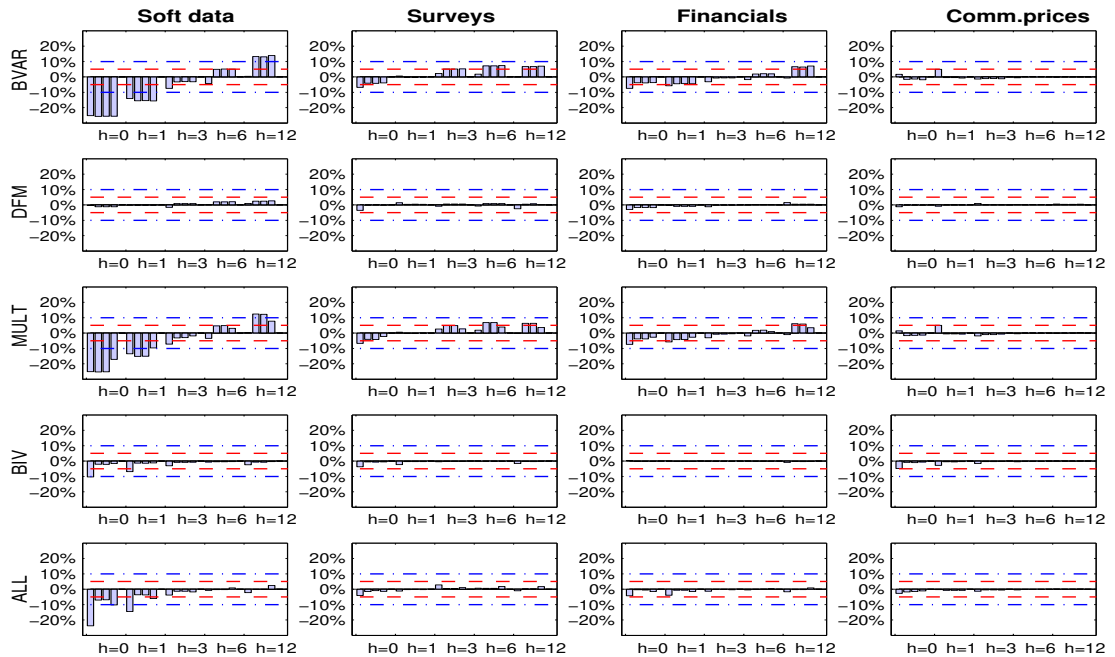
**Notes:** The figure shows for each model the percentage change in RMSFEs from including the different respective block(s) of soft data. In each sub-figure the four consecutive bars for a given horizon displays the results for the forecasts combination schemes used, i.e. av.10%, av.mse, av.d-mse and av.all. The dashed and dashed dotted lines are drawn at the  $\pm 5\%$  and  $\pm 10\%$  threshold respectively.

Figure A.2.12: Marginal predictive ability of soft data for the pers. consumption expenditures price index

(a) Pre-crisis sample



(b) Crisis sample



**Notes:** The figure shows for each model the percentage change in RMSFEs from including the different respective block(s) of soft data. In each sub-figure the four consecutive bars for a given horizon displays the results for the forecasts combination schemes used, i.e. av.10%, av.mse, av.d-mse and av.all. The dashed and dashed dotted lines are drawn at the  $\pm 5\%$  and  $\pm 10\%$  threshold respectively.

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