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Combining forecasts for a flash estimate of Euro area GDP.

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Sommario: Bridge equations models have commonly been investigated to produce flash estimation and forecasts of GDP. However as it is known a single equation model cannot be fully appropriate if the estimates using different span of data are not stable. Combining forecasts stemming from different models has become a current practice. In these situations the naive scheme that assigns equal weights to all models has been used.
In this work we propose a new algorithm based on the so-called directional forecasts that has mainly been applied in the marketing environment. As we argue, in presence of time series with an high degree of persistence this method outperforms three competitors already proposed in the literature.
These results hold both looking at the simulation exercise and in an empirical application to the flash estimation of the GDP using a real-time dataset. Moreover, in terms of accuracy, the proposed Flash estimate obtained with the new algorithm presents better results respect to the single equation approach for the period 2005q1-2007q4.
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Parole chiave: Combining forecasts, Flash estimates, Real-time forecasting.

Contents

1 Introduction

Quarterly Gross Domestic Product (GDP) is one of the key indicators for economic analysis. GDP data for the Euro area are published with a delay of 45 days after the end of the period. Many efforts have been done by Eurostat and National Statistical Institutes (NSI) to improve timeliness, but the target of 30 days achieved in the US and UK seems unrealistic in the near future (at least with an acceptable level of accuracy). This makes difficult the construction of Euro area GDP estimates at 30 days by aggregation of the single Member States (MS) estimates.

An alternative way of producing GDP flash estimates can be reached using well-specified forecasting models which exploit the availability of monthly/quarterly economic indicators promptly observed for the most recent periods. Two main approaches have been used in empirical applications, namely bridge equations and dynamic factor models. In this paper we consider the former approach that implies a model selection structure[1]. There are many examples in the literature showing the good results of bridge approach in terms of forecasting accuracy, among others, Buffettau and Mora (2000), Baffigi, Golinelli, and Parigi (2002), or more recently, Diron (2008).

However, a single forecasting model cannot be fully appropriate for all situations. Even if it proved to be satisfactory in terms of Root Mean Squared Forecast Error (RMSFE) (or any other criteria) for a specific situation, its performance might change according to different sample realizations. If this is the case, an improvement of predictive ability can be achieved by forecasting combination. The idea of combining forecasts from different models is not novel in the literature: an historical review on information combination can be found in Bates and Granger (1969), Clemen (1989) and Timmermann (2005).

However combining has not seen as an attractive strategy to produce flash estimation in real-time. It has just been used as benchmark using the naive scheme of equal weights. Two main reasons for that: combining is a completely different strategy respect to the selection models approach; it is difficult to find a weighting scheme that performs better than the naive one. Concerning this last point, Yang and Zou (2004) and Yang (2004) have proposed a new weighting algorithms (called AFTER) that produce significant better forecast.

In this paper we propose a new algorithm to update sequentially the weights. As shown with a simulation exercise and an application on real data our method improves the results obtained with AFTER.

Our proposed method has been based on the ability of models in tracking the direction (acceleration or decelerations). Its characteristics together with the forecasting ability is evaluated comparing the results both with the AFTER method and its modification proposed by Altavilla and Ciccarelli (2007) and, of course, with the naive scheme.

The forecasting ability of the different combination methods is evaluated through both a simulation exercise and a real time exercise to predict the first published GDP estimates. The results are thus evaluated in terms of one-step ahead forecasting errors.

The paper is organized as follows: the following section presents the different methods used to derive the weighting scheme exploring their characteristics through simulations; section 3

[1] For recent applications on dynamic factor models see for example, Angelini et al., 2008, Banbura et al., 2007 and Altissimo et al. 2007

describes both the dataset and the models utilized to generate flash estimates of Euro area GDP growth; section 4 shows the results of the real-time forecasting exercise and section 5 concludes.

2 The combination of forecasts

Economic forecasts are often based on a limited set of information. Given a large sample and assuming linearity, a single forecast might be considered as a good approximation of the optimum. However, nowadays the amount of potential information is enormous and the sources of nonlinearity are very frequent. Therefore, any economic forecast cannot be the best that could possibly be achieved given all the information in the universe (Granger and Newbold, 1977).

One way to improve the forecasting accuracy is to combine several forecasts of the same quantity in a single forecast. Several combination methods can be used: the combined forecast can be a simple average of the individual forecasts, a weighted average or even a non-linear combination of them.

To show some properties, consider the simple combination of two individual forecasts. Let $y_{t,1}$ and $y_{t,2}$ be forecasts of the same variable Y_t with errors

$$e_{t,j} = Y_t - \hat{y}_{t,j}, \qquad j = 1, 2$$

such that

$$\begin{aligned} E(e_{t,j}) &= 0 \\ E(e_{t,j}^2) &= \sigma_j^2 \\ E(e_{t,1}e_{t,2}) &= \rho\sigma_1\sigma_2. \end{aligned}$$

As a combination of the two forecasts, consider the weighted average

$$\hat{y}_{t,c} = k\hat{y}_{t,1} + (1-k)\hat{y}_{t,2}. \tag{1}$$

The forecast error of $y_{t,c}$ is

$$e_{t,c} = Y_t - \hat{y}_{t,c} = ke_{t,1} + (1-k)e_{t,2} \tag{2}$$

with error variance

$$\sigma_c^2 = k^2\sigma_1^2 + (1-k)^2\sigma_2^2 + 2k(1-k)\rho\sigma_1\sigma_2. \tag{3}$$

It can be shown that the minimum of the error variance (3) is less than the error variances of the individual forecasts, unless either ρ is exactly equal to σ_1/σ_2 or to σ_2/σ_1. Then, any combination of forecasts cannot do worse than the better individual forecast.

However, the optimal combination of forecasts can never be achieved due to the fact that σ_1^2, σ_2^2, and ρ are not known and must be estimated. The quality of estimation of error

variances and correlation coefficients in small samples are generally poor, such to hamper the accuracy of the combined forecast. Many experiments in the literature have found that ignoring correlation (instead of attempting to take it into account) improves the accuracy of the combined forecasts (Newbold and Granger, 1974; Winkler and Makridakis, 1983).
Given the small sample of our experiments, in this work we do not consider correlation of the forecast errors.

The proposed algorithm

In this paper we propose a new combination method where the weights are derived looking at the ability of the model forecasts to detect the growth cycle pattern (acceleration, deceleration). In other words to produce the flash estimate at time t, from the observed value of the series we derive a vector composed by the difference $Y_{t-1} - Y_{t-2}$. The sign of each element is compared with the analogous difference derived with the value of the estimated model. We then build up the following binary matrix:

$$S_{t,j} = \begin{cases} 0 & \text{if} \quad sign(Y_{t-1} - Y_{t-2}) = sign(\hat{y}_{t-1,j} - Y_{t-2,j}) \\ 1 & \text{if} \quad sign(Y_{t-1} - Y_{t-2}) \neq sign(\hat{y}_{t-1,j} - Y_{t-2,j}) \end{cases}$$

Using this matrix together with the negative exponential function we derive the following weighting scheme (hereafter BCIM):

$$W_{t,j} = \frac{\exp^{(-\sum_{i=1}^{t-1} S_{i,j})}}{\sum_j' \exp^{(-\sum_{i=1}^{t-1} S_{i,j'})}}$$

The main characteristics of the proposed scheme rely on the possibility to take into account the whole history of the performances (like AFTER) and to avoid both to be locked in one model and to be influenced by large errors in the estimation. Moreover, it is worth highlighting two other features of BCIM: firstly if for model j the sum $\sum S_{i,j}$ increases, the corresponding weight decreases; secondly if all models exhibit the same performance, the method assigns equal weights.

The competitors algorithms

The first competitor algorithms is the simple average scheme (EW), assigning equal weights to each individual forecast. This method represents a benchmark against which more refined combining solutions can be evaluated, even if it often represents the best solution in empirical exercise.

The second method is the algorithm called AFTER (Aggregated Forecast Through Exponential Reweighting), proposed by Yang (2001). The weights are determined on the basis of the history of errors made by the individual models generating the forecasts. Consider the case of J individual forecasts, $(\hat{y}_{t,1}, \hat{y}_{t,2}, \ldots, \hat{y}_{t,J})$. Let $W_{1,j} = 1/J$, that implies equal weights in the first period. For $t \geq 2$ the weights are given by

$$W_{t,j} = \frac{\prod_{i=1}^{t-1} \hat{\sigma}_{j,i}^{-1/2} \exp(-\frac{1}{2} \sum_{i=1}^{t-1} \frac{(Y_i - \hat{y}_{i,j})^2}{\hat{\sigma}_{j,i}})}{\sum_{j' \geq 1} \prod_{i=1}^{t-1} \hat{\sigma}_{j',i}^{-1/2} \exp(-\frac{1}{2} \sum_{i=1}^{t-1} \frac{(Y_t - \hat{y}_{i,j'})^2}{\hat{\sigma}_{j',i}})}$$

where $\hat{\sigma}_{j,i}$ is the estimated error variance of model j based on information up to i. The weights are constrained to lie between the range [0,1]; the more a weight approaches 1 the larger is the ability of the corresponding model to forecast the actual value in all previous periods. The combined forecast with AFTER scheme is then

$$\hat{y}_{t,AF} = \sum_{j=1}^{J} W_{t,j} \; \hat{y}_{t,j}$$

To simplify the calculation of the weights, the following iteration can be used

$$\begin{aligned} W_{1,j} &= 1/J \\ W_{t,j} &= \frac{W_{t-1,j} \; \hat{\sigma}_{j,t-1}^{-1/2} \exp(-\frac{(Y_{t-1}-\hat{y}_{t-1,j})^2}{2\hat{\sigma}_{j,t-1}})}{\sum_{j' \geq 1} W_{t-1,j'} \hat{\sigma}_{j',t-1}^{-1/2} \exp(-\frac{(Y_{t-1}-\hat{y}_{t-1,j'})^2}{2\hat{\sigma}_{j',t-1}})} \qquad \text{for } t \geq 2 \end{aligned}$$

Finally, in 2007 Altavilla and Ciccarelli (hereafter AC) propose a simplified scheme based on AFTER, assigning weights on the basis of the ability to forecast the actual value not in all previous periods, but only in the previous one:

$$W_{t,j} = \frac{\exp(-\frac{(Y_{t-1}-\hat{y}_{t-1,j})^2}{2S_t^2})}{\sum_{j'} \exp(-\frac{(Y_{t-1}-\hat{y}_{t-1,j'})^2}{2S_t^2})}$$

with S_t^2 the sample variance of the dependent variable up to period $t-1$. Compared to the AFTER method, their scheme awards models with low forecasting errors at $t-1$, without considering the past history of errors.

2.1 Simulation

To illustrate the characteristics of the proposed method (BCIM), following Yang and Zou (2004), we perform a simulation study where the data generation process is either an AR(1) model (case 1) or an AR(2) (case 2). In both cases we derive one-step ahead forecasts from different AR models with order up to 5. Then, we combine them using the proposed methods. For each value of the parameters, we evaluate 100 replications looking at the RMSFE of the combined forecasts.

For example for the case 1, with $\phi = .75$ (table 1) in 40 of the 100 replications BCIM method performs better than the others three. This ranking still holds for $\phi = .5$ but with a slight difference with EW method (33 successes for the first, 30 for the second). With $\phi < .5$ the results obtained by BCIM get worse than the others. AFTER and AC perform better with a number of success quite close to the EW method. To explain these findings we argue that with positive values of ϕ the adjacent observations are positively correlated and the generated series exhibit low frequency trends while with negative values, adjacent observations have negative correlation and the generated series displays rapid oscillations. So, BCIM gives better results in the presence of series with an high degree of persistence.

Table 1: Forecasting performances for AR(1)

ϕ	EW	AFTER	AC	BCIM
0.75	23	20	17	40
0.5	30	17	20	33
0.25	23	30	27	20
-0.25	29	30	20	21
-0.5	27	24	27	22
-0.75	23	31	25	21

Similar results hold for case 2 . When the process is persistent ($\phi_1 = .8$, $\phi_2 = .3$) BCIM is the best method while in the case of low persistence ($\phi_1 = .7$, $\phi_2 = -.3$) AFTER and EW perform better.

Table 2: Forecasting performances for AR(2)

AR(2)	EW	AFTER	AC	BCIM
persistent	27	17	21	35
not persistent	26	27	23	24

3 Data and models for flash estimates of Euro area GDP

In this section the data and the models used to forecast the quarterly growth rates of GDP will be described.

Data

The choice of indicator series for our experiments is guided by several characteristics connected to the production of Euro area GDP flash estimates. As already stated, flash estimates must rely on (hard or soft) information observed in the quarter of interest (or part of it). The first priority in the choice of indicators is timeliness (for a Flash estimates $t+30$ from the reference quarter): only information which is rapidly available to the user is considered. However, very few indicators are released so quickly. Therefore, we also consider monthly indicators which are available up to 60 days after the month: in such cases, the first two months of the quarter are known and can be exploited to predict the remaining month by means of optimal time series forecasts (an example is the industrial production index).

As a consequence, following a common practice with bridge equations, a two-step approach is considered:

1. the monthly indicators are forecast over the months of the quarter where they are not available yet;

2. both the available data and the obtained forecasts are quarterly aggregated in order to predict GDP growth.

Only short-term indicators for the Euro area as a whole are taken into account following our choice to use a direct approach to Euro area GDP estimate.

A relevant aspect of our exercise is the use of vintages of data. GDP and short-term indicators are usually subject to revision due to different reasons, especially in their seasonally adjusted form. Then, it is usually preferable to take into account the various vintages of data for an appropriate evaluation of the forecasting ability of models. Preliminary information of a given month/quarter can be changed in subsequent releases. Considering only the latest release, which includes additional elements of the economic activity not known at that time, might be misleading.
Forecasting exercise based on vintages of data is generally called real-time because it simulates the real situation at the various points in time.
The data used in our exercise are drawn from the real-time dataset developed and maintained by OECD (see Di Fonzo, 2005 and McKenzie, 2006). The database is updated every month (generally in the middle) with a "snapshot" of the monthly publication Main Economic Indicators (MEI). It contains the times series of 21 key economic variables as originally published in the MEI from February 1999 onwards for OECD countries, the Euro area and other large countries. In particular, the database includes our variable of interest, GDP, and the main short-term indicators of economic activity: industrial production, production in construction and retail trade. The vintages considered are those released between January 2005 and March 2008, for a total of 39 versions of each variable. This shortened period is sufficient to our purposes, because it includes preliminary and revised estimates of the most recent years (2005-2007) that are chosen as the forecasting period of the exercise.
Without recurring to back-calculation for some indicators, we have decided to set the quarter 1995q1 as the starting period in the estimation of all models.

For other hard data selected in this work (new car passenger registration, unemployment rate, M1, real effective exchange rate, OECD leading indicator, 10-year Government-bond interest rates, 3-month interest rates, Dow Jones Euro Stoxx 50, HICP), only a single data vintage is considered. Concerning soft data, the complete set of variables from business and consumer surveys (including confidence indices) are taken into account.
The complete dataset used in this exercise is presented in Appendix A, with sources to be intended as the on-line data warehouse from where indicators have been extracted.

Models

In this paper we consider the bridge equations approach as tools for the estimation of real GDP growth. We use various types of monthly indicators, with different combinations of them. Particularly we define 9 bridge equations as shown in table 1. The first six models are the same as the ones estimated in Diron (2006). First, a combination of hard data produced by NSI with new car passengers registration is considered. Models 2-4 are based on different combinations of survey data with better timeliness compared to the hard data of model 1 and not affected by revision. Models 5 and 6 make use, respectively, of financial variables sometimes included in bridge equations because of their leading properties and a composite indicator for the Euro area growth. We consider other three combinations of the indicators according to a partition of the information set driven by the features of the data:

- Model 7: quantitative hard data;
- Model 8: quantitative soft data;
- Model 9: qualitative data.

Table 3: Indicators used in the different bridge equations

	Quantitative - hard data				Quantitative - soft data		Quantitative-Finance			Qualitative				
	GDP(-1)	IPI	IPC	RET	Cars	Oecd-LI	Spread	Exc-rate	Stock	Esi	Ind	Ser	Cons	Ret
Model 1		X	X	X	X									
Model 2	X									X				
Model 3											X	X		
Model 4											X		X	X
Model 5							X	X(-2)	X(-1)					
Model 6	X					X								
Model 7		X	X	X										
Model 8	X				X	X								
Model 9											X	X	X	X

All the equations are estimated using data from the first quarter 1995. It is important to stress we are not looking for the best forecasting model in terms of accuracy. Rather the aim of our exercise is to explore the feasibility of an optimal combination of forecasts from such equations subject to the information available at $t + 30$. This issue will be treated in next section.

4 The real-time forecasting exercise

As already stated, our experiment refers to a real-time exercise because it utilizes different vintages of both dependent and explanatory variables (all related to the Euro area). It produces several ex-post forecasts of the GDP quarterly growth over the span 2005q1 to 2007q4 using monthly indicators and it is aimed at combining such forecasts through different approaches. However some monthly indicators are not always available for the three months of the quarter to be forecast. For example, data for the industrial production and for construction sector are released, respectively, about six weeks and 50 days after the end of the reference month. Instead retail trade data are published one month after the end of the reference month and survey and financial data are available just at the end of the month.

This means that the third month of each quarter for both the index of production in the industrial sector (IPI) and in the construction sector (IPC)[2] has to be estimated.

Although several approaches can be considered, only univariate autoregressive models are utilized to produce one-step ahead forecasts. The model order, that is the number of lags, is selected through the BIC criterion, but not in a pure automatic way because an analysis of stability is carried out over the whole forecasting span. For IPI a unique autoregressive model of order 3 is finally used, while for IPC an autoregressive model of order 2 is always used, but with a different number of outliers according to the particular vintage handled. Table 4 reports some measures computed on the predicted month-to-month growth rates to assess the forecasting performance of the models.

Using the forecast for IPI and IPC each bridge equation is estimated to replicate a real-time situation for the forecast of growth rates of GDP for each quarter from 2005q1 to 2007q4

[2] As far as IPC data are concerned, two-step ahead forecasts are sometimes required in the years 2005 and 2006.

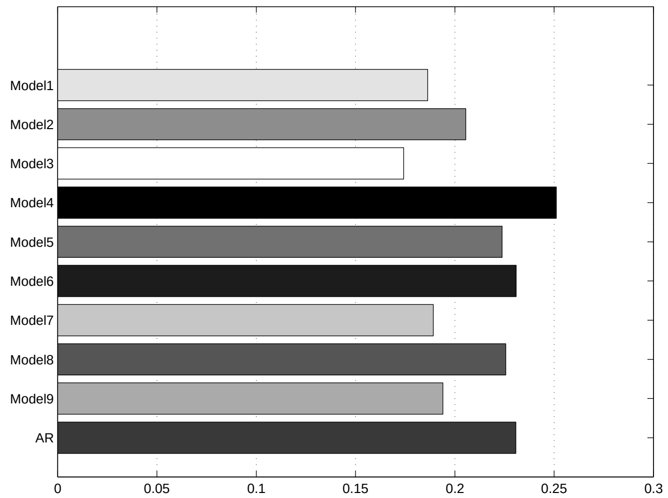
Table 4: Forecasting performances of monthly AR models for IPI and IPC

Indicators	one-step		two-steps	
	$MAFE$	$RMSFE$	$MAFE$	$RMSFE$
IPI	0.46	0.59	–	–
IPC	1.50	2.01	2.34	3.00

Legend: MAFE = Mean of Absolute Forecast Error
RMSFE = Root Mean Squared Forecast Error

(12 quarters). At each iteration the model specification is kept constant, the coefficients are re-estimated and only information available in real time is used. Appendix B reports the equations for the 9 models of table 1 with the estimated parameters and some summary statistics obtained with data from 1995q2 to 2004q4 (excluded missing observations at the beginning due to lags of variables). Figure 1 shows the RMSFE for the 9 models calculated over the range of forecasts for the period 2005q1-2007q4. Model labeled AR is an AR(1) model estimated for the Euro GDP. From the figure it can be noted that model 1 and 3 show a better performance compared to the other models.

Figure 1: RMSFE of the estimated models. Period: 2005q1-2007q4.



Using the 4 different methods presented, we elaborate combining forecasts according to two different strategies:

- Strategy 1 corresponds to the combination of the first 6 models in table 1 as estimated in Diron (2008);
- Strategy 2 considers the combination of the models with financial indicators (model 5), the quantitative hard data model (model 7), the quantitative soft data model (model 8) and the qualitative data model (model 9)

Table 5 reports the RMSFE for each combination. The general finding from our exercise is the reduction of RMSFE of the combined forecasts compared to each single model. Table 5 shows that EW and AC approaches give quite similar results. The BCIM method proposed in this paper gives overall the best RMSFE.

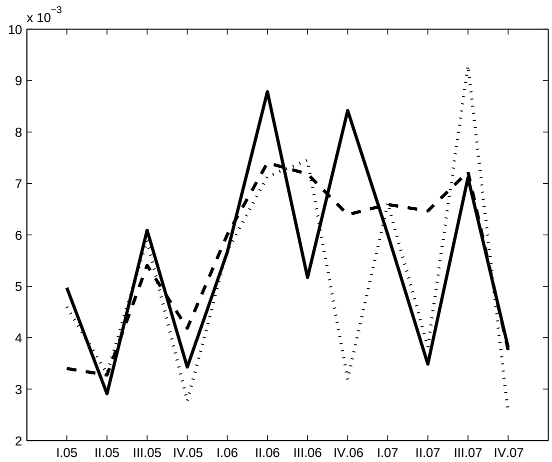
Table 5: RMSFE of different combining methods and strategies. Period: 2005q1-2007q4.

	Strategy 1	Strategy 2
EW	0.162	0.160
AFTER	0.184	0.180
AC	0.165	0.158
BCIM	0.138	0.134

From another perspective, it is interesting to determine in how many periods the change of GDP direction is correctly detected by individual and combined forecasts. BCIM gives positive results in 10 out of 12 quarters while EW in 9, AC in 8 and AFTER in 7.

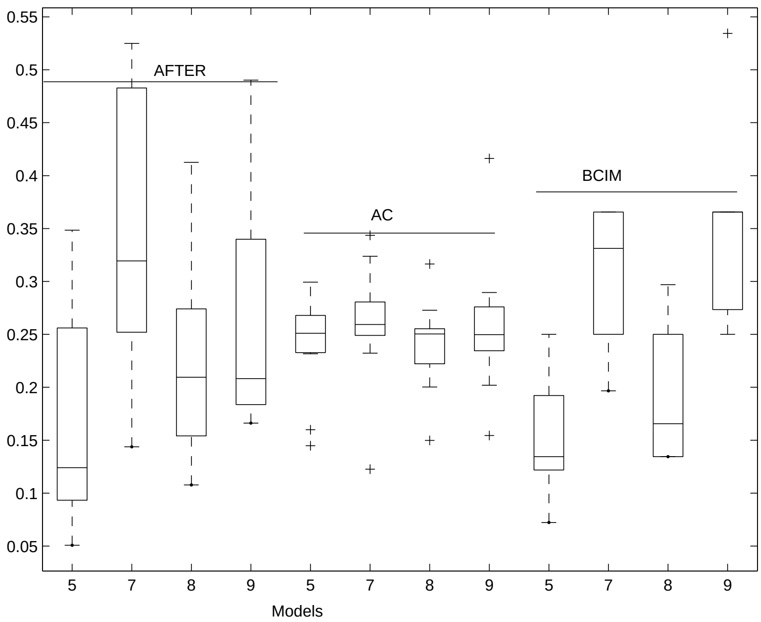
The graph in figure 2 compares the actual GDP growth rates (straight line) with the combined forecasts according to BCIM (Strategy 2, dashed line) and individual forecasts from model 7 (dotted line). The combined forecasts shows a much smoother pattern than the individual forecast: averaging between different forecasts, the risk of producing large errors (like model 7 in 2006q4) is clearly reduced.

Figure 2: Comparison of actual growth rates and forecasts (actual values: straight line, BCIM: dashed line, Model 7: dotted line)



The different behaviour of the combination methods can be interpreted looking at figure 3, showing the boxplot of the weights assigned to each model (model 5, 7, 8, 9) in strategy 2. The central part of the graph shows that AC weights are characterized by a lower variability compared to the other two methods and are quite similar to the EW weights. This explains why the RMSFE for the two methods are not too different. Instead the AFTER algorithm (left part of the graph), because it takes into account at each iteration all the history of forecast errors obtained at the previous steps, has a higher variability in the weights. Moreover AFTER method seems to be more sensitive to large errors in the individual forecasts, producing strong differences in the weights in the case of large forecasting errors. Finally BCIM (right part of the graph) presents an interesting 'middle' behavior between the two previous methods.

Figure 3: Weights assigned to the models for strategy 2



5 Conclusions

In the paper we performed a combining forecasting exercise of the Euro area GDP growth rates.

Firstly following the literature on bridge equations, we estimated different models to obtain flash estimates of GDP growth rates with the information available within 30 days from the reference quarter. A real-time dataset has been used to strengthen the validity of the exercise.

Secondly, we applied different combination methods to the individual forecasts obtained from the bridge equations. In particular, we used two combining methods already known in the literature (AFTER and its modified version) and proposed a new combination approach, based on the ability of the individual models to detect movements of the GDP growth cycle. From the results achieved, our main findings can be summarized as follows:

- the combination of forecasts, whatever the method used, yields a smaller RMSFE than each individual forecast;
- the combining method proposed in this paper outperforms other available schemes when the target is GDP growth rates;
- improvements in the accuracy has been reached with a combining strategy that uses a partition of the information set driven by the features of the data

Clearly, such conclusions are not general but restricted to the data and the models used in this exercise. In particular as shown by simulation, for variables with high persistence as GDP growth rate, BCIM method gives better results compared with the other methods analyzed.

Appendix A: Data description

Code	Description	Country	Frequency	First obs	Last obs	N. of vintages	Source
gdp	GDP	Euro-area	Q	1995-Q1	2007-Q4	39	OECD
gdpger	GDP	Germany	Q	1991-Q1	2007-Q4	39	OECD
gdpfra	GDP	France	Q	1980-Q1	2007-Q4	39	OECD
gdpita	GDP	Italy	Q	1981-Q1	2007-Q4	39	OECD
gdpspa	GDP	Spain	Q	1995-Q1	2007-Q4	39	OECD
gdpnet	GDP	The Netherlands	Q	1988-Q1	2007-Q4	39	OECD
gdpuk	GDP	UK	Q	1980-Q1	2007-Q4	39	OECD
gdpusa	GDP	USA	Q	1980-Q1	2007-Q4	39	OECD
ipi	Industrial production index	Euro-area	M	1980-M1	2007-M12	39	OECD
ipc	Construction index	Euro-area	M	1985-M1	2007-M12	39	OECD
ret	Retail sales index (volume)	Euro-area	M	1995-M1	2007-M12	39	OECD
cars	New car passenger registration	Euro-area	M	1985-M1	2007-M12	1	ACEA
unempl	Unemployment rate	Euro-area	M	1996-M1	2007-M12	1	EUROSTAT
m1	M1	Euro-area	M	1980-M1	2007-M12	1	EUROSTAT
compe12	Real effective exchange rate	Euro-area	M	1990-M1	2007-M12	1	EUROSTAT
cli	OECD leading indicator	Euro-area	M	1980-M1	2007-M12	1	OECD
bond	10 year Government-bond interest rates	Euro-area	M	1990-M1	2007-M12	1	EUROSTAT
inter3	3-month interest rates	Euro-area	M	1990-M1	2007-M12	1	EUROSTAT
spread	Spread	Euro-area	M	1990-M1	2007-M12	1	calculated
dowjeur	Dow Jones EURO STOXX 50	Euro-area	M	1986-M1	2007-M12	1	EUROSTAT
hicp	HICP	Euro-area	M	1996-M1	2007-M12	1	EUROSTAT
share	Share prices index	Euro-area	M	1996-M1	2007-M12	1	EUROSTAT
busclim	Business Climate Indicator	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
sentind	Economic sentiment indicator	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsind1	Production trend observed in recent months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsind2	Employment expectations for the months ahead	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsind3	Assessment of order-book levels	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsind4	Assessment of export order-book levels	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsind5	Assessment of stocks of finished products	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsind6	Production expectations for the months ahead	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsind7	Selling price expectations for the months ahead	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsind8	Industrial confidence indicator	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst1	Trend of activity compared with preceding months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst2	Assessment of order books	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst3	Employment expectations for the months ahead	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst4	Price expectations for the months ahead	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst5	Construction confidence indicator	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst6	Factors limit building activity	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst7	Factors limit building activity - Insufficient demand	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst8	Factors limit building activity - Weather conditions	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst9	Factors limit building activity - Shortage of labour	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst10	Factors limit building activity - Shortage of material	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst11	Factors limit building activity - Other	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsconst12	Factors limit building activity - Fi..ncial constraints	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsret1	Present business situation	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsret2	Assessment of stocks	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsret3	Orders placed with suppliers	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsret4	Expected business situation	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsret5	Employment	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsret6	Retail confidence indicator	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons1	Fi..ncial situation over the last 12 months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons2	Fi..ncial situation over the next 12 months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons3	General economic situation over the last 12 months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons4	General economic situation over the next 12 months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons5	Price trends over the last 12 months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons6	Price trends over the next 12 months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons7	Unemployment expectations over the next 12 months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons8	Major purchases at present	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons9	Major purchases over the next 12 months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons10	Savings at present	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons11	Savings over the next 12 months	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons12	Statement on fi..ncial situation of household	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qscons13	Consumer confidence indicator	Euro-area	M	1985-M1	2007-M12	1	DGECFIN
qsserv1	Assessment of business climate	Euro-area	M	1995-M4	2007-M12	1	DGECFIN
qsserv2	Evolution of demand in recent months	Euro-area	M	1995-M4	2007-M12	1	DGECFIN
qsserv3	Evolution of demand expected in the months ahead	Euro-area	M	1995-M4	2007-M12	1	DGECFIN
qsserv4	Evolution of employment in recent months	Euro-area	M	1995-M4	2007-M12	1	DGECFIN
qsserv5	Evolution of employment expected in the months ahead	Euro-area	M	1995-M4	2007-M12	1	DGECFIN
qsserv6	Services Confidence Indicator	Euro-area	M	1995-M4	2007-M12	1	DGECFIN
bcibe	Business climate indicator (sa)	Euro-area	M	1980-M1	2007-M12	1	DGECFIN

Appendix B: Estimated equations for the 2005q1 forecast

Model1:

$$\Delta gdp_t = \underset{(0.0003)}{0.0027} + \underset{(0.0331)}{0.2936}\,\Delta ipi_t + \underset{(0.0106)}{0.0584}\,\Delta ipc_t + \underset{(0.0531)}{0.1869}\,\Delta ret_t + \underset{(0.0080)}{0.0353}\,\Delta cars_t$$

$$T = 39 \quad \bar{R}^2 = 0.8082 \quad F(4,34) = 41.035 \quad \hat{\sigma} = 0.0015748$$

Model2:

$$\Delta gdp_t = \underset{(0.0009)}{0.0035} + \underset{(0.1455)}{0.2832}\,\Delta gdp_{t-1} + \underset{(0.0001)}{0.0004}\,sentind_t$$

$$T = 38 \quad \bar{R}^2 = 0.3224 \quad F(2,35) = 9.8038 \quad \hat{\sigma} = 0.0029993$$

Model3:

$$\Delta gdp_t = \underset{(0.0008)}{0.0015} + \underset{(0.0001)}{0.0005}\,qsind8_t + \underset{(3.6794e-005)}{0.0002}\,qsserv6_t$$

$$T = 38 \quad \bar{R}^2 = 0.5454 \quad F(2,35) = 23.191 \quad \hat{\sigma} = 0.0024569$$

Model4:

$$\Delta gdp_t = \underset{(0.0010)}{0.0075} + \underset{(0.0001)}{0.0005}\,qsind8_t + \underset{(0.0001)}{0.0005}\,qsret6_t - \underset{(4.9038e-005)}{9.43987\text{e-}5}\,qsconst13_t$$

$$T = 39 \quad \bar{R}^2 = 0.4305 \quad F(3,35) = 10.574 \quad \hat{\sigma} = 0.0027138$$

Model5:

$$\Delta gdp_t = \underset{(0.0013)}{0.0039} + \underset{(0.0052)}{0.0208}\,share_{t-1} - \underset{(0.0185)}{0.0491}\,compe12_{t-2} + \underset{(0.0009)}{0.0006}\,spread_t$$

$$T = 33 \quad \bar{R}^2 = 0.4358 \quad F(3,29) = 9.2401 \quad \hat{\sigma} = 0.0028563$$

Model6:

$$\Delta gdp_t = \underset{(0.0008)}{0.0030} + \underset{(0.1344)}{0.3881}\,\Delta gdp_{t-1} + \underset{(0.0526)}{0.1770}\,cli_t$$

$$T = 38 \quad \bar{R}^2 = 0.3513 \quad F(2,35) = 11.021 \quad \hat{\sigma} = 0.0029346$$

Model7:

$$\Delta gdp_t = \underset{(0.0004)}{0.0029} + \underset{(0.0408)}{0.2914}\,\Delta ipi_t + \underset{(0.0128)}{0.0489}\,\Delta ipc_t + \underset{(0.0655)}{0.1748}\,\Delta ret_t$$

$$T = 39 \quad \bar{R}^2 = 0.7077 \quad F(3,35) = 31.667 \quad \hat{\sigma} = 0.0019442$$

Model8:

$$\Delta gdp_t = \underset{(0.0008)}{0.0029} + \underset{(0.1322)}{0.3872}\,\Delta gdp_{t-1} + \underset{(0.0146)}{0.0214}\,\Delta cars_t + \underset{(0.0518)}{0.1744}\,cli_t$$

$$T = 38 \quad \bar{R}^2 = 0.3719 \quad F(3,34) = 8.3015 \quad \hat{\sigma} = 0.0028878$$

Model9:

$$\Delta gdp_t = \underset{(0.0022)}{0.0025} + \underset{(0.0001)}{0.0005}\,qsind8_t + \underset{(0.0002)}{9.41090\text{e-}5}\,qsret6_t - \underset{(5.6208e-005)}{9.56673\text{e-}6}\,qsconst13_t + \underset{(6.5258e-005)}{0.0002}\,qsserv6_t$$

$$T = 38 \quad \bar{R}^2 = 0.5212 \quad F(4,33) = 11.071 \quad \hat{\sigma} = 0.0025212$$

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