

# 2. THE ASSESSMENT OF SOME MACROECONOMIC FORECASTS FOR SPAIN USING AGGREGATED ACCURACY INDICATORS

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Lucian Liviu ALBU<sup>1</sup>  
Carlos MatéJIMÉNEZ<sup>2</sup>  
Mihaela SIMIONESCU<sup>3</sup>

## Abstract

*In this study, a new accuracy measure is introduced to solve an important practical problem in assessing the forecast accuracy: different predictions' accuracy measures indicate different forecasts as the most accurate. The proposed accuracy measure, called the S indicator, is based on three dimensions of the forecasts accuracy: the summary statistics that take into account the size error, which were aggregated using the S1 indicator, the accuracy measures used in forecasts comparisons that are summarized using the S2 indicator and the directional and sign accuracy based on the S3 measure. For the Spanish inflation, the real GDP rate and the unemployment rate a comparative analysis of accuracy was made for predictions provided over the recent crisis period (2008-2013) by Bank of Spain, European Commission (EC), Organization for Economic Cooperation and Development (OECD) and International Monetary Fund (IMF). Own inflation rate and real GDP rate predictions based on a moving average model, and a auto-regressive moving average model, respectively, outperformed the experts' anticipations.*

**Keywords:** forecasts accuracy, error, inflation rate, unemployment rate, real GDP rate

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<sup>1</sup> Institute for Economic Forecasting of the Romanian Academy, Email: albul@ipe.ro

<sup>2</sup> Institute for Technological Research and Pontifical Comillas University. Madrid. Spain, Email: cmate@upcomillas.es

<sup>3</sup> Corresponding author, Institute for Economic Forecasting of the Romanian Academy, Email: mihaela.simionescu@ipe.ro

## 1. Introduction

The forecast accuracy is one of the dimensions of prediction performance, being related to the errors generated by the uncertainty of the exact value of the predicted variable. The development of macroeconomic forecasting required the evaluation of alternative prognosis for a certain variable. Everyone is interested in the most accurate forecasts, but their evaluation is based on different accuracy measures and accuracy tests. Armstrong (2001) stated that the use of a single accuracy measure is not enough, at least two indicators being necessary. Moreover, the results of the accuracy measures should be compared with the accuracy tests. Hyndman and Koehler (2006) provide a complete classification of accuracy indicators putting forward scaled-dependent measures. Scale-dependent measures, measures based on percentage errors, measures based on relative errors and relative measures. Scaled errors solve the disadvantages of relative measures and measures based on relative errors, the mean absolute scaled error being an indicator proposed by the authors. The forecast accuracy indicators were used in empirical assessment of forecasting methods in the famous M-Competitions. For example, in the M1 competition the recommended accuracy measures were: MSE (Mean square error), MAPE (Mean average percentage error), and Theil's U2-statistic. In the M3 Competition the median symmetric absolute percentage error (msAPE), the symmetric mean absolute percentage error (sMAPE), average ranking, percentage better, and median relative absolute error (mRAE) were also used. It is clear that improvements in the measurement techniques are still required.

In practice, the following problem was observed: some accuracy measures indicate a certain forecast as being the best, while other measures show the superiority of another prediction. Our objective is to select the most accurate prediction. An accuracy test should be applied, but it does not guarantee the selection of the best prediction, because it is also based on a certain accuracy measure. A new solution is proposed by us in this article, by constructing aggregated accuracy measures (S1, S2 and S3) that take into account the nature of base accuracy indicators. The method uses different types of accuracy measures: statistics based on size errors, coefficients for comparisons and directional accuracy measures. However, these aggregated indicators might also show contradictory results. Therefore, another aggregated measure is constructed (the S indicator) that considers the values of S1, S2 and S3 and a single decision is made using it. The values of S1 and S2 should be as low as possible, while S3 should be as high as possible. Therefore, S is built as a ratio: S1 plus S2 is divided by S3. The research question refers to the evaluation of macroeconomic forecasts and the selection of the best prediction using an objective criterion based on an aggregate measure. In Romania, an attempt to quantify macroeconomic predictions was made by Dobrescu (2014) and Simionescu (2014), who used relative indicators for comparisons. The article is structured as follows: after the literature review, the proposed methodology for assessing the forecasts accuracy is described. The empirical evaluation of inflation and unemployment rate predictions for Spain is made in the following section and, finally, some conclusions are drawn.

## II. Literature Review

There are many international organizations that provide economic predictions for various countries. The comparisons between forecasts consider these institutions anticipations (OECD, IMF, World Bank, European Commission, SPF, etc.) and those of other international organizations, and accuracy assessment was performed. The forecast errors for these institutions are in general large and non-systematic. Three international institutions (European Commission - EC, IMF and OECD) made predictions using macroeconomic models, but these forecasts failed to anticipate the downturn from 2007. Other providers of forecasts are statistical institutes, ministries of finance, and private companies such as banks or insurance companies.

Literature usually makes comparisons between the OECD and the IMF forecasts and Consensus Economics forecasts or private predictions. The accuracy is evaluated according to different criteria: forecasts errors and associated accuracy measures, comparisons with naïve predictions that are based on random walk, directional accuracy evaluation.

Amuedo-Dorantes and Wheeler (2001) built a VAR model to assess the effects of European Union on Spanish economy. The conclusion pointed out that the EU influences in a high degree the Spanish economy. Canova (2007) compared the forecast performance of some inflation models of G-7 countries. The univariate methods tend to be better than bivariate and trivariate ones. The author brought improvements in the MSE of the forecasts and turning point prediction models. Krkoska and Teksoz (2007) showed for 25 transition countries that the European Bank for Reconstruction and Development (EBRD) predictions during 1994-2004 improved in accuracy with the progress in transition. The accuracy of these predictions for late GDP are better than those of other institutions by around 0.4 percentage points. The Russian crisis seems to be the only structural break.

The European Commission's forecasts analyzed on the horizon from 1998 to 2005 are comparable in terms of accuracy with those of Consensus Economics, IMF and OECD for variables such as inflation rate, unemployment rate, GDP, total investment, general government balance and current account balance, as Melander *et al.* (2007) stated.

The forecast accuracy of the predictions provided by European Commission before and during the recent economic crisis was assessed by González Cabanillas and Terzi (2012). They compared these forecasts with those provided by Consensus Economics, IMF and OECD. The Commission's forecasts errors have increased because of the low accuracy in 2009 for variables such as GDP, inflation rate, government budget balance, and investment.

The strategic behavior of the private forecasters that placed their expectations away from OECD's and IMF's ones, was assessed by Frenkel *et al.* (2013), the duration of this event being 3 months. Faust and Wright (2013) presented the actual progress in inflation forecasting. The judgmental survey predictions usually outperform the forecasts based on econometric models. The advantages and disadvantages of different forecasting methods are described, offering indicators for inflation expectations in the financial markets.

Groen *et al.* (2013) built a Bayesian model averaging across various regression models based on potential predictors. Model uncertainty and structural changes affect the inflation rate predictions based on an econometric model.

The Greenbook of the Federal Reserve Board of Governors (henceforth, the Greenbook) is a book with predictions of different economic variables for the economy of the United States produced by the Federal Reserve Board before each meeting of the Federal Open Market Committee. The Survey of Professional Forecasters is the oldest quarterly survey of macroeconomic forecasts in the United States. The survey began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990. The Greenbook inflation forecasts are more accurate than those of the private forecasts, Liu and Smith (2014) making comparisons between the predictions provided by Survey of Professional Forecasters, the Greenbook and other private forecasters. The rationality of the predictions provided by SPF and the Greenbook under asymmetric loss was analyzed by Wang and Lee (2014). The inflation rate is over-predicted in the 1980s and 1990s. The inflation prediction presents a high loss asymmetry in intensity and frequency for SPF and the Greenbook. The common approach to evaluate the predictions' usefulness consists in the measurement of the error magnitude, using accuracy measures such as mean square error (MSE) (Diebold and Mariano, 2002), or log of the mean squared error ratio (log MSER). However, these measures do not have an economic interpretation and they neglect the presence of outliers. The directional forecasts technique was used for assessing the macroeconomic forecasts by Pesaran and Timmermann (1994) Artis (1996), Öller and Barot (2000), Pons (2001) and Ashiya (2006).

In this study, the inflation rate, GDP rate and unemployment rate predictions provided by some experts (Bank of Spain, IMF, OECD, and EC) are assessed. Moreover, some moving average models are built for these variables and forecasts are made using these processes. De Dios Tena *et al.* (2008) assessed various strategies to predict Spanish inflation using prices of 57 products from 18 Spanish regions. The authors employed some vector equilibrium correction (VeqC) models with co-integration relations between national prices and those from Andalusia, Valencia, Madrid, Catalonia and the Basque Country. The inflation predictions were improved by aggregating forecasts for different sectors and regions. After the success of the Box-Jenkins methodology, the use of VAR and BVAR models for forecasting macroeconomic indicators became a convention in literature. Although they are flexible, easy to estimate and to predict macroeconomic variables, these models are not based on too much economic theory. For the Spanish economy, different types of DSGE models were employed to predict the macroeconomic indicators, as Fernández-de-Córdoba and Torres (2011) showed. For unemployment predictions in Spain and Switzerland, Patuelli and Mayor (2012) used a SVAR model and a heterogeneous dynamic panel model with spatial heterogeneity and/or spatial autocorrelation in both the levels and the dynamics of unemployment rate. The forecast accuracy was assessed to show the improvement due to regional approach.

### III. Methodological Frameworks

Different methods are used in literature to assess the forecasts accuracy. In practice, there are many cases when some indicators suggest the superiority of certain forecasts while other ones indicate that other predictions are more accurate. Therefore, a new methodology is proposed to solve this contradiction given by the results of accuracy assessment. The method is based on different types of accuracy measures: statistics based on size errors, coefficients for comparisons and directional accuracy measures. These types of indicators were also used by Melander *et al.* (2007), but without any aggregation. We can use one-step-ahead predictions or forecasts made for a longer horizon.

The prediction error at time  $t$  is the simplest indicator based on the comparison of the registered value with the forecasted one and it is denoted by  $e_t$ . Green and Tashman (2008) confirmed that there are two ways of computing the forecast error if  $\hat{y}_t$  is the prediction at time  $t$ :  $e_t = y_t - \hat{y}_t$  or  $e_t = \hat{y}_t - y_t$ . Seven out of eleven members of the International Institute of Forecasters recommended in a survey the use of the first variant ( $e_t = y_t - \hat{y}_t$ ). This is the most used version in literature and it is also used in this study. The following summary statistics were used: root mean squared error, mean squared error, mean error, mean absolute error, mean absolute percentage error. If the horizon length is  $h$  and the length of actual data series is  $n$ , the indicators are computed as in the Table 1.

Table 1

Summary Statistics for Forecasts Accuracy

Indicator	Formula
Mean error- ME	$ME = \frac{1}{h} \sum_{t=n+1}^{n+h} (y_t - \hat{y}_t)$
Mean absolute error- MAE	$MAE = \frac{1}{h} \sum_{t=n+1}^{n+h}  y_t - \hat{y}_t $
Root mean squared error- RMSE	$RMSE = \sqrt{\frac{1}{h} \sum_{t=n+1}^{n+h} (y_t - \hat{y}_t)^2}$
Mean squared error- MSE	$MSE = \frac{1}{h} \sum_{t=n+1}^{n+h} (y_t - \hat{y}_t)^2$
Mean absolute percentage error- MAPE	$MAPE = 100 \cdot \frac{1}{h} \sum_{t=n+1}^{n+h} \left  \frac{y_t - \hat{y}_t}{y_t} \right $

Source: Hyndman and Koehler (2006).

The aggregate statistics for comparisons are based on U1 Theil's statistic, mean relative absolute error, relative RMSE and mean absolute scaled error and they are presented

in Table 2.  $RMSE_b$  is the RMSE for the benchmark.  $e_t^*$  is the benchmark error. In our case, the benchmark is represented by the naïve projection.

Table 2

Statistics for Comparing the Forecasts Accuracy

Indicator	Formula
U1 Theil's statistic	$U_1 = \frac{\sqrt{\sum_{t=n+1}^{n+h} (y_t - \hat{y}_t)^2}}{\sqrt{\sum y_t^2} + \sqrt{\sum \hat{y}_t^2}}$
Mean relative absolute error- MRAE	$MRAE = \frac{1}{h} \sum_{t=n+1}^{n+h} \left  \frac{e_t}{e_t^*} \right $ $e_t^* = y_t - y_{t-1}$
Relative Root mean squared error- RRMSE	$RRMSE = \frac{RMSE}{RMSE_b}$
Mean absolute scaled error-MASE	$MASE = \frac{1}{h} \sum_{t=n+1}^{n+h} \frac{ e_t }{\frac{1}{h-1} \sum_{t=n+1}^{n+h}  y_t - y_{t-1} }$

Source: Hyndman and Koehler (2006).

Positive ME implies underestimated predictions. For optimal predictions ME is zero, but the null value is recorded also when errors offset each other perfectly. MSE penalizes the predictions with high errors. It considers that the high errors are more harmful than the small errors. The positive and the negative errors cannot compensate for each other like in the case of ME, which is an advantage for MSE. There is not a superior limit for MSE and it has a different unit of measurement compared to actual data. The null value is the lowest value of the indicator and it is achieved for perfect precision of the forecasts.

A higher difference between RMSE and MAE implies a higher errors variance. The errors have the same magnitude if RMSE equals MAE. The minimum value of those measures is 0, but there is no superior limit for them. A null value for the MAPE expressed in percentage shows a perfect forecast. MASE is a scale-free error metric that was introduced by Hyndman and Koehler (2006) as a general measure of forecast accuracy. It is used to make comparisons between prediction methods and between predictions accuracy. The percentage of correct forecast sign (PSC) shows the percentage of time the sign of prediction is forecasted correctly. Percentage of correct forecasts of directional accuracy (PDA) shows if the expert correctly anticipates the increase or decrease in the variable. The formulae for the two indicators are presented in Table 3.

Table 3

Measures for Directional and Sign Accuracy

Indicator	Formula	Conditions
Percentage of sign correct forecasts- PSC	$PSC = \frac{100}{h} \sum_{t=n+1}^{n+h} z_t$	$z_t = 1, \quad y_t \cdot \hat{y}_t > 0$ $z_t = 0, \text{ otherwise}$
Percentage of directional accuracy correct forecasts- PDA	$PDA = \frac{100}{h} \sum_{t=n+1}^{n+h} z_t$	$z_t = 1, (y_t - y_{t-1})(\hat{y}_t - y_{t-1}) > 0$ $z_t = 0, \text{ otherwise}$

Source: Hyndman and Koehler (2006).

It measures the ability to correctly predict the turning points. PDA and PSC are located between 0% and 100%. According to Melander *et al.* (2007), the success rate of the indicators should be higher than 50%.

The proposed methodology consists of the following steps: computation of sums of summary statistics after the division to each standard deviation (S1), computation of sum of relative accuracy measures (S2), computation of sum of percentage for directional and sign accuracy (S3).

For the first indicator, S1, the MSE was excluded, because it has the same significance as RMSE. S1 and S2 should be as low as possible, while S3 should be as high as possible. Each indicator of the formula of S1 is divided by the standard deviation of the following data series: absolute errors data set for MAE, errors data series for ME and squared errors for RMSE. Considering the forecast error defined as  $e_t = y_t - \hat{y}_t$ , we compute some standard deviations (SD).

$$SD^{e_t} = \sqrt{\frac{1}{h-1} \sum_{t=n+1}^{n+h} (e_t - \bar{e}_t)^2}, \text{ where } \bar{e}_t = \frac{\sum_{t=n+1}^{n+h} e_t}{h} \quad (1)$$

$$SD^{|e_t|} = \sqrt{\frac{1}{h-1} \sum_{t=n+1}^{n+h} (|e_t| - |\bar{e}_t|)^2}, \quad (2)$$

where:  $|e_t|$  – the forecast error at time t in absolute value

$$SD^{e_t^2} = \sqrt{\frac{1}{h-1} \sum_{t=n+1}^{n+h} (e_t^2 - \bar{e}_t^2)^2}, \text{ where } \bar{e}_t^2 = \frac{\sum_{t=n+1}^{n+h} e_t^2}{h} \quad (3)$$

$$SD^{\frac{|y_t - \hat{y}_t|}{|y_t|}} = SD^{\frac{|e_t|}{|y_t|}} = \sqrt{\frac{1}{h-1} \sum_{t=n+1}^{n+h} \left( \frac{|e_t|}{|y_t|} - \left| \frac{\bar{e}_t}{y_t} \right| \right)^2}, \text{ where } \left| \frac{\bar{e}_t}{y_t} \right| = \frac{\sum_{t=n+1}^{n+h} \frac{|e_t|}{|y_t|}}{h} \quad (4)$$

After these measures assessment, the best forecast is chosen.

$$S_1 = \frac{SD^{e_t}}{|ME|} + \frac{SD^{|e_t|}}{MAE} + \frac{SD^{e_t^2}}{RMSE} + \frac{SD^{\frac{|y_t - \hat{y}_t|}{y_t}}}{MAPE} \quad (5)$$

$$S_2 = U_1 + MRAE + RRMSE + MASE \quad (6)$$

$$S_3 = PSC + PDA \quad (7)$$

These aggregated indicators also might show contradictory results. Therefore, another aggregated measure is constructed (the S indicator), which considers the values of S1, S2 and S3 and a single decision is made with it. The forecasts with the lowest S value are the most accurate. S is:  $S = \left| \frac{S_1 + S_2}{S_3} \right|$  (8)

#### IV. The Assessment and Improvement of Inflation Rate, Real GDP Growth Rate and Unemployment Rate Forecasts for Spain

For the unemployment rate, the real GDP growth rate and the inflation rate during the economic crisis (2008-2013), we used the predictions provided by the following institutions: European Commission (EC), Bank of Spain, International Monetary Fund (IMF) and Organization for Economic Cooperation and Development (OECD). One-step-ahead forecasts were provided. The European Commission releases spring and winter reports with the projections of the main macroeconomic indicators for the European Union countries, the Euro Zone, and other major economies outside the European territory. These projections are the work of European Central Bank experts and specialists of national banks. These forecasts are used for evaluating the economic development degree and the risks to price stability.

The IMF created the World Economic Outlook (WEO) database, the publication of the short and medium run forecasts being done in April and September. There are some discussions for the important issues of developing and industrial states and also for the countries with the economy in transition to market. For the years 2014 and 2015, the IMF estimated that the inflation would decrease, but this would cause problems to developed countries such as Spain. The unemployment rate tends to decrease in the next years, after a constant increase until 2012. The IMF experts recommend that Spain make more efforts to achieve price stability. In the last few years, a slow increase is anticipated for the real GDP growth, but Spain was very affected by the crisis. In general, the forecasters' expectations related to economic growth over the crisis period were too optimistic, the reality proving that Spain encountered high difficulties in solving the economic problems. The OECD Economic Survey of Spain has also considered the decrease in high unemployment in Spain starting in 2013. Many reforms are recommended to Spain by the OECD in order to improve the labor market. A moderate recovery is projected by the OECD for the next few years in Spain. In the Bank of Spain, the *Servicio de Estudios* forecasts quarterly the main economic indicators for the Spanish economy over a horizon of 2-3 years. These predictions appear in the Economic Bulletin. Twice a year, these results are combined with the predictions

provided by ECB and Eurosystem National Central Banks. In Figure 1, the actual and predicted values of the variables with annual frequency are displayed over the period 2008-2013 that covers the economic crisis. The forecasts are one-step-ahead, being provided by the European Commission (EC), the Bank of Spain, the International Monetary Fund (IMF), the Organization for Economic Cooperation and Development (OECD) on the 2008-2013 horizon.

After the accession to the European Union, the Spanish economy was affected by high inflation. The Spanish Peseta devaluation in September 1992 did not stop the inflation growth. In the analyzed period (2008-2013), the inflation rate increased on average by 1.8 percentage points. The inflation rate decreased by 0.2% in 2013 as compared to 2008. Spain was forced to import the fossil fuels because of the lack of resources, growing the inflation pressure. The high decrease in oil prices in the second part of 2008 brought a very low inflation rate in Spain in 2009 (a negative value, the lowest in the last 40 years). Starting in 2010, the economic contraction determined by the global crisis caused rises in prices. For 2009, all the forecasters anticipated a higher inflation rate than the registered one, because the oil price fall was not foreseen. The OECD was the single expert that anticipated a lower inflation rate than registered over 2010-2013.

In October 2008, Spain witnessed the highest unemployment ever registered and it became the EU country with the largest unemployment crisis in 2008. In the mentioned period, the unemployment rate in Spain increased on average by 18.4 percentage points. The unemployment rate rose by 8.57 percentage points in 2013 as compared to 2008. Even if in 2013 the unemployment rate decreased as compared to 2010, 2011 and 2012, it remained high, especially the youth unemployment. The inflexible labor market created a long-run structural unemployment. The Bank of Spain predicted higher unemployment rate than the registered ones for each year in the forecast horizon.

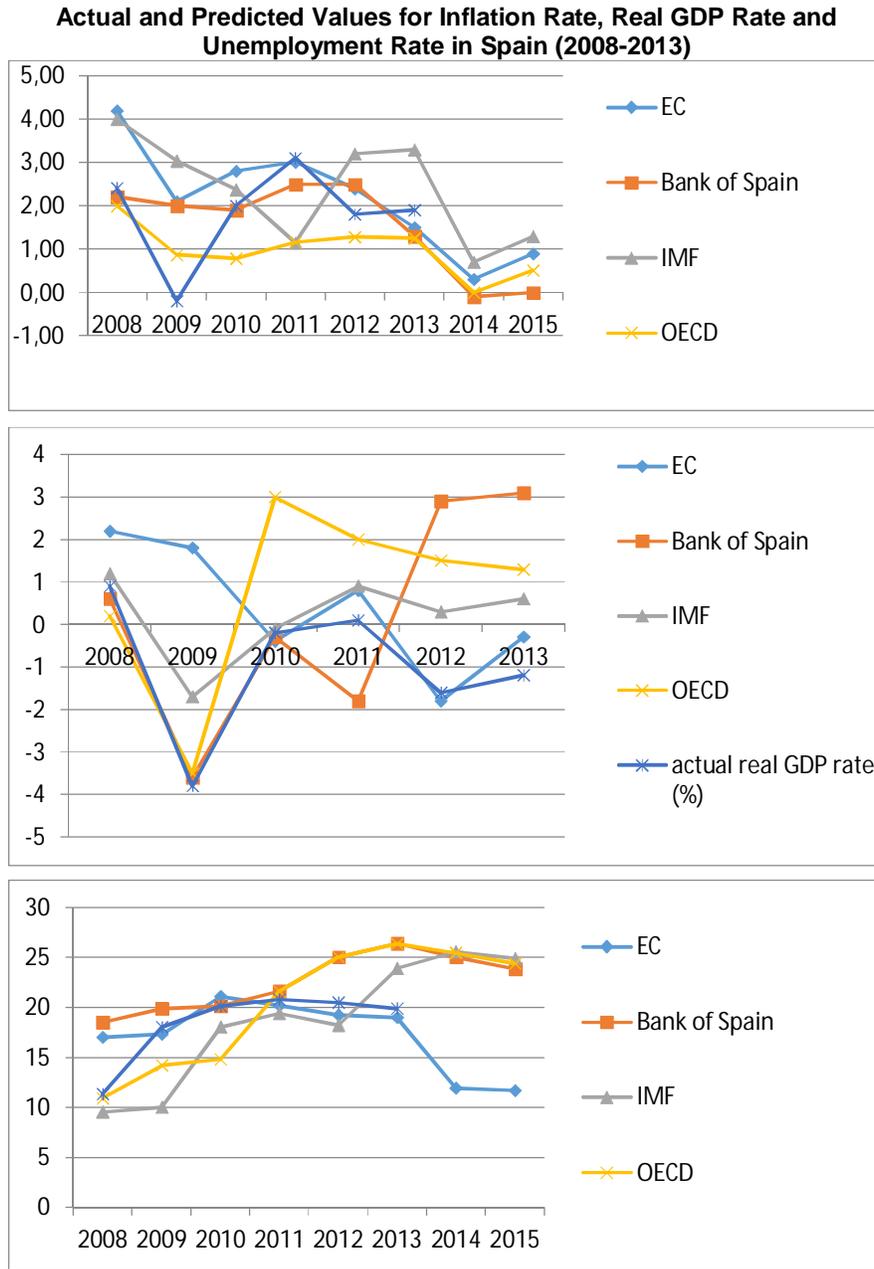
In the 1990s and the beginning of the 2000s, Spain saw a fast economic growth. For Spain, the unemployment rate forecasting is important, the future trends in labor market being analyzed by Congregado *et al.* (2014).

The global credit crisis has negatively affected the Spanish economy in 2008. The property market collapsed and Spain still fights to recover from the deep recession. Since 2008, the GDP decrease in Spain was caused by many factors, such as: the recession in the EU, the banking crisis, the property market collapse, the overvalued exports and austerity policies such as the government spending cuts. The real GDP rate decreased by 0.51 percentage points in 2013 as compared to 2008. The average growth rate over 2008-2013 was about 1.8%. For 2009, none of the experts anticipated a negative GDP rate.

We provided our own one-step-ahead forecasts based on ARMA models for the 2008-2013 horizon. In order to estimate the ARMA models, we used annual data series for inflation rate, unemployment rate and real GDP rate for the period from 1986 to 2012.

For constructing the ARMA models the data stationarity is checked by the ADF test, and the results are presented in Appendix 1. The results of the test indicated that the data sets were not stationary, some transformations being applied. Therefore, in order to become stationary, the inflation rate is once differentiated (the new variable is denoted by  $d_i$ ) while the logarithm is applied to unemployment rate series that is then twice differentiated (the new variable is denoted by  $d_u$ ). The real GDP rate is differentiated once to have a stationary data set (the new variable is denoted by  $d_{rgdp}$ ).

Figure 1



According to Granger causality tests, there is no causality between the three transformed variables, the results being presented in Table 4.

**Table 4**

**Granger Causality Test for the Transformed Variables**

Null hypothesis	F-statistic	Probability
UR does not Granger Cause DI	1.10902	0.35031
DI does not Granger Cause UR	0.90009	0.42318
D_RGDP does not Granger Cause UR	0.02040	0.9798
UR does not Granger Cause D_RGDP	2.05235	0.1546
D_RGDP does not Granger Cause DI	1.65448	0.2176

Source: Own computations.

We tried initially to estimate an auto-regressive model, but it was not valid in all cases for the inflation, real GDP rate and unemployment data in Spain.

The transformed data series of unemployment rate (*ur*) follows a moving average (MA) process of order 1, while differentiated inflation rate (*di*) is modelled using a MA(2). The GDP rate is stationary in first difference (*d\_rgdg*), this transformed data set following an ARMA model. The standard deviations of the coefficients are displayed below and also the probabilities associated to *t* statistics. For predicting the values of the indicator in 2008, we used the following models:

$$di_t = -0.169 + \varepsilon_t - 0.916 \cdot \varepsilon_{t-1} \quad (9)$$

SD= 0.054                  SD= 0.112  
 (prob.=0.005)              (prob.=0.000)

DW=1.91, JB=0.599 (prob.=0.741), Prob. chi-square(5) (White test)=0.65

$$ur_t = 0.012 + \varepsilon_t - 0.486 \cdot \varepsilon_{t-2} \quad (10)$$

SD=0.017                  SD=0.191  
 (prob.=0.5)                  (prob.=0.018)

DW=1.7, JB=2.4 (prob.=0.3), Prob. chi-square(5) (White test)=0.753

$$d\_rgdp_t = -0.212 + 0.65 \cdot d\_rgdp_{t-1} - 0.999 \cdot \varepsilon_{t-1} + \varepsilon_t \quad (11)$$

SD=0.506                  SD=0.293                  SD=0.053  
 (prob.=0.085)              (prob.=0.025)              (prob.=0.000)

DW=2.04, JB=0.64 (prob.=0.72), Prob. chi-square(5) (White test)=0.856

## The Assessment of Some Macroeconomic Forecasts

The errors are independent for all models, according to correlograms and DW statistic values, and their distribution follows a normal repartition, according to Jarque-Bera (JB) test. According to the White test, the errors are homoscedastic.

The inflation rate predictions provided by the EC, the Bank of Spain and the IMF are underestimated, while OECD forecasts are overestimated over 2008-2013. The Bank of Spain recorded the lowest values for ME, MAE, RMSE, MSE, MAPE, U1 statistics, relative RMSE and MASE compared to the other forecasters. PSC was the same for all the types of predictions. A better directional accuracy was observed for the EC and the Bank of Spain according to Table 5.

**Table 5**

**The Evaluation of Accuracy Measures for Inflation Rate Forecasts in Spain (2008-2013)C**

Indicator	EC	Bank of Spain	IMF	OECD	MA(1) forecasts
Mean error- ME	0.832	0.232	1.005	-0.608	-0.447
Mean absolute error- MAE	0.999	0.735	1.658	0.967	0.447
Root mean squared error- RMSE	1.269	1.009	1.865	1.099	0.765
Mean squared error- MSE	1.611	1.017	3.480	1.208	0.585
Mean absolute percentage error- MAPE	219.445%	199.781%	318.125%	122.893%	39.208%
U1 Theil's statistic	0.260	0.240	0.368	0.325	0.195
Mean relative absolute error- MRAE	0.354	0.849	2.126	1.285	-0.140
Relative Root mean squared error- RRMSE	0.736	0.585	1.082	0.637	0.414
Mean absolute scaled error-MASE	0.606	0.482	0.891	0.525	0.371
Percentage of sign correct forecasts- PSC	83.33%	83.33%	83.33%	83.33%	83.33%
Percentage of directional accuracy correct forecasts- PDA	83.33%	83.33%	66.664%	66.664%	100%

Source: Own computations.

The unemployment rate predictions provided by EC, Bank of Spain and OECD are underestimated, while IMF forecasts are overestimated over the period 2008-2013. The EC recorded the lowest values for ME, MAE, RMSE, MSE, MAPE, MRAE, U1 statistics, relative RMSE and MASE as compared to the other forecasters. PSC recorded the same value for all the types of predictions. The best directional accuracy (PDA) was observed for EC (100%) as Table 6 shows.

All the predictions of the real GDP rate are overestimated. Except for the value for mean error, IMF provided the lowest values for the absolute accuracy indicators. Only the ARMA forecasts and EC predictions are better than the naïve projections of the GDP rate. However, for all the other relative indicators the IMF outperformed the other predictions proposed by the EC, the OECD and the Bank of Spain. In terms of directional and sign accuracy, EC is the leader.

Table 6

**The evaluation of accuracy measures for unemployment rate forecasts in Spain (2008-2013)**

Indicator	EC	Bank of Spain	IMF	OECD	MA(2) forecasts
Mean error- ME	0.529	3.479	-1.934	0.383	-0.863
Mean absolute error- MAE	1.696	3.479	3.267	3.558	3.071
Root mean squared error- RMSE	2.468	4.439	3.975	4.195	3.738
Mean squared error- MSE	6.089	19.700	15.798	17.602	13.970
Mean absolute percentage error- MAPE	12.068%	21.969%	18.084%	18.228%	17.598%
U1 Theil's statistics	0.065	0.109	0.110	0.109	0.100
Mean relative absolute error- MRAE	0.409	3.659	1.586	3.570	1.589
Relative Root mean squared error- RRMSE	0.791	1.422	1.273	1.344	1.198
Mean absolute scaled error-MASE	0.132	0.237	0.212	0.224	0.200
Percentage of sign correct forecasts- PSC	100%	100%	100%	100%	100%
Percentage of directional accuracy correct forecasts- PDA	100%	66.664%	49.98%	49.98%	66.664%

Source: Own computations.

Table 7

**The Evaluation of Accuracy Measures for Real GDP Growth Rate Forecasts in Spain (2008-2013)**

Indicator	EC	Bank of Spain	IMF	OECD	ARMA(1) forecasts
Mean error- ME	-1.350	-1.117	-1.167	-1.717	-2.100
Mean absolute error- MAE	1.483	1.883	1.167	1.950	2.475
Root mean squared error- RMSE	2.395	2.661	1.414	2.247	3.480
Mean squared error- MSE	5.738	7.082	2.000	5.048	12.108
Mean absolute percentage error- MAPE	196.552	438.030	201.224	664.626	314.857
U1 Theil's statistic	0.744	0.634	0.512	0.562	0.744
Mean relative absolute error- MRAE	2.205	2.171	1.297	11.859	2.205
Relative Root mean squared error- RRMSE	0.914	1.016	0.540	0.858	0.914
Mean absolute scaled error-MASE	0.416	2.575	1.095	1.815	0.416
Percentage of sign correct forecasts- PSC	83.33%	50%	66.67%	50%	66.67%
Percentage of directional accuracy correct forecasts- PDA	83.33%	83.33%	83.33%	83.33%	88.33%

Source: Own computations.

The aggregated proposed indicators were assessed in order to establish which institution predicted the best each variable. The numerical results of these indicators are shown in Table 8 and they are replaced in the formula of S in order to have a single indicator for making the comparisons between forecasts.

Table 8

**The Values of S, S1, S2 and S3 Indicators for Assessing the Accuracy of  
Inflation, Unemployment Rate and Real GDP Rate Forecasts in Spain  
(2008-2013)**

Variable	Indicator	EC	Bank of Spain	IMF	OECD	Own forecasts
Inflation rate	S1	4.8375	7.7243	12.2204	13.6058	4.5578
	S2	1.956	2.156	4.467	2.772	0.839
	S3	166.66%	166.66%	149.99%	149.99%	183.33%
	S	4.076263	5.928417	11.12568	10.91926	2.9437
Unemployment rate	S1	11.3504	6.8118	8.7961	16.4973	9.5938
	S2	0.579	-1.891	0.009	-1.893	-0.0915
	S3	200%	167%	150%	150%	167%
	S	5.9647	2.946587	5.870067	9.7362	5.091198
Real GDP growth rate	S1	3.842419	7.556444	4.242189	3.496804	3.0245
	S2	4.279	6.396	3.444	15.093	4.002
	S3	166.67%	133.33%	150%	133.33%	150%
	S	4.872754	10.46459	5.124126	13.9427	4.684333

Source: Own computations.

According to the S1 values, our own model provided the inflation forecasts with the lowest variation with respect to the actual values, being followed by the EC, the Bank of Spain, the IMF and the OECD. The S2 indicator showed another hierarchy: EC, Bank of Spain, OECD and IMF. The directional and sign accuracy indicator, S3, confirmed the superiority of forecasts provided by EC and Bank of Spain. For the unemployment rate predictions, the S1 indicator showed that Bank of Spain predictions had the lowest variation as compared to the registered values. In relative terms, IMF performed the best over 2008-2013. EC forecasts are the best in terms of directional and sign accuracy. According to the S indicator, for experts' forecasts the best accuracy was assessed for our own inflation predictions and for Bank of Spain unemployment rate predictions. The MA predictions for inflation are more accurate than all the experts' anticipations. Accurate inflation forecasts were then provided by the EC, the Bank of Spain, the OECD and the IMF. The hierarchy for unemployment anticipations, according to the S measure is given by: Bank of Spain, own forecasts, IMF, EC and OECD. The economic crisis and its persistence were not correctly anticipated by the forecasters, our ARMA model performing better according to S1 and S measures. According to the S values, a similar accuracy was obtained by EC predictions, being followed by IMF, Bank of Spain and OECD. It could be recommended the use of ARMA models in predicting the real GDP rate and inflation rate in Spain.

## V. Conclusions

There are many indicators used to assess the forecasts accuracy, but in many cases the results are contradictory. Our methodology was applied to Spanish inflation, real GDP rate and unemployment rate predictions over the crisis period (2008-2013) and it took into account more aspects of accuracy concept. The directional and sign accuracy

was also included, an important aspect that was neglected by the absolute and relative accuracy measures and also by the accuracy tests. It seems that the moving average model proposed by us generated more accurate predictions than experts' anticipations.

The novelty of the proposed global accuracy measure (S indicator) is brought by the inclusion of different aspects of forecasts accuracy. In decision making, all the dimensions of accuracy should be taken into account. For example, for policy decisions neglecting directional accuracy could have large negative consequences. The general public might be interested only in the error size, but for processes where the error sign and detailed aspects of accuracy evaluation are relevant the use of a global accuracy measure is essential. One type of policy is elaborated when we expect a decrease in inflation and another one when an increase is anticipated. For the forecasting in an economic environment with many sources of uncertainty, such as the economic crisis period, the specialists recommend the conservatism translated into the use of simple prediction methods, for example, simple econometric models such as random walk. For inflation in Spain, the use of MA(1) model in forecasting proved to be an inspired choice. It is advisable to use ARMA models in predicting the real GDP rate in Spain.

For further research, we may choose another objective statistical criterion to select the most accurate forecasts and we can compare it with the S indicator. For example, the multi-criteria ranking might help us to establish the best predictions from more simultaneous criteria. This is a statistical approach for solving the problem and its results might be compared with our aggregated indicator.

The proposed indicator could be used in practice when the absolute, relative and directional accuracy measures provide contradictory results. The selection of the best prediction improves the decisional process at macroeconomic level. The government will choose the most accurate prediction in establishing the new policy. The forecaster that performed the best in the last few years is likely to provide the best predictions in the near future. Moreover, the accuracy assessment is a very good tool for forecasters to improve their future predictions. The selection of the best prediction is also important for business environment and for making the firm marketing plan.

**Appendix 1**

**Results of Augmented Dickey-Fuller (ADF) Test**

Variable	Exogenous	Augmented Dickey-Fuller test		t-Statistic	Prob.*
Inflation rate	Constant, Linear Trend	ADF test statistic		-3.830718	0.0324
		1% level		-4.394309	
		5% level		-3.612199	
		10% level		-3.243079	
	Constant	ADF test statistic		-2.978422	0.0514
		1% level		-3.737853	
		5% level		-2.991878	
		10% level		-2.635542	
	None	ADF test statistic		-1.858443	0.0612
		1% level		-2.664853	

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Variable	Exogenous	Augmented Dickey-Fuller test		t-Statistic	Prob.*
		5% level		-1.955681	
		10% level		-1.608793	
Transformed unemployment rate (ur)	Constant, Linear Trend	ADF test statistic		-4.967785	0.0033
		1% level		-4.440739	
		5% level		-3.632896	
		10% level		-3.254671	
	Constant	ADF test statistic		-5.124785	0.0005
		1% level		-3.769597	
		5% level		-3.004861	
		10% level		-2.642242	
	None	ADF test statistic		-5.240318	0.0000
		1% level		-2.674290	
		5% level		-1.957204	
		10% level		-1.608175	
Real GDP rate	Constant, Linear Trend	ADF test statistic		-2.138726	0.4830
		1% level		-4.800080	
		5% level		-3.791172	
		10% level		-3.342253	
	Constant	ADF test statistic		-1.577281	0.4652
		1% level		-4.057910	
		5% level		-3.119910	
		10% level		-2.701103	
	None	ADF test statistic		-0.457582	0.4967
		1% level		-2.754993	
		5% level		-1.970978	
		10% level		-1.603693	
di	Constant, Linear Trend	ADF test statistic		-6.745791	0.0001
		1% level		-4.416345	
		5% level		-3.622033	
		10% level		-3.248592	
	Constant	ADF test statistic		-6.916346	0.0000
		1% level		-3.752946	
		5% level		-2.998064	
		10% level		-2.638752	
	None	ADF test statistic		-7.050683	0.0000
		1% level		-2.669359	
		5% level		-1.956406	
		10% level		-1.608495	

Variable	Exogenous	Augmented Dickey-Fuller test	t-Statistic	Prob.*
d_rgd	Constant, Linear Trend	ADF test statistic	-4.837342	0.0425
		1% level	-5.295384	
		5% level	-4.008157	
		10% level	-3.460791	
	Constant	ADF test statistic	-7.008166	0.0001
		1% level	-4.057910	
		5% level	-3.119910	
		10% level	-2.701103	
	None	ADF test statistic	-7.463785	0.0000
		1% level	-2.754993	
		5% level	-1.970978	
		10% level	-1.603693	

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