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Point forecasts based on the limits of the forecast intervals to improve the SPF predictions

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Many researchers are interested in making predictions for macroeconomic variables, but few of them studied the accuracy of their forecasts. The problem is essential, especially in crisis periods, because from many forecasts made for the same indicator only one or few are the most accurate. In this research, some alternative forecasts for the annual rate of change for the HICP for EU were developed. Their accuracy was evaluated and compared with the accuracy of SPF predictions. All the proposed predictions for January 2010-May 2012 (those based on a random walk developed for 1997-2009, combined forecasts, the median and the mean of forecasts, predictions based on different econometric models that take into account the previous SPF forecasts) were not more accurate than the naïve forecasts or SPF ones. A considerably improvement of the accuracy was gotten for predictions based on mean error of SPF expectations for 1997-2009 and the previous registered value. This empirical strategy of building more accurate forecasts was better than the classical theoretical approaches from literature, but it is still less accurate than the naïve forecasts that could be made for UE inflation rate. The point forecasts based on the lower limit of intervals built using root mean squared indicator generated an improvement in accuracy, outperforming the SPF predictions and also the naïve forecasts.

JEL Classifications: C54, E37

Keywords: Forecasts accuracy, forecasts intervals, combined forecasts, naïve forecasts, Survey of Professional Forecasters (SPF)

Introduction

In addition to economic analysis, the elaboration of forecasts is an essential aspect that conducts the way of developing the activity al macroeconomic level. But any forecast must be accompanied by macroeconomic explanations of its performance. The purpose of this evaluation is related to different aspects: the improvement of the model on which the forecast was based, adjustment of gouverment policies, the planning of results. Basically, performance evaluation in this context refers directly to the degree of trust confered to the prediction. Although the literature on forecasting methods and techniques used in describing the evolution of an economic phenomenon is particularly rich, surprisingly, few researchers have dealt with the methods used to improve the measurement of forecast uncertainty. The aspect is important, because the macroeconomic predictions must not be easily accepted, taking into account the negative consequences of macroeconomic forecasts failures, consequences that affect the state policies. The decisions of economic policy are based on these forecasts. Hence, there is an evident interest of improving their performance.

In literature there are three directions in evaluating the performance of macroeconomic forecasts: accuracy, bias and efficiency. A large number of articles have considered the problem of comparing the accuracy measures.

Meese and Rogoff's (1983) paper, "Empirical exchange rate models of the seventies", remains the starting point for many researches on the comparing of accuracy and bias. Recently, (Dovern and Weisser, 2011) examines in the same article, "Accuracy, unbiasedness and efficiency of professional macroeconomic forecasts: An empirical comparison for the G7" the three criteria using the empirical data from the G7 economies.

Forecasts accuracy in literature

Forecast accuracy is a large chapter in the literature related to the evaluation of forecasts uncertainty. There are two methods used in comparing the prediction quality: vertical methods (e.g., mean squared error) and horizontal methods (such as distance in time). An exhaustive presentation of the problem taking into account all the achievements in literature is impossible, but will outline some important conclusions.

In literature, there are several traditional ways of measurement, which can be ranked according to the dependence or independence of measurement scale. A complete classification is made by Hyndman and Koehler (2006) in their reference study in the field, "Another Look at Measures of Forecast Accuracy ".

Hyndman and Koehler introduce in this class of errors "Mean Absolute Scaled Error" (MASE) in order to compare the accuracy of forecasts of more time series.

Other authors, like Fildes and Steckler (2000) use another criterion to classify accuracy measures. If we consider, $\hat{X}_t(k)$ the predicted value after *k* periods from the origin time *t*, then the error at future time (*t*+*k*) is: $e_t(t+k)$. Indicators used to evaluate the forecast accuracy can be classified according to their usage. Thus, the forecast accuracy measurement can be done independently or by comparison with another forecast.

Independent measures of accuracy

In this case, it is usually used a loss function, but we can also choose the distance criterion proposed by Granger and Jeon (2003) for evaluating forecasts based on economic models. The most used indicators are:

a. Mean Square Error (MSE)
b. Root Mean Squared Error (RMSE)
c. Generalized Forecast Error Second Moment (GFESM)
d. Mean Absolute Percentage Error (MAPE)
e. Symmetric Median Absolute Percent Error (SMAPE)
f. Mean error (ME)
g. Mean absolute error (MAE).

In practice, the most used measures of forecast error are:

- Root Mean Squared Error (RMSE) $RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n} e_X^2\,(T_0 + j, k)}$

- Mean error (ME) $ME = \frac{1}{n}\sum_{j=1}^{n} e_X(T_0 + j, k)$

The sign of indicator value provides important information: if it has a positive value, then the current value of the variable was underestimated, which means expected average values too small. A negative value of the indicator shows expected values too high on average.

- Mean absolute error (MAE) $MAE = \frac{1}{n}\sum_{j=1}^{n} | e_X(T_0 + j, k) |$

These measures of accuracy have some disadvantages. For example, RMSE is affected by outliers. Armstrong and Collopy (2000) stresses that these measures are not independent of the unit of measurement, unless if they are expressed as percentage. The purpose of using the abovementioned indicators is related to the characterization of distribution errors. Clements and Hendry (1995) have proposed a generalized version of the RMSE based on errors intercorrelation, when at least two series of macroeconomic data are used. If we have two forecasts with the same mean absolute error, RMSE penalizes the one with the biggest errors.

Measures for the evaluation of the relative accuracy of forecasts

Relative accuracy measures are related to the comparison of the forecast with a forecast of reference, found in the literature as the 'benchmark forecast' or 'naive forecast (Bratu, 2012a). However, it remains a subjective step to choose the forecast used for comparison Problems may occur in this case are related to these aspects: the existence of outliers or inappropriate choice of models used for predictions and the emergence of shocks. A first measure of relative accuracy is Theil's U statistic, which uses as reference forecast the last observed value recorded in the data series. Armstrong and Collopy (2000) have proposed instead of U a new similar indicator (RAE). Thompson improved MSE indicator, suggesting a statistically determined MSE- log mean squared error ratio.

A common practice is to compare the forecast errors with those based on a random-walk. “Naïve model” method assumes that the variable value in the next period is equal to the one recorded at actual moment. U-Theil proposed the calculation of U, that takes into account both changes in the negative and the positive sense of an indicator:

$$U = \sqrt{\frac{\sum (X_{t+k} - \hat{X}_t(k))^2}{\sum X_{t+k}^2}}\ .$$

U Theil’s statistic is calculated in two variants by the Australian Treasury (2008) in order to evaluate the forecasts accuracy.

The following notations are used:

a- the registered results

p- the predicted results

t- reference time

e- the error (*e*=*a*-*p*)

n- number of time periods

$$U_1 = \frac{\sqrt{\sum_{t=1}^{n}(a_t - p_t)^2}}{\sqrt{\sum_{t=1}^{n} a_t^2} + \sqrt{\sum_{t=1}^{n} p_t^2}}$$

The more closer of zero is, the forecasts accuracy is higher.

$$U_2 = \sqrt{\frac{\sum_{t=1}^{n-1}(\frac{p_{t+1} - a_{t+1}}{a_t})^2}{\sum_{t=1}^{n-1}(\frac{a_{t+1} - a_t}{a_t})^2}}$$

If U_2=1=> there are not differences in terms of accuracy between the two forecasts to compare

If U_2<1=> the forecast to compare has a higher degree of accuracy than the naive one

If U_2>1=> the forecast to compare has a lower degree of accuracy than the naive one

Hyndman and Koehler (2006) proposed scale errors based on the mean absolute error of a naive forecasting method. Naive forecast values are considered to be the current ones recorded during the previous period. MASE is used both to compare forecast methods applied to a given set of data and also to compare the accuracy of several series. If the scale error is less than 1, the compared forecast is better than the reference one (naïve forecast).

One of the business objectives in forecasting was empirical validation. Famous results have been registered making comparisons between different methods of forecasting. In literature the results are known as "M-competition". Ex-ante forecast errors for 21 methods were compared with predictions based on 1001 economic series. Accuracy criteria used in the M competition were: central tendency error (APE median), MSE, which gives more weight to larger error, MAPE, which is the basic measure. This is the measure recommended in reference books in forecast accuracy domain, written by Hanke and Reitsch (1995) or Bowerman, O'Connell and Koehler (2004).

Armstrong and Collopy (2000) used MdRAE, MdAPE and GMRAE. In M3 competition, Makridakis (1984) recommended MdRAE, sMAPE and sMdAPE.

Recent studies target accuracy analysis using as comparison criterion different models used in making predictions or the analysis of forecasted values for the same macroeconomic indicators registered in several countries.

Ericsson (1992) shows that the parameters stability and mean square error of prediction are two key measures in evaluation of forecast accuracy, but they are not sufficient and it is necessary the introduction of a new statistical test.

Considering the AR(1) process, which is represented as $y_t = \beta y_{t-1} + u_t$, Hoque, Magnus, and Pesaran (1988) show that for small values of β the prediction mean square error is a decreasing function in comparison with the number of forecast periods.

Granger and Jeon (2003) consider four models for U.S. inflation: a univariate model, a model based on an indicator used to measure inflation, a univariate model based on the two previous models and a bivariate model. Applying the mean square error criterion, the best prediction made is the one based on an autoregressive model of order 1 (AR(1)). Applying distance-time method, the best model is the one based on an indicator used to measure the inflation.

Ledolter (2006) compares the mean square error of ex-post and ex ante forecasts of regression models with transfer function with the mean square error of univariate models that ignore the covariance and show superiority of predictions based on transfer functions.

Teräsvirta, van Dijk, Medeiros (2005) examine the accuracy of forecasts based on linear autoregressive models, autoregressive with smooth transition (STAR) and neural networks (neural network-NN) time series for 47 months of the macroeconomic variables of G7 economies. For each model is used a dynamic specification and it is showed that STAR models generate better forecasts than linear autoregressive ones. Neural networks over long horizon forecast generat better predictions than the models using an approach from private to general.

Heilemann and Stekler (2007) explain why macroeconomic forecast accuracy in the last 50 years in G7 has not improved. The first explanation refers to the critic brought to macroeconometrics models and to forecasting models, and the second one is related to the unrealistic expectations of forecast accuracy. Problems related to the forecasts bias, data quality, the forecast process, predicted indicators, the relationship between forecast accuracy and forecast horizon are analyzed.

Ruth (2008), using the empirical studies, obtained forecasts with a higher degree of accuracy for European macroeconomic variables by combining specific sub-groups predictions in comparison with forecasts based on a single model for the whole Union.

Gorr (2009) showed that the univariate method of prediction is suitable for normal conditions of forecasting while using conventional measures for accuracy, but multivariate models are recommended for predicting exceptional conditions when ROC curve is used to measure accuracy.

Dovern and Weisser (2011) uses a broad set of individual forecasts to analyze four macroeconomic variables in G7 countries. Analyzing accuracy, bias and forecasts efficiency, resulted large discrepancies between countries and also in the the same country for different variables. In general, the forecasts are biased and only a fraction of GDP forecasts are closer to the results registered in reality.

In Netherlands, experts make predictions starting from the macroeconomic model used by the Netherlands Bureau for Economic Policy Analysis (CPB). For the period 1997-2008 was reconstructed the model of the experts macroeconomic variables evolution and it was compared with the base model. The conclusions of Franses, Kranendonk, and Lanser (2011) were that the CPB model forecasts are in general biased and with a higher degree of accuracy.

Assessing the forecasts accuracy

The monthly data for the annual rate of change for the harmonised index of consumer prices (HICP) is published by Eurostat and the predictions are made by SPF (Survey of Professional Forecasters) for January 2010- May 2012.

The monthly data for the annual rate of change for the HICP is not stationary, being necessary to differentiate the data. The stationarized data series for January 1997-December 2009 follows a random walk process: $\Delta ir_t = 0.339 \cdot \Delta ir_{t-1} + \varepsilon_t$. Starting from this econometric model, the predictions for January 2010- May 2012 are made.

We refer to the most used combination approaches used in order to improve the forecasts accuracy:

- optimal combination (OPT), with weak results according to Timmermann (2006);
- equal-weights-scheme (EW);
- inverse MSE weighting scheme (INV).

Bates and Granger (1969) considered two predictions p_{1t} and p_{2t}, for the same variable X_t, derived h periods ago. If the forecasts are unbiased, the error is calculated as: $e_{i,t} = X_{i,t} - p_{i,t}$. The errors follow a normal distribution of parameters 0 and σ_i^2. If ρ is the correlation between the errors, then their covariance is $\sigma_{12} = \rho \cdot \sigma_1 \cdot \sigma_2$. The linear combination of the two predictions is a weighted average: $c_t = m \cdot p_{1t} + (1-m) \cdot p_{2t}$. The error of the combined forecast is: $e_{c,t} = m \cdot e_{1t} + (1-m) \cdot e_{2t}$. The mean of the combined forecast is zero and the variance is:

$\sigma_c^2 = m^2 \cdot \sigma_1^2 + (1-m)^2 \cdot \sigma_{2t}^2 + 2 \cdot m \cdot (1-m) \cdot \sigma_{12}$. By minimizing the error variance, the optimal value for m is determined (m_{opt}): $m_{opt} = \frac{\sigma_2^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2 \cdot \sigma_{12}}$. The individual forecasts are inversely weighted to their relative mean squared forecast error (MSE) resulting INV. In this case, the inverse weight (m_{inv}) is: $m_{inv} = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$. Equally weighted combined forecasts (EW) are received when the same weights are given to all models.

The SPF forecasts are the best ones, because of the low values for all accuracy indicators.

TABLE 1. INDICATORS OF FORECASTS ACCURACY (January 2010 - May 2012)

Accuracy indicators	Predictions based on random walk	SPF predictions	Combined forecasts (OPT scheme)	Combined forecasts (INV scheme)	Combined forecasts (EW scheme)	Mean of the forecasts	Median of the forecasts	Forecasts based on M1	Forecasts based on M2
RMSE	0.634	0.204	0.231	0.271	0.221	0.281	0.231	0.833	0.422
ME	-0.521	-0.018	-0.113	-0.171	-0.094	-0.183	-0.113	-0.617	0.332
MAE	0.534	0.157	0.172	0.204	0.165	0.214	0.172	0.702	0.362
MAPE	0.223	0.065	0.070	0.082	0.067	0.087	0.070	0.247	0.154
U1	0.129	0.038	0.044	0.052	0.042	0.054	0.044	0.178	0.074
U2	3.195	1.068	1.226	1.426	1.177	1.477	1.226	2.948	1.946

Source: Processing of data provided by Eurostat and SPF

All the predictions are overestimated, the ME values being negative. In average the SPF errors differ with 6.5% from the registered values. All the mentioned predictions are not better than the naïve ones, because of the values greater than 1 for U2 statistics. The median of forecasts is equal to the optimal combined prediction on the entire forecasting horizon.

We can build new forecasts starting from a regression model that explains the registered values of the rate of change using the SPF values. The regression uses time series from 1997-2010 to make predictions for 2010 - May 2012. Two valid regression models were selected: M1 and M2.

EFFECTIV = 2.127022766 - 0.05534008024*SPF

EFFECTIV = 1.689861546 + 0.6027484692*(1/SPF)

The new forecasts are gotten starting from these regression models and knowing the SPF values.

Another interesting strategy is, according to Bratu (2012b) to build new predictions considering that these have as MPE, the mean percentage error, or other accuracy indicator registered for 1997-2009. We used the MPE of SPF predictions or of forecasts based on the AR(1) model. We can replace MPE with the other indicators (ME, MAE, RMSE).

$$MPE = \frac{X_{t+1} - X_t}{X_t} \Rightarrow \frac{X_{t+1}}{X_t} - 1 = MPE \Rightarrow X_{t+1} = (MPE + 1) \cdot X_t$$

$$ME = X_{t+1} - X_t \Rightarrow X_{t+1} = ME + X_t$$

$$MAE1 = X_{t+1} - X_t \Rightarrow X_{t+1} = MAE1 + X_t$$
$$MAE2 = -X_{t+1} + X_t \Rightarrow X_{t+1} = -MAE2 + X_t$$
$$RMSE^2 = X_{t+1} - X_t \Rightarrow X_{t+1} = RMSE^2 + X_t$$

TABLE 2. ACCURACY MEASURES FOR FORECASTS OF ANNUAL CHANGE OF HICP (1997-2009)

	ME	MAE	RMSE	MPE
SPF forecasts	-0.021	0.403	0.518	-0.023

To build the predictions for 2010- May 2012 we take into account the accuracy indicator for 1997-2009 and the previous SPF forecasted value, but all the predictions have a lower degree of accuracy than SPF forecasts and the random walk. All the new predictions are overestimated with a rather high degree of accuracy, because of the negative values of ME.

TABLE 3. ACCURACY MEASURES OF FORECASTS BASED ON A HISTORICAL ACCURACY INDICATOR

Accuracy indicators	Forecasts based on ME and SPF previous predictions	Forecasts based on MAE1 and SPF previous predictions	Forecasts based on MAE2 and SPF previous predictions	Forecasts based on RMSE and SPF previous predictions	Forecasts based on MPE and SPF previous predictions	SPF predictions
RMSE	0.787	0.508	1.119	0.577	0.799	0.204
ME	-0.638	-0.215	-1.020	-0.348	-0.664	-0.018
MAE	0.649	0.424	1.020	0.471	0.668	0.157
MAPE	0.275	0.178	0.424	0.199	0.282	0.065
U1	0.163	0.097	0.250	0.113	0.167	0.038
U2	4.067	2.701	5.548	3.078	4.089	1.068

We can also use the variant when we take into account the previous effective value and the accuracy indicator. In this case, we have an improvement of SPF forecasts according to all accuracy indicators for the predictions based on ME and the previous registered value for the annual change of price index. However, these predictions are not better than the naïve forecasts.

A rather low degree of accuracy was registered for predictions based on MPE and the previous predicted value of SPF. All the new forecasts, excepting those based on MAE1, are overestimated.

Forecasts intervals were built for the SPF predictions and the lower and the upper limits were considered as point forecasts. The accuracy of those predictions was assessed and we got an improvement in accuracy for the forecasts based on the inferior limit of the intervals. The historical errors method was used to build the intervals, the RMSE indicator being used. The form of these intervals is the following:

Average (inflation) - t*RMSE(t) < forecasted_inflation < average(inflation) + t*RMSE(t). Where *t* - the critical value for t-Student distribution with parameters 0.05 and *n-1* (*n*-number of observations in the data set)

The accuracy measures are computed for the two types of forecasts.

TABLE 4. ACCURACY MEASURES FOR THE POINT FORECASTS BASED ON THE LOWER AND THE UPPER LIMITS OF THE FORECAST INTERVALS

Accuracy indicators	Forecasts based on the lower limits of intervals	Forecasts based on the upper limits of intervals	SPF predictions
RMSE	0.2011	0.347	0.204
ME	-0.019	-0.107	-0.018
MAE	0.153	0.327	0.157
MAPE	0.078	0.138	0.065
U1	0.035	0.055	0.038
U2	0.963	1.755	1.068

Source: Own computations using Excel

According to U1 statistic the forecasts based on the lower limit of the intervals are more accurate, outperforming even the naïve forecasts. The predictions based on the intervals limits are also overestimated. So, a suitable strategy to improve accuracy of short term forecasts is to use the inferior limit of the forecast intervals.

Conclusion

The accuracy indicators of ex-post forecasts gives us a hint about the way we will chose to build better forecasts, according to the indicator we want to have the lowest value. In this study, the accuracy of SPF forecasts for monthly annual rate of change for HICP was evaluated and some strategies to improve the accuracy were proposed. It seems that the classical approaches from literature didn't improve the accuracy, but the empirical strategy proposed by Bratu (2012b) for USA gave good results for EU. So, we have an improvement of SPF forecasts according to all accuracy indicators for the predictions based on ME and the previous registered value for the annual change of HICP.

A strategy that proved to improve the predictions accuracy is the one based on the lower limit of the forecast intervals when the historical errors method based on RMSE indicator is used to build the interval.

In conclusion, macroeconomic forecasts evaluation is necessary to inform the public about the way in which SPF or other institution predicted the economic phenomenon.

Further, the public will chose a certain strategy to improve the SPF predictions, according to historical approaches.

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Appendix

COMBINED FORECASTS BASED ON RANDOM WALK PROCESS AND SPF PREDICTIONS ON THE FORECASTING HORIZON 2010-MAY 2012

Month	Combined forecasts (%) (OPT scheme)	Combined forecasts (%) (INV scheme)	Combined forecasts (%) (EW scheme)	Mean of the forecasts .%)	Median of the forecasts (%)	Forecasts based on M1	Forecasts based on M2
Ian.10	1.450	1.314	1.492	1.285	1.450	2.099	1.991
Feb.10	1.605	1.504	1.636	1.483	1.605	2.077	2.232
Mar.10	1.332	1.271	1.351	1.257	1.332	2.077	2.232
Apr.10	1.912	1.754	1.962	1.719	1.912	2.083	2.172
May10	2.034	1.972	2.053	1.958	2.034	2.039	2.654
Iun.10	2.006	1.948	2.024	1.936	2.006	2.039	2.654
Iul.10	1.807	1.792	1.812	1.789	1.807	2.033	2.714
Aug.10	2.042	1.965	2.066	1.948	2.042	2.044	2.594
Sep.10	1.916	1.885	1.926	1.879	1.916	2.033	2.714
Oct.10	2.251	2.158	2.280	2.138	2.251	2.039	2.654
Nov.10	2.225	2.179	2.239	2.169	2.225	2.022	2.835
Dec.10	2.225	2.179	2.239	2.169	2.225	2.022	2.835
Ian.11	2.660	2.552	2.694	2.528	2.660	2.022	2.835
Feb.11	2.606	2.548	2.624	2.536	2.606	2.005	3.016
Mar.11	2.842	2.765	2.866	2.748	2.842	2.000	3.076
Apr.11	3.023	2.935	3.051	2.915	3.023	1.994	3.136
May11	3.242	3.165	3.266	3.148	3.242	1.978	3.317
Iun.11	3.097	3.055	3.111	3.046	3.097	1.972	3.377
Iul.11	2.997	2.955	3.011	2.946	2.997	1.978	3.317
Aug.11	2.807	2.792	2.812	2.789	2.807	1.978	3.317
Sep.11	2.952	2.902	2.968	2.891	2.952	1.983	3.257
Oct.11	3.232	3.128	3.265	3.105	3.232	1.989	3.197
Nov.11	3.352	3.302	3.368	3.291	3.352	1.961	3.498
Dec.11	3.216	3.185	3.226	3.179	3.216	1.961	3.498
Ian.12	2.917	2.929	2.914	2.932	2.917	1.961	3.498
Feb.12	2.835	2.816	2.841	2.812	2.835	1.978	3.317
Mar.12	2.862	2.839	2.870	2.834	2.862	1.978	3.317
Apr.12	2.844	2.809	2.854	2.801	2.844	1.983	3.257
May12	2.645	2.653	2.642	2.654	2.645	1.978	3.317

Source: own calculations using Excel