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Model Pooling and Changes in the Informational Content of Predictors: an Empirical Investigation for the Euro Area

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JEL classification: C53, E37.

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1 Introduction

Short-term forecasting of GDP is an important task to guide policy makers. Central banks need to assess the current state of the economy to conduct monetary policy. Governments incorporate forecasts of economic activity into their budgetary procedures and international organizations rely on forecasts to provide guidance to their stakeholder.

Models used for short-term forecasting should be able to deal with data irregularities that may emerge from different publication delays of the predictor variables. In the forecasting literature this is known as the 'ragged-edge' problem. Another difficulty arises because of different sampling frequencies. For example, GDP is available only at quarterly frequency whereas many business cycle indicators are available on a monthly basis. For a detailed discussion of these issues see e.g. Giannone et al. (2008).

Bridge equation (BE) models provide a simple framework to deal with these data irregularities and are frequently used in policy institutions (see e.g. Kitchen and Monaco (2003), Sédillot and Pain (2003) or ECB (2008)). One reason for their widespread use in applied work is that BE models allow for an economic interpretation of the forecast, because they are typically parameterized parsimoniously as described by Diron (2008) and Antipa et al. (2012). The usefulness of the BE model approach to forecast euro area GDP growth is documented in Baffigi et al. (2004), Golinelli and Parigi (2007),Rünstler et al. (2009),Angelini et al. (2011) and Foroni and Marcellino (2014).[1]

The Great Recession and the global financial crisis have led to a large downturn in world economic activity. Furthermore, many euro area countries experienced a double-dip recession due the emergence of the sovereign-debt crisis. Professional forecasters were heavily criticized for providing very poor forecasts during this period. From a forecasters' perspective this critique might seem unfair because it is well known that crisis events can lead to model and parameter instabilities which are hard to detect in real-time. Therefore, as pointed out recently by Timmerman and van Dijk (2013), one of the main challenges of the forecasting profession is to identify robust methods to account for instabilities. These methods should be able to outperform simple benchmark models over various periods of time.

The empirical literature studying the stability properties of different short-term forecasting techniques for economic activity during recent crisis is still in an early stage. From a theoretical point of view, the pooling of forecasts provides a robust tool in the presence of instabilities (see Timmerman (2006)). Recent papers by Kuzin et al. (2013) and Drechsel and Scheufele (2012) find that model pooling is capable of outperforming simple benchmark models in the period before and during the Great Recession. Schumacher (2014) analyses the performance of single equation models for euro area GDP growth. In particular, the paper focuses on a comparison of the BE and the MIDAS modelling approach during and after the Great Recession.

I analyse the performance of single predictor BE models as well as model selection and model pooling techniques for short-term forecasting euro area GDP growth. In a recursive forecast evaluation exercise I analyse to what extend single predictors are able to outperform a simple autoregressive benchmark model in the period be-

[1]Of course, there are alternative short-term forecasting techniques, besides the BE model, that perform well in forecasting euro area GDP growth. See e.g. Kuzin et al. (2011) for the use of mixed-frequency vector autoregressions (MF-VAR) and mixed data sampling (MIDAS) models, Foroni and Marcellino (2014) for the use of factor augmented MIDAS models or Bańbura and Rünstler (2011) for the use of a dynamic factor model (DFM) in state space form.

fore, during and after the Great Recession in terms of the relative mean squared forecasr error (MSFE). Therefore, I define three evaluation sub-samples, namely the period before the Great Recession (Q1:2003-Q4:2007), the period during the Great Recession (Q1:2008-Q4:2009) and the period after the Great Recession (Q1:2010-Q4:2013). Furthermore, I discuss to what extend model selection and model pooling techniques are able to outperform the simple benchmark model in these three sub-samples.

The first contribution of the paper is to study in detail how the importance of different groups of predictor variables (e.g. survey data, monetary and financial data, etc.) changes over the three sub-samples. So far, the existing literature is quite silent about what types of predictors performed well before, during and after the Great Recession in the euro area.

The second contribution of the paper is to analyse empirically whether model selection or model pooling techniques are robust to changes in the informational content of single predictors. In this regard, the results presented here can be seen as an extension to the work of Kuzin et al. (2013), who analysed the forecast performance of model pooling and model selection techniques for six industrialized countries. In particular, I apply Cross-Validation and Mallows model averaging for the case of ragged-edge and mixed frequency data. These techniques were proposed in a series of papers by Hansen (2007, 2008, 2010) and Hansen and Racine (2012), but so far are rarely used in applied work, despite their theoretical property to minimize forecast risk. I compare these pooling techniques to five other pooling techniques which are frequently used in the existing literature, namely, weights based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), weights based on past forecast performance and simple equal weight averaging and the median. The usefulness of sequential model selection using information criteria was put forward e.g. Inoue and Kilian (2006).

Certain model pooling techniques such as Cross-Validation and Mallows model averaging allow to identify the importance of certain predictors in real-time by looking at the model weights. Therefore, the final contribution is to discuss the evolution of the model weights assigned to specific groups of predictor variables over the three sub-samples. In doing so, it is possible to identify the main driving forces of the pooled forecast. From a forecasters perspective this issue is very important because the forecaster typically is not only interested in forecasting a single number but also in providing an economic interpretation of the forecast.

The remainder of the paper is structured as follows. Section 2 presents the BE model used for forecasting and explains the model pooling techniques. In section 3, I describe the forecast evaluation design and the dataset. In Section 4 the results of the forecasting exercise are discussed and finally section 5 concludes.

2 Forecast models

2.1 Single predictor BE models

For each predictor variable $m = 1, ..., M$, I estimate a single BE model according to equation (1). Y_{t+h} is the quarterly growth rate of real GDP and $h = \{1, 2\}$ is the forecast horizon. c is a constant and Y_{t-i} denotes lagged values of the dependent variable. The forecast is obtained using the direct step method. The monthly predictors are released three times during a quarter. Each time a new monthly observations becomes available I adjust the construction of the quarterly series derived from the monthly predictor.

In equation (1), this quarterly series is represented by $X^m_{d,t+1}$. For this regressor the subscript $d = 0, 1, 2, 3$ denotes the number of available monthly observations at the current data edge. For $d = 0$, no monthly observation is available and consequently the regressor drops from the regression. For $d = 1, 2, 3$ the average of the available monthly observations is used to construct $X^m_{d,t+1}$, the quarterly series. $X^m_{3,t-j}$ denotes lagged values of the predictor for which all monthly observations are available. e^m_{t+h} are the model residuals and T denotes the number of observations used for estimation.

$$Y_{t+h} = c + \sum_{i=0}^{p} \gamma_i Y_{t-i} + \alpha X^m_{d,t+1} + \sum_{j=0}^{q} \delta_j X^m_{3,t-j} + e^m_{t+h}. \tag{1}$$

I estimate the BE model using ordinary least squares. The model specification is based on the BIC, allowing for $p_{max} = 1$ and $q_{max} = 2$. For later reference, it is convenient to re-write the forecast model into a more compact form:

$$Y_{t+h} = Z^m_t \beta^m + e^m_{t+h}, \tag{2}$$

where Z^m_t is a $1 \times k$ vector of regressors and β^m is a $k \times 1$ vector of coefficients. The out - of - sample forecast of an individual model m is give by $\hat{Y}^m_{T+h} = Z^m_T \hat{\beta}^m$.

Since the focus of the analysis is on the stability of the forecasting performance, I do not forecast missing values of the predictor at the current data edge to fill the missing monthly observations. Otherwise, it would not be possible to assess if a change in the forecasting performance of a predictor is due to a change in the information content of the predictor or to a change in the forecastability of the predictor itself at the current data edge. Instead, I follow Kitchen and Monaco (2003) or Drechsel and Maurin (2011) and re-estimate equation (1) whenever new information on the predictor becomes available.

2.2 Pooling techniques

In general, the combined forecast of each pooling technique is obtained by calculating a weighted average over all individual model forecasts, i.e.:

$$\hat{Y}^{pool}_{T+h} = \sum_{m=1}^{M} \hat{w}^m_{T+h} \hat{Y}^m_{T+h}, \tag{3}$$

where $\hat{w}^m_{T+h}$ is the estimated weight assigned to model m.

Overall, I use seven pooling techniques: equal weighted averaging (EWA), the median, AIC weights (AICw), BIC weights (BICw), weights based on past forecast performance (MSEw), Mallows model averaging (MMA) and Cross - Validation model averaging (CVMA).

As shown by Stock and Watson (2003, 2004) EWA and the median perform well, despite their simplicity. For EWA, the model weights are $w^m = w = \frac{1}{M}$. The other pooling techniques are described in more detail below.

2.2.1 AIC and BIC model averaging

The use of the AIC for model combination was put forward by Buckland et al. (1997) and Burnham and Anderson (2002). The AIC weight for model m is

$$w^m_{T+h} = \frac{exp(-\frac{1}{2}\Delta AIC^m_{T+h})}{\sum_{l=1}^{M} exp(-\frac{1}{2}\Delta AIC^l_{T+h})}, \tag{4}$$

where $\Delta AIC^m_{T+h} = AIC^m_{T+h} - AIC^{min}_{T+h}$ is the difference between the AIC of indicator model m and the indicator model with the smallest AIC. The AIC^m_{T+h} is computed as:

$$AIC^m_{T+h} = T\,ln((\hat{\sigma}^m)^2) + 2\,k^m \tag{5}$$

where $(\hat{\sigma}^m)^2 = 1/T \sum_{t+h=1}^{T} (\hat{e}^m_{t+h})^2$ is an estimate for the error variance of model m and k^m is the number of regressors. Other forecast evaluation studies using the AIC weights are e.g. Kapetanios et al. (2008) or Drechsel and Maurin (2011).

As an alternative, it is also possible to calculate the weights using the BIC (see e.g. Hansen (2007) and Hansen (2008))

$$w^m_{T+h} = \frac{exp(-\frac{1}{2}\Delta BIC^m_{T+h})}{\sum_{l=1}^{M} exp(-\frac{1}{2}\Delta BIC^l_{T+h})}, \tag{6}$$

where $\Delta BIC^m_{T+h} = BIC^m_{T+h} - BIC^{min}_{T+h}$ is the difference between the BIC of indicator model m and the indicator model with the smallest BIC. The BIC^m_{T+h} is computed as:

$$BIC^m_{T+h} = T\,ln((\hat{\sigma}^m)^2) + k^m\,ln(T) \tag{7}$$

and $(\hat{\sigma}^m)^2$ is defined as above.

2.2.2 MSE weights

The idea of pooling models according to their past forecast performance was introduced by Bates and Granger (1969). Following Timmerman (2006) the MSE weights are computed as:

$$w^m_{T+h} = \frac{1/MSE^m_{T+h}}{\sum_{l=1}^{M} 1/MSE^l_{T+h}}, \tag{8}$$

with

$$MSE^m_{T+h} = \frac{1}{v} \sum_{t+h=T-v+1}^{T} (e^m_{t+h})^2. \tag{9}$$

The sequence of out-of-sample errors, e^m_{t+h}, are computed over the last v available quarters. As in Kuzin et al. (2013) I calculate the MSE over the previous four quarters, i.e. $v = 4$.

2.2.3 Mallows model averaging (MMA)

The Mallows C_p criterion for model selection was introduced by Mallows (1973). The idea of using the Mallows criterion for model pooling was introduced by Hansen (2007). Hansen (2008) shows that using the Mallows criterion for model pooling provides an asymptotically unbiased estimator for the mean squared forecast error when the observations are stationary time-series. The Mallows criterion for selecting the weights is defined as the penalized sum of the squared residuals

$$C_{T+h}(\mathbf{w}) = \mathbf{w}'\hat{\mathbf{e}}'\hat{\mathbf{e}}\mathbf{w} + 2\tilde{\sigma}^2\mathbf{w}'\mathbf{K}, \tag{10}$$

where $\mathbf{w} = [w^1, ..., w^M]'$ is the weighting vector, and $\hat{\mathbf{e}} = [\hat{\mathbf{e}}^{\mathbf{1}}, ..., \hat{\mathbf{e}}^{\mathbf{M}}]$ is a matrix containing the in-sample errors of the individual models to be combined. The vector $\mathbf{K} = [k^1, ..., k^M]'$ contains the number of regressors included in each of the individual models and $\tilde{\sigma}^2 = \frac{1}{T-k_{max}} \sum_{t=1}^{T} (\hat{e}_{t+h}^{k_{max}})^2$ is an estimate of the error variance of the model with the largest number of regressors, k_{max}. The MMA weighting vector $\mathbf{w}$ is obtained by minimizing $C_{T+h}(\mathbf{w})$. As pointed out by Hansen (2008), to get feasible values for $\mathbf{w}$ it is necessary to impose two additional restrictions for the minimization. First, the weights should sum up to one. Second, the weights should only take values between zero and one. Accordingly, the MMA weighting vector is defined as:

$$\hat{\mathbf{w}} = \mathbf{argmin}\, C_{T+h}(\mathbf{w}) \tag{11}$$

$$s.t.$$

$$\sum_{m=1}^{M} w_{T+h}^{m} = 1 \tag{12}$$

$$0 \leq w_{T+h}^{m} \leq 1 \tag{13}$$

This is a quadratic programming problem which can not be solved analytically.[2]

2.2.4 Cross-Validation Model Averaging (CVMA)

The Cross-Validation (CV) criterion for model selection was introduced by Allen (1974), Geisser (1974) and Stone (1974). The idea of using the CV criterion for model pooling was put forward by Hansen and Racine (2012), who proposed a "jackknife model averaging" (JMA) estimator to obtain the model weights for one-step ahead forecasts. The advantage of JMA over the Mallows criterion is that it does not require the error terms, e_{t+h}^{m}, to be conditionally homoskedastic. Hansen (2010) generalized this framework to allow also for multi-step ahead forecasting by introducing Cross-Validation model averaging (CVMA), which relaxes the assumption that the errors terms need to be serially uncorrelated. For a forecast horizon of h=1, JMA and CVMA deliver the same model weights. The CVMA criterion for selecting the weights is

$$CVMA_{T+h,h}(\mathbf{w}) = \frac{1}{T}\mathbf{w}'\tilde{\mathbf{e}}_{\mathbf{h}}'\tilde{\mathbf{e}}_{\mathbf{h}}\mathbf{w}, \tag{14}$$

where $\mathbf{w}$ is the weighting vector defined as above and $\tilde{\mathbf{e}}_{\mathbf{h}} = [\tilde{\mathbf{e}}_{\mathbf{h}}^{\mathbf{1}}, ..., \tilde{\mathbf{e}}_{\mathbf{h}}^{\mathbf{M}}]$ is a matrix containing the leave-h-out residuals of the individual models to be combined. The leave-h-out residual of model m for observation t is defined as

$$\tilde{e}_{t+h,h}^{m} = Y_{t+h} - Z_{t}^{m}\, \tilde{\beta}_{t,h}^{m}, \tag{15}$$

where $\tilde{\beta}_{t,h}^{m}$ is the coefficient vector obtained from regression (1) leaving out the observations $\{t-h+1, ..., t+h-1\}$. For further details the reader is referred to Hansen (2010).

The $CVMA_{T+h,h}$ weight vector is then defined as:

$$\hat{\mathbf{w}} = \mathbf{argmin}\, CVMA_{T+h,h}(\mathbf{w}) \tag{16}$$

$$s.t.$$

$$\sum_{m=1}^{M} w_{T+h}^{m} = 1 \tag{17}$$

$$0 \leq w_{T+h}^{m} \leq 1 \tag{18}$$

[2] The MATLAB program **quadprog** provides numerical algorithms to solve these kind of problems.

MMA and CVMA have in common that they explicitly explore the co-variance structure of the forecast errors to minimize forecast risk. This is an distinguishing feature with respect to the other model pooling techniques used in this paper. Therefore, one can think of these pooling techniques in a similar way as of an investor who wants to minimize the risk of an investment portfolio.

3 Data and forecasting design

3.1 Dataset

The dataset for the euro area consists of a quarterly real GDP series from Q1:1991 to Q4:2013 and 39 predictor variables available at monthly frequency over a sample ranging from M1:1991 to M12:2013. All series are seasonally adjusted. The predictor variables include sentiment indicators, indicators of real economic activity as well as monetary and financial variables. For convenience, I distinguish five broad data categories: Survey data (SD), hard business cycle data (HD), monetary and financial data (MFD), international data (ID) and the composite leading indicator (CLI) of the OECD. I decide to put the CLI into a separate category because it is constructed using many other data series as an input. The data sources are the European Commission, Eurostat, the European Central Bank (ECB) and the OECD. The data for euro area GDP provided by Eurostat is only available from Q1:1995 onwards. I therefore backdate the missing values using the Area-wide Model (AWM) database provided by the ECB. Monthly data for production in construction, retail trade volumes and the harmonized unemployment rate are not available either for the whole time period at the primary source. In order to backdate the missing values for these variables I use the December 2012 edition of the OECD original release data and revisions database. A detailed list of all predictor variables, data transformations and data sources can be found in the appendix. I use a final revised dataset and not a real-time dataset. Thus, the impact of data revisions is not addressed in the analysis. However, Diron (2008) finds that pseudo real time exercises of forecasting euro area GDP growth overall provide reliable results. In addition, the studies of Faust and Wright (2009) and Wolters (2015) find that the ranking of different forecasting models hardly changes when using revised or real-time data.

3.2 Evaluation design

The forecast evaluation is performed using a pseudo real-time design. This approach replicates the availability pattern of the data at the time the forecast is computed. In general, the availability of the data at a specific information set differs with respect to the indicator groups, e.g. sentiment indicators are typically available more timely than industrial production data. To mimic the ragged-edge data structure in the forecasting experiment I follow the recent literature (e.g. Giannone et al. (2008), Bańbura and Rünstler (2011) and Marcellino and Schumacher (2010)) and store the missing data values at the end of the sample at the date of the download. In the evaluation exercise, the GDP forecast is updated on a bi-weekly basis. Therefore, I downloaded the data twice (on the 5th June 2014 and on the 20th June 2014). Table 1 shows the delays of the most prominent predictor series.[3] For example at the beginning of June 2014

[3]A detailed overview of the delays for all predictors can be found in table (6) in the appendix.

Table 1: Publication lags.

Variable	Publishing lag at 5th day	Publishing lag at 20th day
Economic sentiment	1 month	1 month
Business climate	1 month	1 month
Employment expectations	1 month	1 month
Industrial production	3 month	2 month
Retail sales	2 month	2 month
Car registrations	2 month	1 month
Money supply	2 month	2 month
Exchange rates	1 month	1 month
Stock index	1 month	1 month

sentiment indicators are available until May 2014, whereas industrial production data is only available until March 2014. Two weeks later one more observation becomes available for industrial production, since it is published roughly 45 days after the end of the month. For GDP, which is a quarterly variable and not listed here, I impose that a new observation becomes available 45 days after the end of the respective quarter. This is in line with the data release calendar of Eurostat. Moreover, I assume that the data releases follow a fixed pattern throughout the whole forecast evaluation. For the evaluation exercise I use the data vintage downloaded on the 20th of June 2014.

Table 2 presents a typical forecasting round, which consists of 12 information sets. Q_t is the quarter the forecaster wishes to forecast. The first forecast is made on the 20th day in the 2nd month in the quarter Q_{t-1}, i.e. right after the publication of GDP of Q_{t-2}, using only data which is available at this point in time. The forecast for GDP is then updated on a bi-weekly basis. The forecasting round ends on the 5th day in the 2nd month in the quarter Q_{t+1}. This is roughly two weeks before the first estimate of GDP is published by Eurostat. For information sets 1-6, the observation of GDP growth for the quarter Q_{t-1} is not available for the forecaster. During a forecasting round the single indicator models and the the model weights are re-estimated for every information set. The estimation sample expands recursively.[4]

Table 2: A typical forecasting round.

Forecast Quarter	Information set (IS)	Forecast made on	forecast horizon
Q_t	1	Q_{t-1}, 2nd Month, 20th day	h=2
	2	Q_{t-1}, 3rd Month, 5th day	
	3	Q_{t-1}, 3rd Month, 20th day	
	4	Q_t, 1st Month, 5th day	
	5	Q_t, 1st Month, 20th day	
	6	Q_t, 2nd Month, 5th day	
	7	Q_t, 2nd Month, 20th day	h=1
	8	Q_t, 3rd Month, 5th day	
	9	Q_t, 3rd Month, 20th day	
	10	Q_{t+1}, 1st Month, 5th day	
	11	Q_{t+1}, 1st Month, 20th day	
	12	Q_{t+1}, 2nd Month, 5th day	

[4]The use of a recursive scheme is done frequently in the existing literature studying the euro area growth, see e.g. Foroni and Marcellino (2014), Kuzin et al. (2011) or Drechsel and Maurin (2011), among others.

For the forecast evaluation I reserve the period from the first quarter of the year 2003 (Q1:2003) till the fourth quarter of the year 2013 (Q4:2013). This sample is further divided into three sub-samples, denoted as $S_i = S_1, S_2, S_3$, in order to analyse the forecast performance for the periods before, during and after the Great Recession. S_1 ranges from Q1:2003 to Q4:2007, whereas S_2 covers the period during the Great Recession, which I define from Q1:2008 to Q4:2009. S_3 covers the period from Q1:2010 to Q4:2013.

The forecast performance of a single indicator model, a model pooling or a model selection technique is measured in terms of the mean squared forecast error (MSFE) relative to the MSFE of an AR(1) benchmark model

$$rel.\,MSFE_{IS}^{S_i} = \frac{\sum_{t+h=T_0^{S_i}}^{T_1^{S_i}} \left(Y_{t+h} - \hat{Y}_{t+h|IS}\right)^2}{\sum_{t+h=T_0^{S_i}}^{T_1^{S_i}} \left(Y_{t+h} - \hat{Y}_{t+h|IS}^{AR}\right)^2}. \tag{19}$$

As shown in equation (19), the relative MSFE is computed separately for each of the three sub - samples and for each of the 12 information sets. $T_0^{S_i}$ and $T_1^{S_i}$ refer to the beginning and the end of the respective evaluation sub-sample and IS = 1,...,12 denotes the information set at which the forecast is computed. Y_{t+h} is the realization of GDP growth, $\hat{Y}_{t+h|IS}$ is a forecast of a single indicator model, a model pooling or a model selection technique and $\hat{Y}_{t+h|IS}^{AR}$ is the forecast of the benchmark model. Both forecasts only incorporate information which are available at the point in time the forecast is computed.

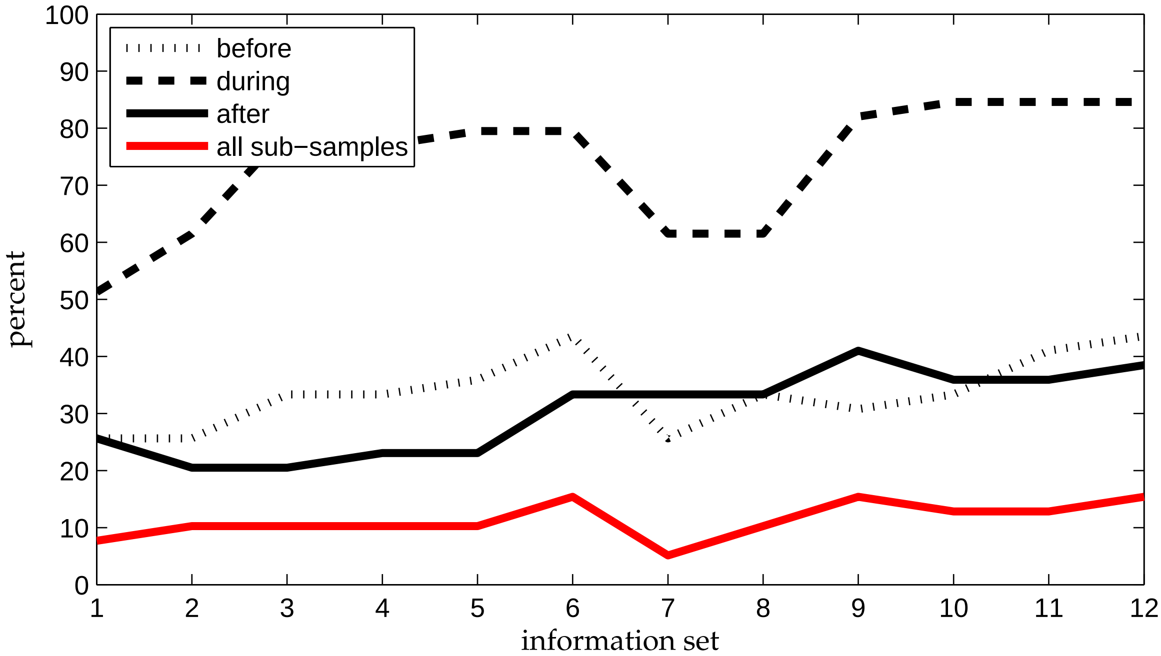
4 Results

4.1 Assessing changes in the informational content of predictors

It is well known that the informational content of a single predictor variable might vary over time. In order to get a first impression to what extent this is an issue for the euro area, figure (1) shows the share of BE models that outperform the AR(1) in terms of the MSFE for the period before (black dotted line), during (black dashed line) and after (black solid line) the Great Recession. In the period before and after the Great Recession, roughly 20 to 40 percent of the predictors provide some additional information, depending on the information set. During the Great Recession this share becomes twice as large, which can be seen as evidence in favor of the conjecture that the informational content of predictors is subject to considerable changes. However, to shed some more light on this issue, I also report the share of single predictor BE models which outperform the benchmark in each of the three sub-samples (red solid line). The number of these models is very small and ranges between 5 and 15 percent. Such an environment is quite challenging, because a forecaster who selects a model that performs best over a particular sample (say, during the Great Recession), might produce a very poor forecast in the period after the Great Recession if the informational content of this specific predictor changes. The noticeable kink that occurs when moving from information set 6 to 7 is due to the fact that performance benchmark model improves because one more observation for GDP becomes available for the forecaster.

To further asses the forecast performance of the BE models, table (3) reports summary statistics for a given information set and over the three sub-samples. I follow

Figure 1: Share of single predictor BE models that outperform the benchmark.



Stock and Watson (2012) and show the relative MSFE at the 10th, 25th, 50th, 75th and 90th percentile of the distribution of the individual BE model forecasts. For the period before the Great Recession (Q1:2003-Q4:2007) the best 10 percent of the models are able to moderately outperform the benchmark. Depending on the information set, the improvement over the benchmark ranges between 10 to 20 percent. The middle part of table (3) shows the results for the period during the Great Recession. In this evaluation sample the MSFE of the benchmark is much larger than for the period before the Great Recession. While the absolute performance of all models deteriorates the relative performance with respect the benchmark improves substantially. The best ten percent of the BE models outperform the benchmark at least by 35 percent. At the end of the forecasting round the relative MSFE is 0.18. The lower part of table (3) reports the results for the period after the Great Recession (Q1:2010-Q4:2013). In this evaluation period the MSFE of the benchmark model is much lower than duting the Great recession period, but still about twice as large as in the period before the Great Recession. In terms of the relative MSFE the best ten percent of the BE models perform better than in the period before the Great Recession but worse compared to the period during the Great Recession.

Regarding the forecast performance of individual BE models I briefly summarize the main findings.[5] For the period before the Great Recession I find that for information set 1 to 6 monetary and financial as well as survey indicators, namely $M1$ and the stock index as well as the economic sentiment indicator, the consumer confidence indicator and consumer employment expectations yield the largest gains over the benchmark model. The relative MSFE of these variables is between 0.7 and 0.8. For information set 7 to 12, the variables $M1$ and the stock index again clearly outperform the the benchmark model, but also some hard business cycle indicators show a relative MSFE below one. The industrial production of consumer non-durables and new cars registrations work quite well. Predictors that represent the international environment barely outperform the benchmark model and also Composite Leading Indicator (CLI) has a very

[5]Detailed results for all individual models can be found in table 7 ,8 and 9 in the appendix.

Table 3: Forecast performance of single predictor BE models.

IS	1	2	3	4	5	6	7	8	9	10	11	12
	h=2						h=1					
	Q1:2003-Q4:2007											
AR(1)	MSFE 0.07						MSFE 0.05					
	relative MSFE						relative MSFE					
percentile												
10	0.83	0.89	0.89	0.89	0.89	0.89	0.89	0.81	0.84	0.85	0.80	0.80
25	1.00	1.00	0.96	0.98	0.98	0.94	1.00	0.98	0.98	0.95	0.91	0.91
50	1.08	1.08	1.11	1.07	1.04	1.04	1.13	1.07	1.07	1.06	1.04	1.04
75	1.24	1.21	1.16	1.16	1.19	1.20	1.28	1.27	1.20	1.20	1.15	1.13
90	1.31	1.31	1.28	1.28	1.33	1.33	1.38	1.38	1.30	1.30	1.28	1.25
	Q1:2008-Q4:2009											
AR(1)	MSFE 2.69						MSFE 1.68					
	relative MSFE						relative MSFE					
percentile												
10	0.62	0.58	0.57	0.52	0.52	0.48	0.64	0.60	0.35	0.35	0.18	0.18
25	0.88	0.82	0.75	0.73	0.68	0.67	0.82	0.80	0.65	0.59	0.58	0.57
50	1.00	0.99	0.90	0.89	0.82	0.82	0.96	0.96	0.84	0.76	0.71	0.71
75	1.05	1.05	1.00	1.00	0.99	0.98	1.06	1.04	0.98	0.96	0.93	0.93
90	1.22	1.19	1.07	1.07	1.07	1.07	1.26	1.16	1.10	1.08	1.08	1.07
	Q1:2010-Q4:2013											
AR(1)	MSFE 0.14						MSFE 0.10					
	relative MSFE						relative MSFE					
percentile												
10	0.86	0.73	0.73	0.73	0.73	0.68	0.80	0.79	0.68	0.62	0.65	0.71
25	0.98	1.02	1.03	1.05	1.04	0.96	0.96	0.96	0.92	0.92	0.92	0.92
50	1.14	1.16	1.16	1.16	1.19	1.15	1.10	1.10	1.02	1.03	1.04	1.04
75	1.44	1.49	1.44	1.44	1.45	1.45	1.19	1.25	1.25	1.24	1.20	1.24
90	2.55	2.55	2.63	2.63	2.35	2.35	1.49	1.51	1.52	1.59	1.61	1.54

Notes: IS = information set, h = forecast horizon.

poor forecast performance.

For the period during the Great Recession (Q1:2008-Q4:2009) I observe that the ranking of the indicators changes a lot. The CLI shows large improvements in the relative forecasting performance for all information sets. At the end of the forecasting round the relative MSFE of this predictor is 0.35. Also the relative performance of indicators describing the international environment improves. However, substantial gains are only present for information sets 7 to 12. With respect to the hard business cycle indicators I find that industrial production in manufacturing yields the best forecast performance at the end of the forecasting round whereas industrial production of consumer non-durables which works quite well in the period before the Great Recession hardly beats the benchmark model. The forecast performance of the surveys improves to a large extent. Nearly all considered indicators are able to beat the benchmark model. However, there is no clear tendency in favor of a specific indicator. Finally, for monetary and financial indicators the improvement in the relative forecast performance is only limited. The stock index and $M1$ show a relative MSFE which is very similar to the period before the Great Recession.

For the period after the Great Recession (Q1:2010-Q4:2013) the monetary aggregate $M1$ works quite well at all forecast horizons, whereas stock market developments which worked well in the period before and during the Great Recession seem to lose their informational content. The relative performance of surveys worsens compared to the period during the Great Recession and only a few indicators have a MSFE lower than one. For information set 1 to 6 the economic sentiment and retail confidence indicator as well as employment expectations in the retail sector show the best performance whereas for information set 7 to 12 employment expectations in the construction sector works well.

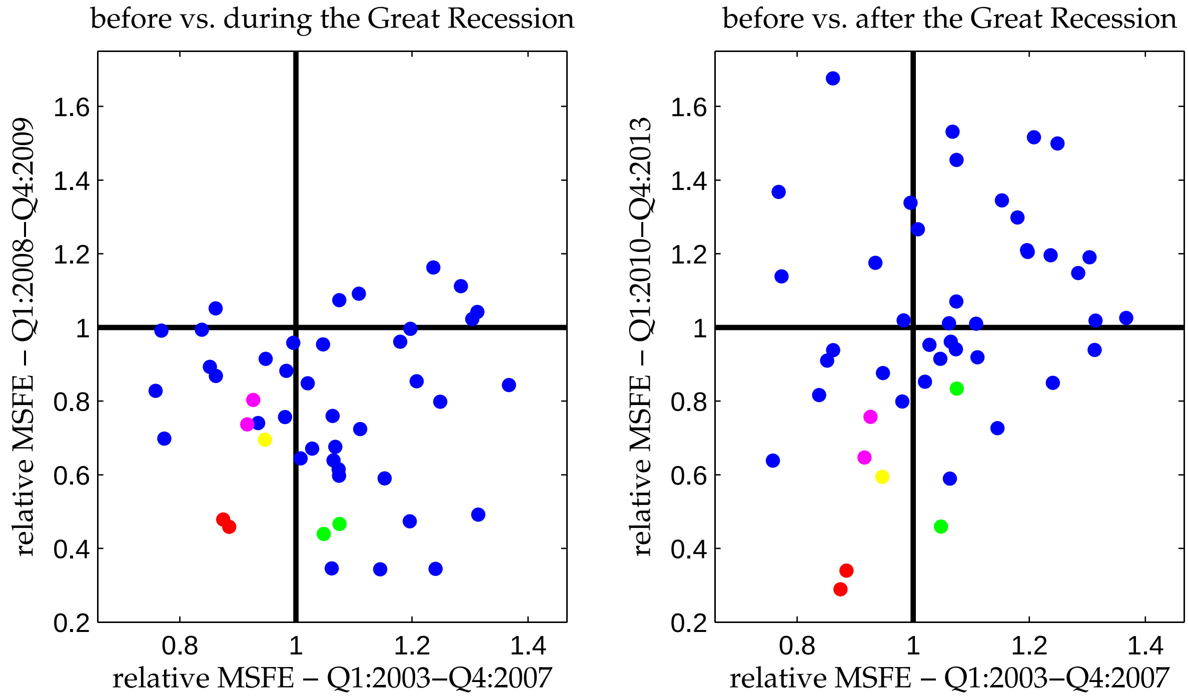
4.2 The forecast performance of model pooling techniques

The results from the previous section suggest that the informational content of single predictors is subject to considerable changes. In the following I therefore investigate to what extent model pooling techniques are able to cope with this environment. In order to get an impression of the performance of the model pooling techniques relative to the individual BE models, figure (2) plots the results for information set 9. This information set is of particular interest because it replicates a typical nowcast situation in which the first month of industrial production data for the current quarter is available.[6] On the left hand side I plot the relative MSFE of the period before the Great Recession against the relative MSFE of the period during the Great Recession. On the right hand side I plot the relative MSFE of the period before the Great Recession against the period after the Great Recession.

One advantage of this graphical representation is that one can easily track the forecast performance of a single BE model over different sub-samples. Remember that a value of the relative MSFE below one implies that the respective model is better than the benchmark. According to Stock and Watson (2004), one would expect the dots to cluster around the 45 degree line when the models have a stable forecast performance. The blue dots denote the BE models. For convenience I grouped the model pooling techniques. The red dots represent CVMA and MMA, whereas the green dots represent AIC and BIC model pooling. Finally, model pooling based on the MSE is in yellow and EWA as well as the median are in purple.

[6]Scatter plots for the other information sets are give in figures 8 to 11 in the appendix.

Figure 2: Relative MSFE comparison for information set 9.



Notes: Blue dots: single predictor BE models, red dots: CV and Mallows model averaging, yellow dot: MSE weights, green dots: BIC and AIC weights, purple dots: equal weight averaging and median.

As shown on the left hand side of figure (2), there are a some BE models that outperform the benchmark before as well as during the crisis. Interestingly, a large number of predictors which did not perform well before the Great Recession, turn out to beat the benchmark during the Great Recession. However, this results in the unpleasant situation in which the predictors that work best in the period before the crisis provide a poor performance compared to the best predictors in the period during the crisis. In such an environment, model pooling techniques provide a possibility to guard against changes in the relative forecast performance. Five out of seven pooling techniques beat the benchmark model in both sub-samples.

As shown on the right had side of figure (2), the number of BE models which outperform the benchmark in the period before and after the Great Recession is very small. This finding is in line with figure (1). Moreover it becomes apparent that a number of BE models locate in the upper left and lower right quadrant, meaning that the informational content of these predictor variables is different for the period before and after the Great Recession. Interestingly, MMA and CVMA are able to outperform all BE models in the period after the Great Recession.

So far, I only report the results for information set 9. Table 4 contains the detailed results for all information sets. The upper part shows the forecasting performance for the model pooling techniques in the period before the Great Recession. A striking feature is that CVMA and MMA outperform the other pooling techniques at all information sets. The gains compared to the benchmark range between 10 and 20 percent, depending on the information set. MSE weights, EWA and the median also outperform the autoregression. However, their performance slightly lacks behind the aforementioned pooling techniques. On the contrary, BIC and AIC model pooling have difficulties in beating the benchmark model. Comparing the model pooling techniques with the BE models, I find that CVMA and MMA perform as good as 10th percentile of the BE

Table 4: Forecast performance of model pooling techniques.

IS	1	2	3	4	5	6	7	8	9	10	11	12
	h=2						h=1					
	Q1:2003-Q4:2007											
AR(1)	MSFE 0.07						MSFE 0.05					
	relative MSFE						relative MSFE					
pooling technique												
CVMA	0.94	0.82	0.78	0.85	0.87	0.85	0.91	0.87	0.88	0.88	0.79	0.77
MMA	0.99	0.83	0.79	0.88	0.90	0.84	0.97	0.97	0.87	0.87	0.80	0.77
MSEw	0.96	0.91	0.91	0.91	0.90	0.89	0.99	0.95	0.95	0.94	0.87	0.86
BICw	1.14	0.95	0.89	1.01	1.06	1.01	1.04	1.01	1.05	1.05	0.85	0.85
AICw	1.06	0.99	0.91	0.99	1.07	1.02	1.02	1.00	1.08	1.02	0.85	0.84
EWA	0.99	0.96	0.93	0.91	0.91	0.90	0.98	0.96	0.92	0.91	0.87	0.87
MEDIAN	0.99	0.97	0.94	0.91	0.90	0.91	1.00	0.93	0.93	0.92	0.91	0.91
	Q1:2008-Q4:2009											
AR(1)	MSFE 2.69						MSFE 1.68					
	relative MSFE						relative MSFE					
pooling technique												
CVMA	0.81	0.73	0.60	0.58	0.58	0.50	0.85	0.87	0.46	0.47	0.24	0.24
MMA	0.84	0.78	0.63	0.61	0.63	0.57	0.82	0.81	0.48	0.49	0.26	0.26
MSEw	0.91	0.87	0.81	0.77	0.74	0.70	0.91	0.88	0.70	0.65	0.49	0.47
BICw	0.80	0.73	0.62	0.55	0.55	0.46	0.76	0.80	0.44	0.45	0.13	0.13
AICw	0.84	0.79	0.58	0.54	0.53	0.43	0.78	0.83	0.47	0.48	0.12	0.13
EWA	0.92	0.88	0.82	0.79	0.75	0.72	0.91	0.88	0.74	0.68	0.62	0.60
MEDIAN	0.94	0.93	0.87	0.82	0.80	0.78	0.92	0.90	0.80	0.77	0.76	0.75
	Q1:2010-Q4:2013											
AR(1)	MSFE 0.14						MSFE 0.10					
	relative MSFE						relative MSFE					
pooling technique												
CVMA	0.65	0.63	0.49	0.46	0.46	0.30	0.67	0.87	0.34	0.35	0.34	0.35
MMA	0.58	0.62	0.46	0.45	0.45	0.35	0.84	0.84	0.29	0.32	0.40	0.42
MSEw	0.75	0.75	0.68	0.65	0.67	0.60	0.80	0.77	0.59	0.60	0.61	0.63
BICw	0.91	1.11	0.71	0.58	0.57	0.79	0.93	1.01	0.46	0.46	1.04	1.04
AICw	0.83	1.03	0.77	0.62	0.62	0.80	0.94	1.08	0.83	0.83	1.04	1.04
EWA	0.85	0.83	0.79	0.78	0.79	0.74	0.84	0.80	0.65	0.64	0.63	0.64
MEDIAN	0.87	0.82	0.85	0.84	0.85	0.84	0.85	0.84	0.76	0.74	0.70	0.71

Notes: IS = information set, h = forecast horizon, CVMA = Cross - Validation model averaging, MMA = Mallows model averaging, MSEw = MSE weights, BICw = BIC weights, AICw = AIC weights, EWA = equal weight averaging, MEDIAN = median forecast.

models.

The middle part of table 4 reports the results for the period during the Great Recession. In this period, all considered pooling techniques are able to outperform the benchmark model for all information sets. AIC and BIC weights work best. However, the difference in the relative MSFE, especially to MMA and CVMA, is not large. Compared to the BE models, the performance of model pooling techniques lacks somewhat behind the 10th percentile of the BE models, especially for information sets 1 and 2 as well as information sets 7 and 8. For these information sets, the 10th percentile BE model has a 0.1 to 0.2 lower relative MSFE than the best model pooling technique. For the other information sets this difference is below 0.1.

Finally, the lower part of table 4 shows the results for the period after the Great Recession. In this period the ranking of the model pooling techniques changes substantially compared to the period during the Great Recession. CVMA and MMA provide the best forecast performance in this period. Except for information set 8, these two techniques outperform all other model pooling techniques for a quite substantial degree and, in addition, they provide more accurate forecasts than the 10th percentile of the BE models. MSE weights as well as EWA and the median forecast also outperform the benchmark model for all information sets. The results for model pooling according to the AIC and BIC results are mixed. They outperform the benchmark only for 8 out of 12 information sets and they clearly lack behind CVMA and MMA.

Overall, five model pooling techniques are able to outperform the benchmark model in all three sub-samples and at all informations sets, namely CVMA, MMA, MSE weights, EWA and the median forecast. Out of these five, CVMA and MMA give the most accurate forecasts. On the contrary, for AIC and BIC model pooling the results are quite mixed. They perform well in the period during the Great Recession, but provide very poor forecasts in the period before the Great Recession. In the period after the Great Recession they outperform the benchmark for 8 out of 12 information sets.

However, outperforming the ex-post best performing BE model is quite difficult for all considered model pooling techniques. This reflects the argument put forward by Hibon and Evgeniou (2005), that model pooling does not necessarily lead to the best possible forecast but pooling provides a viable tool to reduce forecast risk.

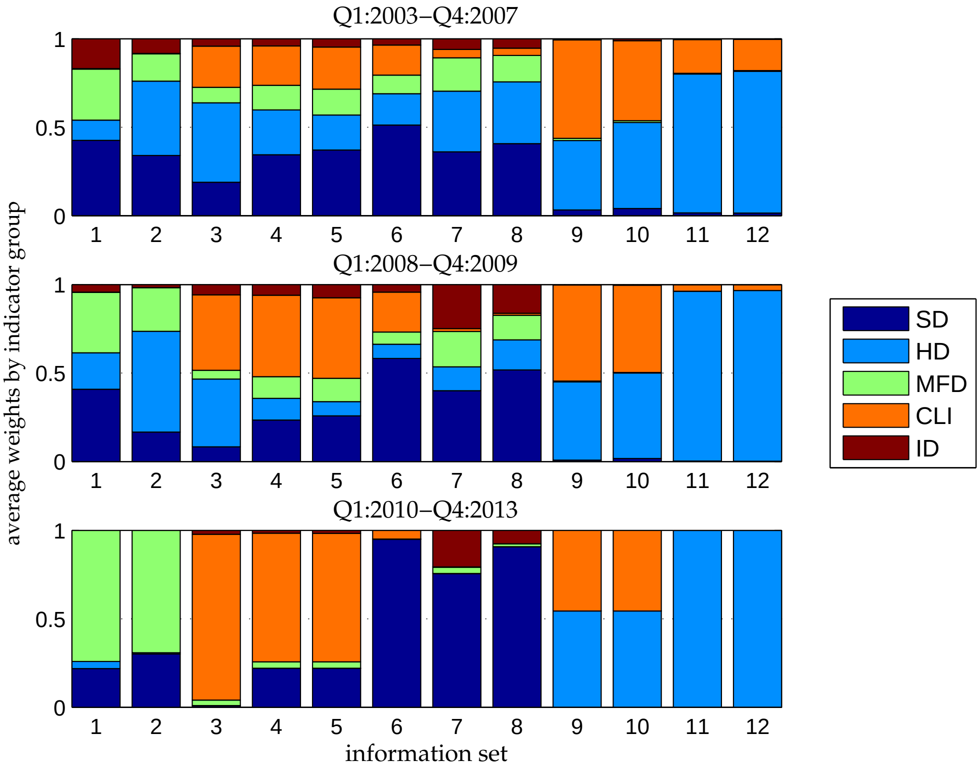
4.3 The evolution of the model weights

In the following, I discuss the evolution of the model weights to identify the main drivers of the pooled forecast. Therefore, I plot the average weights assigned to each group of indicators for each information set and for the three sub-samples in figures 3 to 7.[7]

With respect to the evolution of the model weights over the different information sets one would expect that some predictors are more useful at the beginning of a forecasting round than at the end and vice versa, e.g. due to different publication lags of the predictors or differences in the lead/lag relation between a predictor and the target variable. For the euro area, Drechsel and Maurin (2011) showed that the model weights indeed vary substantially over different information sets. For my dataset the following patterns emerge for BIC and AIC weights as well as CVMA and MMA. Surveys tend to get high weights at the beginning and the middle of the forecasting round

[7]EWA and the median are not discussed below because for the former the weights are constant by definition and for the latter a single model receives a weight of one.

Figure 3: Weights for BIC

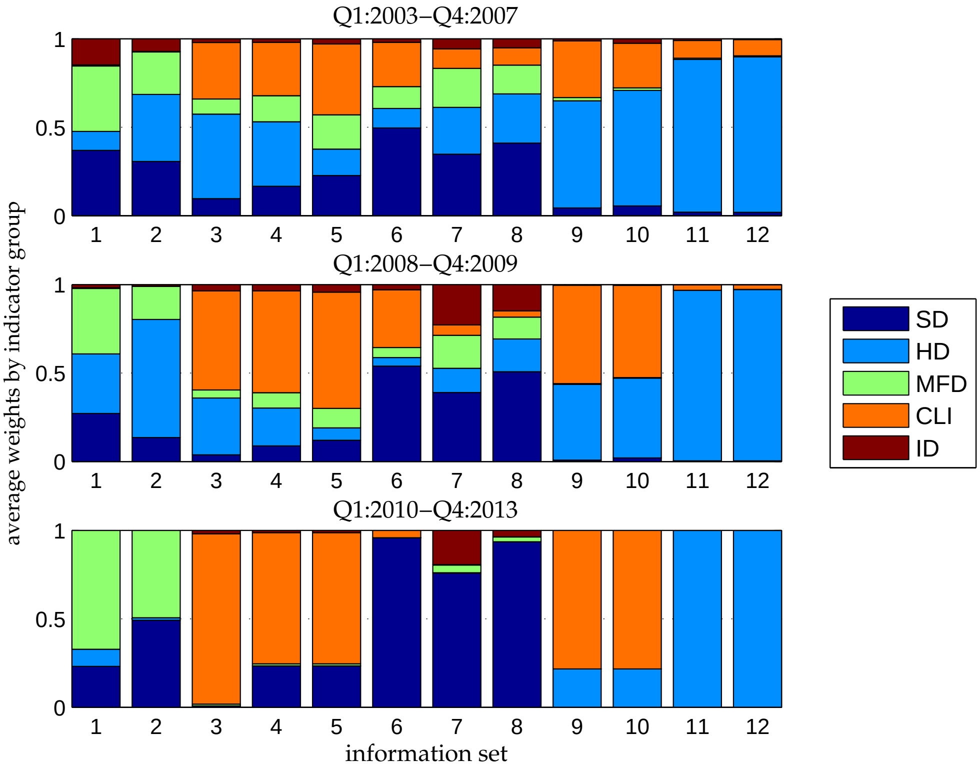


Notes: SD = Survey data, HD = Hard data, MFD = Monetary & Financial data, CLI = Composite Leading Indicator, ID = International data.

(information sets 1 to 8), whereas they get almost zero weight at the end of the forecasting round (information sets 9-12). The same pattern also holds for monetary and financial variables. On the contrary, hard business cycle indicators receive the largest weights at the end of the forecasting round when industrial production data becomes available for the current quarter. For the CLI there is no clear pattern over the different information sets, but relatively the indicator receives quite a large weight for nearly all information sets. International variables play only a minor role compared to the other indicator groups at all information sets.

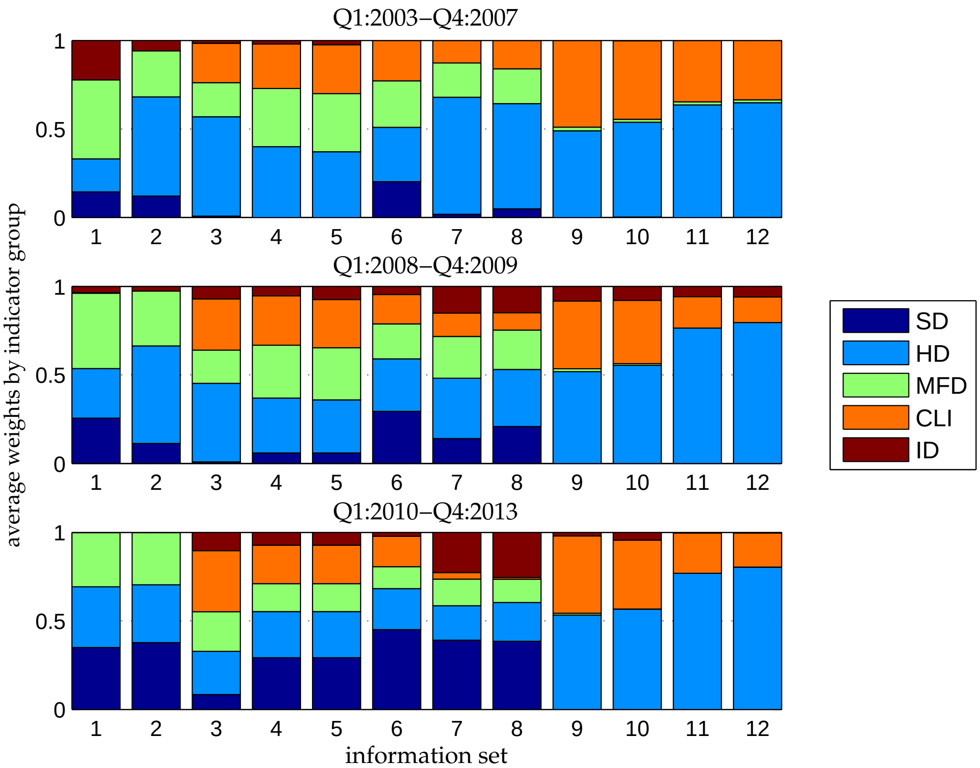
With respect to the evolution of the model weights over time one would expect that the weights assigned to a specific predictor or group of predictors adopt according to the changes in the predictive content of the predictors as documented in the previous section. For survey indicators the weights are increasing over time. Indeed, this fits to the finding of the previous section that the forecast performance of surveys is considerably better during the Great Recession than before. In addition, this may also reflect the idea recently put forward by Bloom (2009) and Baker et al. (2013) that macroeconomic uncertainty is an important driver of business cycles. In this sense, the sharp and persistent drop in business and consumer confidence surveys observed in the euro area for the period during and after the Great Recession can be interpreted as a period of high uncertainty. This argument is in line with the findings of Bachmann et al. (2013), who showed for the United States and Germany that survey data provides a reasonable source for measuring uncertainty. To a smaller extend this is also true for the international variables. The weights increase in the periods during and after the Great Recession. This may reflect the fact that the trade channel has become more important for forecasting euro area GDP growth since the Great Recession due to the large degree of synchronization of the international business cycle. Also for the CLI the weights also

Figure 4: Weights for AIC



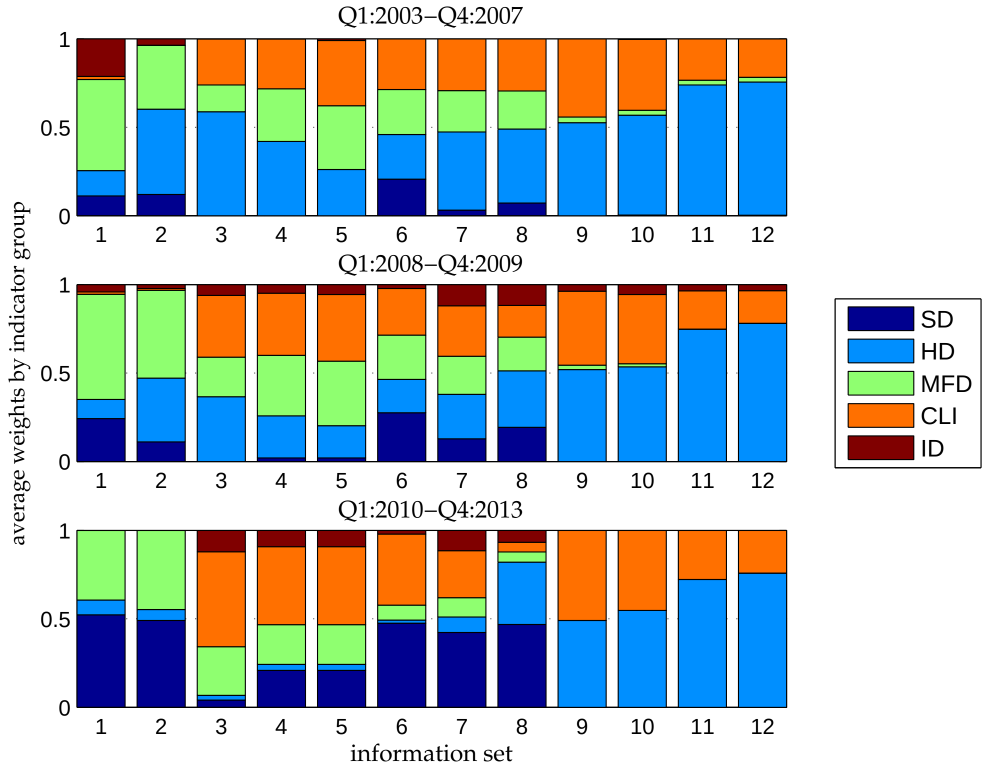
Notes: SD = Survey data, HD = Hard data, MFD = Monetary & Financial data, CLI = Composite Leading Indicator, ID = International data.

Figure 5: Weights for Mallows model averaging.



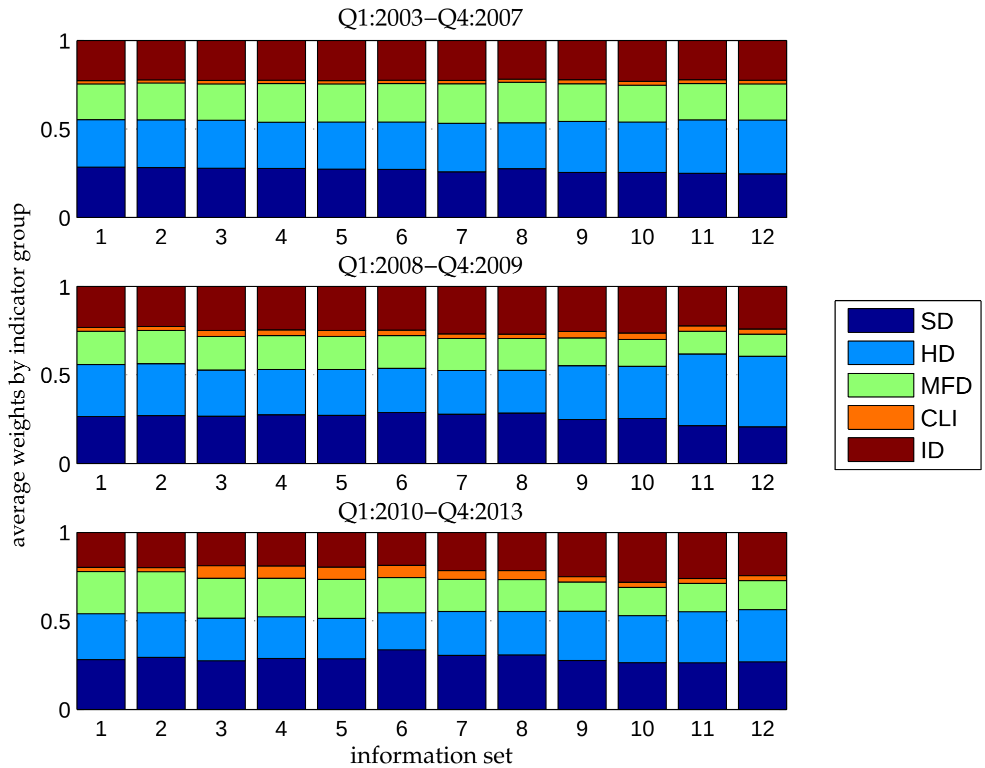
Notes: SD = Survey data, HD = Hard data, MFD = Monetary & Financial data, CLI = Composite Leading Indicator, ID = International data.

Figure 6: Weights for CVMA



Notes: SD = Survey data, HD = Hard data, MFD = Monetary & Financial data, CLI = Composite Leading Indicator, ID = International data.

Figure 7: Weights for MSE



Notes: SD = Survey data, HD = Hard data, MFD = Monetary & Financial data, CLI = Composite Leading Indicator, ID = International data.

increase over time, which is again consistent with the finding that the performance of this indicator turns out to be quite good in the period during the Great Recession. On the contrary, the weights for monetary and financial indicators tend to become smaller over time except for information set 1 and 2. Furthermore, the weights for hard business cycle indicators become substantially smaller over time, especially for the information sets 1 to 8, while they remain important at the end of the forecasting round in all subperiods. These observations hold for all 4 pooling techniques.

With respect to the forecast performance of the pooling techniques these shifts in the model weights turn out to be quite successful for the period during the Great Recession. CVMA, MMA as well as AIC and BIC model weights outperform the other pooling techniques at all information sets. However, for the period after the Great Recession there is also a prominent difference between MMA and CVMA on the one hand and AIC and BIC model pooling on the other hand. The latter two, tend to assign very high weights to a specific indicator group, namely monetary and financial indicators and the CLI. These indicators receive high weights for information sets 1 to 2 and 3 to 5, respectively. Furthermore, surveys receive a very high weight for information sets 6 to 8. This leads to worse forecasts for the AIC and BIC model weights compared to CVMA and MMA for which the evolution of the weights looks more balanced as shown in the previous section.

MSE weights behave much different than the aforementioned pooling techniques (see figure (7)). The variability in the weights over the information sets and over the three sub-samples is extremely small and mirrors to a large extent the share of the predictor groups in the overall sample. This explains why the forecast performance of MSE weight is in fact very similar to the performance the EWA.

4.4 Is model selection a viable alternative to model pooling?

The above analysis documented the usefulness of model pooling techniques in outperforming the benchmark model. However, in the most cases there exist a single predictor BE model that outperforms all model pooling techniques. This finding suggests that model selection might be a promising alternative to pooling. However, knowing the ex-post best performing BE model does not necessarily mean that a forecaster is able to select this model in real-time. To shed light on this issue, I also report the results based on model selection of one of the 39 BE models. For simplicity, I follow Kuzin et al. (2013) and select the model which receives the largest weight in the pooled forecast.

As shown in table 5, model selection works very badly in the period before the Great Recession. The relative MSFE is in most cases larger than unity. On the contrary, in the period during the Great Recession relative forecast performance improves substantially and is close to the forecast performance of the respective pooling techniques. In the period after the Great Recession the forecast performance of model selection deteriorates again. In most cases the relative MSFE is larger than unity and the gains obtained for some information sets are behind the gains of model pooling. Given these results, I conclude that model selection is a very risky choice when the informational content of single predictors is subject to considerable changes.

Table 5: Forecast performance of model selection.

IS	1	2	3	4	5	6	7	8	9	10	11	12
	h=2						h=1					
	Q1:2003-Q4:2007											
AR(1)	MSFE 0.07						MSFE 0.05					
	relative MSFE						relative MSFE					
CVMAsel	1.29	1.54	1.37	1.57	1.20	1.84	1.81	1.76	1.18	1.47	1.28	1.23
MMAsel	1.98	0.97	0.96	1.92	1.93	1.69	1.53	1.72	1.06	1.23	1.17	1.37
MSEsel	1.39	1.18	1.13	1.00	1.21	1.20	1.49	1.55	0.99	1.28	1.24	1.23
BICsel	1.46	1.38	1.09	1.26	1.32	1.14	1.51	1.40	1.18	1.37	0.96	1.05
AICsel	1.64	1.38	1.24	1.23	1.22	1.13	1.32	1.36	1.36	1.21	0.90	0.99
	Q1:2008-Q4:2009											
AR(1)	MSFE 2.69						MSFE 1.68					
	relative MSFE						relative MSFE					
CVMAsel	0.68	0.70	0.52	0.52	0.48	0.51	0.80	0.84	0.48	0.48	0.21	0.23
MMAsel	0.87	0.87	0.73	0.48	0.48	0.53	0.79	0.85	0.48	0.48	0.20	0.19
MSEsel	0.92	0.91	0.76	0.49	0.64	0.61	1.05	1.02	0.96	0.95	0.95	0.95
BICsel	0.80	0.70	0.73	0.49	0.49	0.41	0.79	0.82	0.53	0.53	0.11	0.11
AICsel	0.82	0.87	0.50	0.50	0.48	0.34	0.79	0.86	0.50	0.50	0.11	0.11
	Q1:2010-Q4:2013											
AR(1)	MSFE 0.14						MSFE 0.10					
	relative MSFE						relative MSFE					
CVMAsel	0.80	0.84	0.80	0.80	0.80	1.21	1.35	1.19	1.01	1.09	1.14	1.20
MMAsel	1.11	1.11	0.80	0.86	0.86	0.99	0.96	1.22	1.01	1.05	1.05	1.01
MSEsel	2.35	1.95	1.93	1.89	1.95	1.98	1.22	1.36	1.63	1.57	1.49	1.51
BICsel	1.08	1.39	0.80	0.80	0.80	0.99	0.96	1.07	0.96	0.96	1.04	1.04
AICsel	1.30	1.39	0.80	0.80	0.80	0.99	0.96	1.07	0.98	0.98	1.04	1.04

Notes: The model with the largest weight is selected. CVMAsel = Cross - Validation model selection, MMAsel = Mallows model selection, MSEsel = MSE selection, BICsel = BIC selection, AICsel = AIC selection.

5 Conclusion

In this paper, I analyse the performance of BE models as well as model selection and model pooling techniques for forecasting euro area GDP growth. I show that there is a substantial variation in the informational content of single predictor BE models. Depending on the information set, only 5 to 15 percent of the predictors outperform the benchmark model in the periods before, during and after the Great Recession. Moreover, I find that model selection does not provide a safeguard against the variation in the informational content of single predictor variables. In the periods before and after the Great Recession model selection techniques are not able to outperform the benchmark model in most cases. On the contrary, model pooling is quite robust against changes in the informational content. Five out of seven pooling techniques outperform the benchmark model in all sub-samples. Out of these five, CVMA and MMA are the most accurate model pooling techniques in terms of the relative MSFE.

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Appendix

Table 6: The dataset

No.	Variable name	Label	Data transformation log	1st diff.	publishing lag at 5th day	20th day	Source	Datastream Code
I. Survey data (SD) (N=10)								
1.	Economic Sentiment	ESI	no	yes	1	1	EU Commission	EKEUSESIG
2.	Consumer Confidence	CC	no	yes	1	1	EU Commission	EKCNFCONQ
3.	Industry Sector Confidence	IC	no	yes	1	1	EU Commission	EKCNFBUSQ
4.	Retail Sector Confidence	RC	no	yes	1	1	EU Commission	EKTTR99BQ
5.	Construction Sector Confidence	$CSTC$	no	yes	1	1	EU Commission	EK45.99BQ
6.	Business Climate	BC	no	yes	1	1	EU Commission	EKEUBCI.R
7.	Employment Expectations, Consumers	CC_{emex}	no	yes	1	1	EU Commission	EKTOT7BSQ
8.	Employment Expectations, Industry	IC_{emex}	no	yes	1	1	EU Commission	EKEUIMF7Q
9.	Employment Expectations, Retail	RC_{emex}	no	yes	1	1	EU Commission	EKTTR5BSQ
10.	Employment Expectations, Construction	$CSTC_{emex}$	no	yes	1	1	EU Commission	EK45.4BSQ
II. Hard data (HD) (N=11)								
11.	Industrial Production, ex. Construction	IP_{tot}	yes	yes	3	2	EUROSTAT	EKIPTOT.G
12.	Industrial Production, Manufacturing	IP_{man}	yes	yes	3	2	EUROSTAT	EKIPMAN.G
13.	Industrial Production, Construction	IP_{cons}	yes	yes	3	2	EUROSTAT	EKESCONMG
14.	Industrial Production, Energy	IP_{ener}	yes	yes	3	2	EUROSTAT	EKESIENGG
15.	Industrial Production, Intermediate Goods	IP_{int}	yes	yes	3	2	EUROSTAT	EKESIITRG
16.	Industrial Production, Capital Goods	IP_{cap}	yes	yes	3	2	EUROSTAT	EKESICTLG
17.	Industrial Production, Consumer Durables	IP_{cd}	yes	yes	3	2	EUROSTAT	EKESICODG
18.	Industrial Production, Consumer Non-Durables	IP_{cnd}	yes	yes	3	2	EUROSTAT	EKESICNDG
19.	Unemployment Rate	EA_{UN}	no	yes	2	2	EUROSTAT	EKESUNEMO
20.	Retail Sales Volume	RS	yes	yes	2	2	EUROSTAT	EMRETTOTG
21.	New Passenger Car Registrations	$CARS$	yes	yes	2	1	ECB	EKEBCARRO
III. Monetary & Financial data (MFD) (N=7)								
22.	10-Year Government Bond Yield	GOV_{bond}	no	yes	1	1	ECB	EMGBOND.
23.	Euro STOXX Index	$EUSTOXX$	yes	yes	1	1	STOXX	DJEURST
24.	M1	$M1$	yes	yes	2	2	ECB	EMM1....B
25.	M3	$M3$	yes	yes	2	2	ECB	EMM3....B
26.	Effective Exchange Rate, 12 Partners, Real	$REER$	yes	yes	1	1	ECB	EMECBRCCR
27.	Effective Exchange Rate, 12 Partners, Nominal	$NEER$	yes	yes	1	1	ECB	EMECBNOCR
28.	$ - Euro Exchange Rate	$EDER$	yes	yes	1	1	ECB	EMXRUSD
IV. Composite Leading Indicator (CLI) (N=1)								

29.	OECD Composite Leading Indicator	EA_{CLI}	yes	yes	3	3	OECD	EKOL2001T
V. International data (ID) (N=10)								
30.	World Trade, CPB	CPB_{WT}	yes	yes	3	3	CPB	WDCPBTBWG
31.	US, OECD Composite Leading Indicator	US_{CLI}	yes	yes	3	3	OECD	USCYLEADT
32.	US, Industrial Production	US_{IP}	yes	yes	3	2	Federal Reserve	USIPTOT.G
33.	US, Unemployment Rate	US_{UN}	no	yes	2	1	BLS	USUN%TOTQ
34.	UK, OECD Composite Leading Indicator	UK_{CLI}	yes	yes	3	3	OECD	UKCYLEADT
35.	UK, Industrial Production	UK_{IP}	yes	yes	3	2	ONS	UKIPTOT.G
36.	UK, Unemployment Rate	UK_{UN}	no	yes	2	1	ONS	UKUN%TOTQ
37.	JP, OECD Composite Leading Indicator	JP_{CLI}	yes	yes	3	3	OECD	JPOL2001T
38.	JP, Industrial Production	JP_{IP}	yes	yes	3	2	Ministry of Economy, Trade and Industry	JPIPTOT.G
39.	JP, Unemployment Rate	JP_{UN}	no	yes	2	2	Statistics Bureau	JPUN%TOTQ

Notes:

Table 7: Forecast evaluation of all BE models for the period before the Great Recession (Q1:2003-Q4:2007).

IS	1	2	3	4	5	6	7	8	9	10	11	12
	h=2						h=1					
AR(1)	MSFE 0.07						MSFE 0.05					
	relative MSFE						relative MSFE					
SD												
ESI	0.94	0.94	0.94	0.88	0.88	0.88	1.01	1.03	1.03	1.02	1.02	1.02
CC	0.69	0.72	0.72	0.71	0.71	0.77	0.96	0.93	0.93	0.94	0.94	0.94
IC	1.18	1.15	1.15	1.07	1.07	1.12	1.17	1.07	1.07	1.04	1.04	1.04
RC	0.97	0.94	0.94	0.91	0.91	0.91	0.96	0.86	0.86	0.87	0.87	0.87
$CSTC$	0.79	0.91	0.91	1.01	1.01	1.01	0.98	0.98	0.98	1.09	1.09	1.09
BC	1.26	1.16	1.16	1.16	1.16	1.04	1.07	1.07	1.07	1.05	1.05	1.05
CC_{emex}	0.78	0.76	0.76	0.76	0.76	0.89	1.14	1.01	1.01	0.96	0.96	0.96
IC_{emex}	1.11	1.09	1.09	1.02	1.02	0.97	1.15	1.06	1.06	0.98	0.98	0.98
RC_{emex}	1.00	1.00	1.00	0.99	0.99	0.92	1.00	1.02	1.02	1.04	1.04	1.04
$CSTC_{emex}$	1.22	1.21	1.21	1.01	1.01	1.00	1.24	0.98	0.98	0.92	0.92	0.92
HD												
IP_{tot}	1.03	1.03	1.07	1.07	1.06	1.06	1.40	1.40	1.31	1.31	1.02	1.02
IP_{man}	1.05	1.05	0.98	0.98	1.07	1.07	1.49	1.49	1.24	1.24	0.78	0.78
IP_{cons}	1.03	1.03	1.04	1.04	1.04	1.04	0.94	0.94	0.95	0.95	0.87	0.87
IP_{ener}	1.06	1.06	1.13	1.13	1.13	1.13	1.03	1.03	1.07	1.07	1.04	1.04
IP_{int}	1.22	1.22	1.11	1.11	1.41	1.41	1.60	1.60	1.14	1.14	1.18	1.18
IP_{cap}	1.03	1.03	1.17	1.17	1.20	1.20	1.28	1.28	1.20	1.20	0.93	0.93
IP_{cd}	1.05	1.05	1.12	1.12	0.98	0.98	1.18	1.18	1.18	1.18	0.90	0.90
IP_{cnd}	1.16	1.16	0.96	0.96	0.96	0.96	0.77	0.77	0.77	0.77	0.77	0.77
EA_{UN}	1.07	0.90	0.90	1.00	1.00	0.85	1.11	1.25	1.25	1.27	1.27	1.14
RS	0.90	1.03	1.03	1.03	1.03	1.04	1.03	1.11	1.11	1.09	1.09	1.04
$CARS$	1.02	1.02	1.02	1.02	1.02	1.02	0.79	0.79	0.85	0.85	0.86	0.86
MFD												
GOV_{bond}	1.08	1.08	1.08	1.07	1.07	0.95	1.01	0.84	0.84	0.85	0.85	0.85
$EUSTOXX$	0.75	0.76	0.76	0.71	0.71	0.71	0.77	0.77	0.77	0.77	0.77	0.77
$M1$	0.89	0.89	0.89	0.89	0.89	0.89	1.04	0.76	0.76	0.76	0.76	0.76
$M3$	1.31	1.22	1.22	1.16	1.16	1.20	1.21	1.21	1.21	1.21	1.21	1.21
$REER$	1.34	1.36	1.36	1.34	1.34	1.34	1.28	1.28	1.28	1.28	1.28	1.28
$NEER$	1.34	1.37	1.37	1.35	1.35	1.35	1.30	1.30	1.30	1.30	1.30	1.30
$EDER$	1.21	1.21	1.21	1.21	1.21	1.21	1.20	1.20	1.20	1.20	1.20	1.20

CLI												
EA_{CLI}	1.30	1.30	1.23	1.23	1.23	1.23	1.40	1.40	1.06	1.06	1.06	1.06
ID												
CPB_{WT}	1.21	1.14	1.14	1.21	1.21	1.20	1.32	1.24	1.24	1.28	1.28	0.93
US_{CLI}	1.26	1.26	1.13	1.13	1.13	1.13	1.13	1.13	1.11	1.11	1.11	1.11
US_{IP}	1.06	1.06	1.12	1.12	1.10	1.10	1.31	1.31	1.07	1.07	1.13	1.13
US_{UN}	0.95	0.95	0.95	0.95	0.95	0.95	0.86	0.86	0.86	0.86	0.86	0.86
UK_{CLI}	1.16	1.16	1.30	1.30	1.30	1.30	1.19	1.19	1.15	1.15	1.15	1.15
UK_{IP}	1.31	1.31	1.16	1.16	0.93	0.93	1.12	1.12	1.06	1.06	1.13	1.13
UK_{UN}	1.53	1.53	1.41	1.41	1.43	1.43	1.37	1.37	1.37	1.37	1.37	1.37
JP_{CLI}	1.19	1.19	0.98	0.98	0.98	0.98	0.99	0.99	1.05	1.05	1.05	1.05
JP_{IP}	1.24	1.15	1.15	0.99	0.99	0.93	1.00	1.00	1.00	1.00	1.00	1.00
JP_{UN}	1.27	1.27	1.27	1.27	1.27	1.27	1.34	1.31	1.31	1.38	1.38	1.39

Notes: SD = Survey data, HD = Hard data, MFD = Monetary & Financial data, CLI = Composite Leading Indicator, ID = International data; indicator labels are explained in table (6).

Table 8: Forecast evaluation of all BE models for the period during the Great Recession (Q1:2008-Q4:2009).

IS	1	2	3	4	5	6	7	8	9	10	11	12
	h=2						h=1					
AR(1)	MSFE 2.69						MSFE 1.68					
	relative MSFE						relative MSFE					
SD												
ESI	0.63	0.59	0.59	0.54	0.54	0.49	0.70	0.67	0.67	0.66	0.66	0.66
CC	0.60	0.60	0.60	0.57	0.57	0.54	0.79	0.74	0.74	0.71	0.71	0.71
IC	0.66	0.57	0.57	0.52	0.52	0.50	0.67	0.61	0.61	0.62	0.62	0.62
RC	0.89	0.83	0.83	0.77	0.77	0.68	0.89	0.87	0.87	0.86	0.86	0.86
$CSTC$	0.87	0.82	0.82	0.76	0.76	0.71	0.87	0.88	0.88	0.80	0.80	0.80
BC	0.72	0.61	0.61	0.55	0.55	0.48	0.62	0.60	0.60	0.57	0.57	0.57
CC_{emex}	0.72	0.63	0.63	0.58	0.58	0.50	0.72	0.64	0.64	0.60	0.60	0.60
IC_{emex}	0.77	0.67	0.67	0.54	0.54	0.47	0.77	0.64	0.64	0.58	0.58	0.58
RC_{emex}	1.00	0.93	0.93	0.82	0.82	0.82	0.94	0.85	0.85	0.77	0.77	0.77
HD												
IP_{tot}	1.05	1.05	0.89	0.89	0.69	0.69	1.15	1.15	0.49	0.49	0.17	0.17
IP_{man}	1.06	1.06	0.82	0.82	0.67	0.67	1.30	1.30	0.34	0.34	0.11	0.11
IP_{cons}	1.05	1.05	1.02	1.02	1.02	1.02	1.16	1.16	0.91	0.91	0.94	0.94
IP_{ener}	1.00	1.00	0.99	0.99	0.99	0.99	1.04	1.04	1.07	1.07	1.07	1.07
IP_{int}	0.99	0.99	0.99	0.99	0.70	0.70	1.14	1.14	0.34	0.34	0.19	0.19
IP_{cap}	0.91	0.91	0.87	0.87	0.88	0.88	0.98	0.98	0.47	0.47	0.21	0.21
IP_{cd}	1.04	1.04	1.04	1.04	0.72	0.72	1.01	1.01	0.96	0.96	0.52	0.52
IP_{cnd}	1.02	1.02	1.01	1.01	1.01	1.01	1.01	1.01	0.99	0.99	0.91	0.91
EA_{UN}	1.02	0.90	0.90	0.68	0.68	0.67	1.09	0.80	0.80	0.66	0.66	0.48
RS	0.88	0.88	0.88	0.88	0.88	0.88	0.89	1.09	1.09	1.09	1.09	1.07
$CARS$	0.93	0.93	0.90	0.90	0.92	0.92	0.82	0.82	0.89	0.89	0.90	0.90
MFD												
GOV_{bond}	1.02	1.02	1.02	1.02	1.02	1.01	0.99	0.99	0.99	0.99	0.99	0.99
$EUSTOXX$	0.62	0.56	0.56	0.55	0.55	0.55	0.70	0.70	0.70	0.70	0.70	0.70
$M1$	0.73	0.73	0.73	0.73	0.73	0.73	0.79	0.83	0.83	0.82	0.82	0.82
$M3$	0.92	0.91	0.91	0.89	0.89	0.89	0.85	0.85	0.85	0.85	0.85	0.85
$REER$	1.05	1.06	1.06	1.05	1.05	1.05	1.11	1.11	1.11	1.11	1.11	1.11
$NEER$	1.04	1.05	1.05	1.03	1.03	1.03	1.02	1.02	1.02	1.02	1.02	1.02
$EDER$	0.99	0.99	0.99	0.99	0.99	0.99	0.96	1.00	1.00	0.99	0.99	0.99

CLI												
EA_{CLI}	1.01	1.01	0.48	0.48	0.48	0.48	0.87	0.87	0.35	0.35	0.35	0.35
ID												
CPB_{WT}	1.00	1.00	1.00	0.99	0.99	0.91	1.21	1.16	1.16	0.54	0.54	0.33
US_{CLI}	1.23	1.23	0.89	0.89	0.89	0.89	1.10	1.10	0.72	0.72	0.72	0.72
US_{IP}	0.99	0.99	0.93	0.93	0.82	0.82	0.59	0.59	0.68	0.68	0.67	0.67
US_{UN}	1.12	1.12	1.17	1.17	1.21	1.21	1.04	1.04	1.05	1.05	1.02	1.02
UK_{CLI}	1.16	1.16	0.73	0.73	0.73	0.73	0.92	0.92	0.59	0.59	0.59	0.59
UK_{IP}	1.22	1.22	0.90	0.90	0.82	0.82	0.99	0.99	0.76	0.76	0.64	0.64
UK_{UN}	1.02	1.02	1.00	1.00	0.96	0.96	0.94	0.94	0.84	0.84	0.78	0.78
JP_{CLI}	1.08	1.08	1.09	1.09	1.09	1.09	1.07	1.07	0.95	0.95	0.95	0.95
JP_{IP}	1.33	0.94	0.94	0.89	0.89	0.81	1.58	0.96	0.96	0.37	0.37	0.25
JP_{UN}	1.01	0.92	0.92	1.01	1.01	1.01	1.00	1.04	1.04	1.02	1.02	1.01

Notes: SD = Survey data, HD = Hard data, MFD = Monetary & Financial data, CLI = Composite Leading Indicator, ID = International data; indicator labels are explained in table (6).

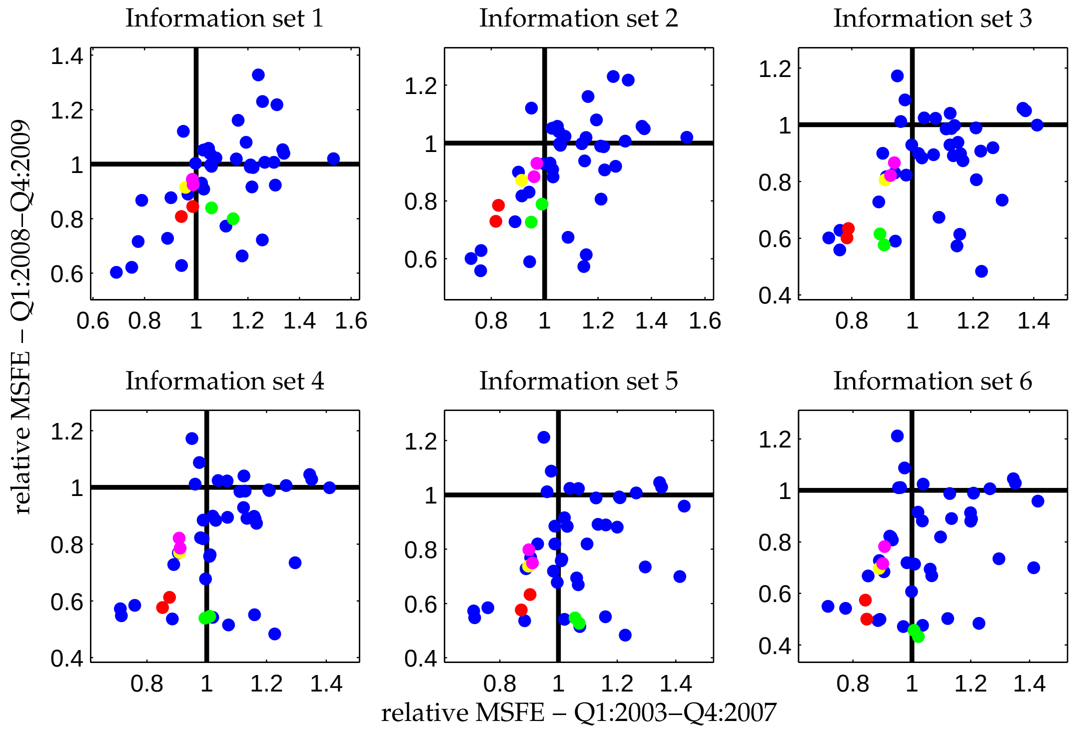
Table 9: Forecast evaluation of all BE models for the period after the Great Recession (Q1:2010-Q4:2013).

IS	1	2	3	4	5	6	7	8	9	10	11	12
	h=2						h=1					
AR(1)	MSFE 0.14						MSFE 0.10					
	relative MSFE						relative MSFE					
SD												
ESI	0.89	0.88	0.88	0.87	0.87	0.62	0.88	0.95	0.95	1.03	1.03	1.03
CC	1.03	1.01	1.01	1.15	1.15	0.96	0.99	1.18	1.18	1.25	1.25	1.25
IC	0.87	1.03	1.03	1.04	1.04	0.75	0.85	0.94	0.94	0.98	0.98	0.98
RC	0.90	0.75	0.75	0.77	0.77	0.89	0.91	0.94	0.94	1.01	1.01	1.01
CSTC	1.35	1.38	1.38	1.27	1.27	1.17	1.03	1.02	1.02	0.98	0.98	0.98
BC	1.06	1.15	1.15	1.12	1.12	0.99	0.90	1.07	1.07	1.16	1.16	1.16
CC_{emex}	1.23	1.21	1.21	1.21	1.21	1.15	1.17	1.27	1.27	1.30	1.30	1.30
IC_{emex}	1.12	1.18	1.18	1.19	1.19	1.23	1.14	0.96	0.96	1.09	1.09	1.09
RC_{emex}	0.86	0.71	0.71	0.70	0.70	0.78	0.86	0.85	0.85	1.03	1.03	1.03
$CSTC_{emex}$	1.58	1.53	1.53	1.43	1.43	0.97	0.86	0.80	0.80	0.80	0.80	0.80
HD												
IP_{tot}	2.61	2.61	1.12	1.12	1.32	1.32	1.29	1.29	1.02	1.02	1.08	1.08
IP_{man}	2.78	2.78	3.13	3.13	1.48	1.48	1.30	1.30	0.85	0.85	1.04	1.04
IP_{cons}	0.97	0.97	0.91	0.91	0.91	0.91	1.00	1.00	0.88	0.88	0.97	0.97
IP_{ener}	1.11	1.11	1.11	1.11	1.10	1.10	0.79	0.79	1.45	1.45	0.79	0.79
IP_{int}	2.32	2.32	1.44	1.44	1.56	1.56	1.44	1.44	0.73	0.73	0.81	0.81
IP_{cap}	2.48	2.48	2.86	2.86	3.57	3.57	1.44	1.44	1.21	1.21	1.13	1.13
IP_{cd}	1.36	1.36	1.34	1.34	1.58	1.58	1.10	1.10	1.30	1.30	1.57	1.57
IP_{cnd}	0.86	0.86	1.12	1.12	1.14	1.14	1.15	1.15	1.37	1.37	1.28	1.28
EA_{UN}	1.15	1.53	1.53	1.59	1.59	1.66	1.12	1.50	1.50	1.64	1.64	1.46
RS	1.11	1.11	1.11	1.11	1.11	1.08	1.10	1.01	1.01	1.01	1.01	0.96
CARS	1.05	1.05	1.25	1.25	1.19	1.19	1.13	1.13	0.91	0.91	0.91	0.91
MFD												
GOV_{bond}	0.95	0.95	0.95	0.95	0.95	0.95	0.82	0.82	0.82	0.82	0.82	0.82
EUSTOXX	1.08	1.23	1.23	1.26	1.26	1.26	1.32	1.14	1.14	1.17	1.17	1.17
M1	0.34	0.34	0.34	0.34	0.34	0.34	0.64	0.64	0.64	0.64	0.64	0.64
M3	2.18	1.80	1.80	1.77	1.77	1.74	1.48	1.52	1.52	1.48	1.48	1.48
REER	1.19	1.19	1.19	1.19	1.19	1.19	1.15	1.15	1.15	1.15	1.15	1.15
NEER	1.22	1.22	1.22	1.22	1.22	1.22	1.19	1.19	1.19	1.19	1.19	1.19
EDER	1.14	1.14	1.14	1.14	1.14	1.14	1.21	1.21	1.21	1.21	1.21	1.21

CLI												
EA_{CLI}	1.32	1.32	0.80	0.80	0.80	0.80	1.01	1.01	1.01	1.01	1.01	1.01
ID												
CPB_{WT}	1.46	1.16	1.16	1.16	1.16	1.37	1.20	1.20	1.20	0.60	0.60	0.82
US_{CLI}	0.97	0.97	1.45	1.45	1.45	1.45	0.98	0.98	0.92	0.92	0.92	0.92
US_{IP}	1.91	1.91	1.93	1.93	1.89	1.89	1.55	1.55	1.53	1.53	1.48	1.48
US_{UN}	1.85	1.85	2.35	2.35	2.71	2.71	1.49	1.49	1.68	1.68	1.77	1.77
UK_{CLI}	1.02	1.02	1.76	1.76	1.76	1.76	1.05	1.05	1.34	1.34	1.34	1.34
UK_{IP}	1.02	1.02	1.15	1.15	1.06	1.06	0.95	0.95	0.59	0.59	0.66	0.66
UK_{UN}	1.58	1.58	1.44	1.44	1.45	1.45	1.02	1.02	1.03	1.03	1.09	1.09
JP_{CLI}	1.34	1.34	0.98	0.98	0.98	0.98	1.11	1.11	0.91	0.91	0.91	0.91
JP_{IP}	1.38	1.12	1.12	1.15	1.15	1.14	1.07	1.34	1.34	1.19	1.19	1.50
JP_{UN}	0.93	1.04	1.04	0.87	0.87	0.90	1.04	0.94	0.94	0.94	0.94	0.94

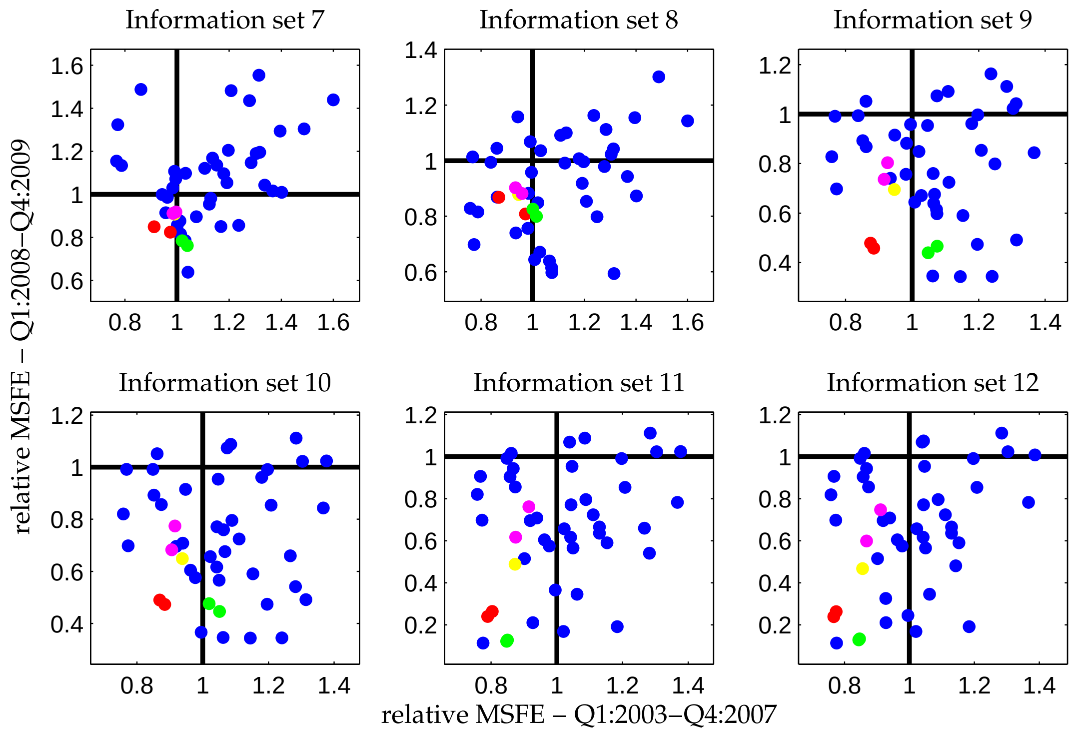
Notes: SD = Survey data, HD = Hard data, MFD = Monetary & Financial data, CLI = Composite Leading Indicator, ID = International data; indicator labels are explained in table (6).

Figure 8: Relative MSFE comparison before and during the crisis, h=2



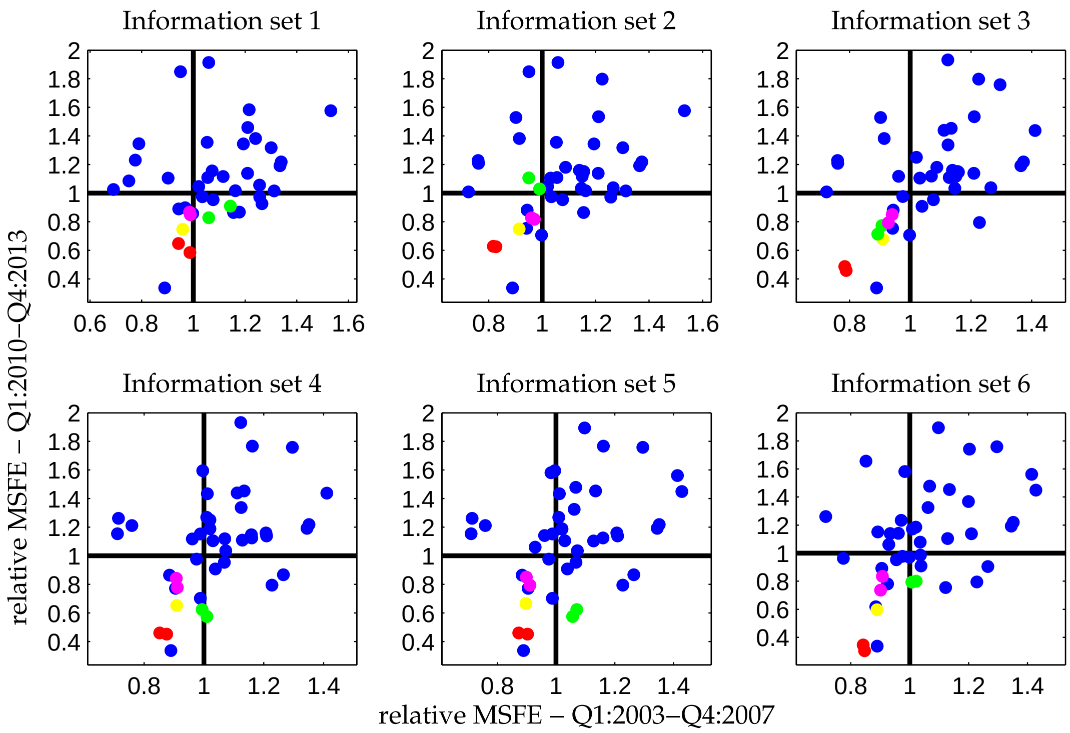
Notes: Blue dots: single indicator models, red dots: CV and Mallows model averaging, yellow dot: MSE weights, green dots: BIC and AIC weights, green circle: BIC model selection, purple dots: equal weight averaging and median.

Figure 9: Relative MSFE comparison before and during the crisis,h=1



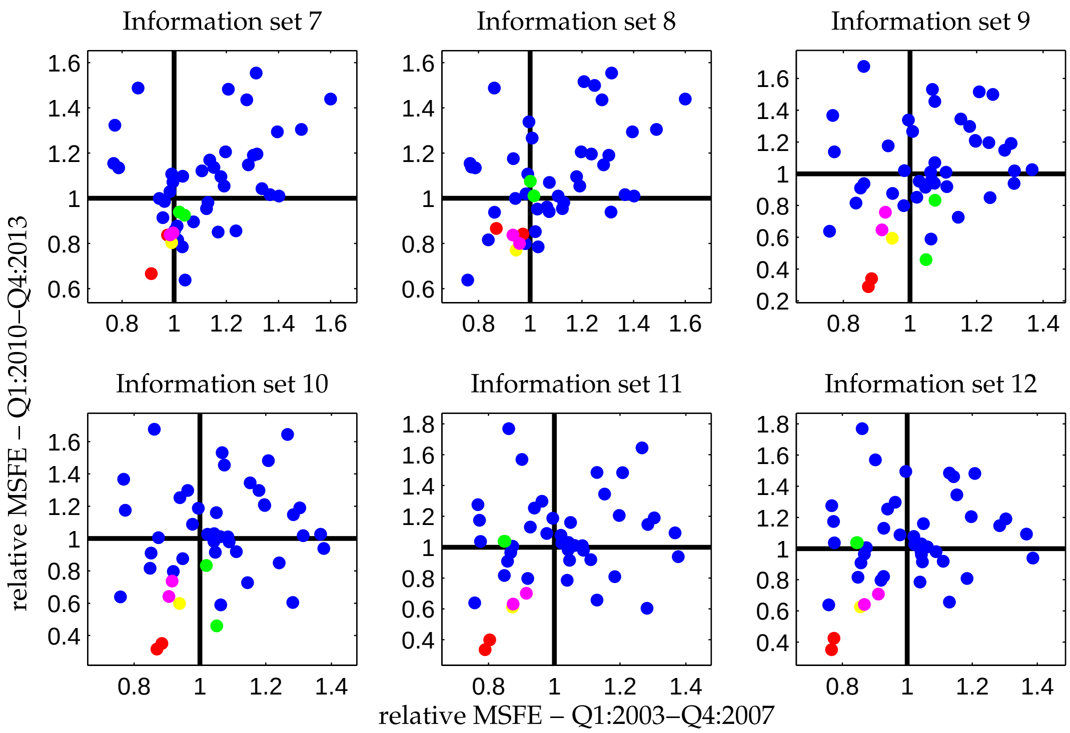
Notes: Blue dots: single indicator models, red dots: CV and Mallows model averaging, yellow dot: MSE weights, green dots: BIC and AIC weights, green circle: BIC model selection, purple dots: equal weight averaging and median.

Figure 10: Relative MSFE comparison before and after the crisis, h=2



Notes: Blue dots: single indicator models, red dots: CV and Mallows model averaging, yellow dot: MSE weights, green dots: BIC and AIC weights, purple dots: equal weight averaging and median.

Figure 11: Relative MSFE comparison before and after the crisis, h=1



Notes: Blue dots: single indicator models, red dots: CV and Mallows model averaging, yellow dot: MSE weights, green dots: BIC and AIC weights, purple dots: equal weight averaging and median.