THE ACCURACY AND BIAS EVALUATION OF THE USA UNEMPLOYMENT RATE FORECASTS. METHODS TO IMPROVE THE FORECASTS ACCURACY

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ABSTRACT. In *this study some alternative forecasts for the unemployment rate of USA made by* four institutions (International Monetary Fund (IMF), Organization for Economic Co-operation and Development (OECD), Congressional Budget Office (CBO) and Blue Chips (BC)) are evaluated regarding the accuracy and the biasness. *The most accurate predictions on the forecasting horizon 201-2011 were provided by IMF, followed by OECD, CBO and BC.. These results were gotten using U1 Theil's statistic and a new method that has not been used before in literature in this context. The multi-criteria ranking was applied to make a hierarchy of the institutions regarding the accuracy and five important accuracy measures were taken into account at the same time: mean errors, mean squared error, root mean squared error, U1 and U2 statistics of Theil. The IMF, OECD and CBO predictions are unbiased. The combined forecasts of institutions' predictions are a suitable strategy to improve the forecasts accuracy of IMF and OECD forecasts when all combination schemes are used, but INV one is the best. The filtered and smoothed original predictions based on Hodrick-Prescott filter, respectively Holt-Winters technique are a good strategy of improving only the BC expectations. The proposed strategies to improve the accuracy do not solve the problem of biasness. The assessment and improvement of forecasts accuracy have an important contribution in growing the quality of decisional process.*

KEY WORDS: *forecasts; accuracy; multi-criteria ranking; combined forecasts; Hodrick-Prescott filter; Holt-Winters smoothing exponential technique.*

JEL CLASSIFICATION: *E21, E27,C51, C53*

1. INTRODUCTION

The evaluation of forecasts accuracy is necessary for establishing the decisional process. When more institutions in a country provide forecasts for the same

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macroeconomic variable, the deciders have to choose the one with the highest accuracy. The term of “accuracy” is put in correlation with the errors that affect the forecasting process, because only by hazard the predicted value of an indicator is exactly equal with its real value.

The original contribution of this research is related to the proposal of a new method of assessing the forecasts accuracy, taking into account more accuracy measures at the same time. The multi-criteria ranking let us make a classification of the institution according to more accuracy indicators.

On the other hand, the literature reports the necessity of improving the forecasts accuracy. We proposed as strategy of getting better predictions than the original ones the combined forecasts and the filtered and smoothed predictions and we made comparisons with the original predictions to measure the degree of improvement.

2. LITERATURE

The forecasts accuracy evaluation is one of the current concerns of many researchers. One purpose of this assessment is related to the need of improving the predictions. The current economic and financial crisis emphasized the struggles of uncertainty reduction. The forecasts accuracy is a very large domain of research, an exhaustive presentation of it being impossible. But, some of the recent results will be described.

To assess the forecast accuracy, as well as their ordering, statisticians have developed several measures of accuracy. For comparisons between the MSE indicators of forecasts, Granger and Newbold proposed a statistic. Another statistic is presented by Diebold and Mariano (1995) for comparison of other quantitative measures of errors. Diebold and Mariano test proposed in 1995 a test to compare the accuracy of two forecasts under the null hypothesis that assumes no differences in accuracy. The test proposed by them was later improved by Ashley and Harvey, who developed a new statistic based on a bootstrap inference. Subsequently, Diebold and Christoffersen have developed a new way of measuring the accuracy while preserving the co-integration relation between variables.

Meese and Rogoff's paper, " Empirical exchange rate models of the seventies”, remains the starting point for many researches on the comparing of accuracy and bias. 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.

Allan (2012) obtained a good accuracy for the OECD forecasts combined with outturn values of GDP growth for G7 countries between 1984 and 2010. The same author mentioned two groups of accuracy techniques used in assessing the predictions: quantitative forecasts accuracy statistics and qualitative accuracy methods.

Deschamps and Bianchi (2012) concluded that there are large differences between macroeconomic forecasts for China regarding the accuracy measures for consumption and investment, GDP and inflation. The slow adjustment to structural shocks generated biased predictions, the information being utilized relatively inefficient.

Dovern and Weisser (2011) used 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 same country for different variables.

Most international institutions provide their own macroeconomic forecasts. It is interesting that many researchers compare the predictions of those institutions (Melander for European Commission, Vogel for OECD, Timmermann for IMF) with registered values and those of other international organizations, but it is omitted the comparison with official predictions of government.

Abreu (2011) evaluated the performance of macroeconomic forecasts made by IMF, European Commission and OECD and two private institutions (Consensus Economics and The Economist). The author analized the directional accuracy and the ability of predicting an eventual economic crisis.

In Netherlands, experts made 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.

Reeve and Vigfusson (2011) compared the performance of forecasts based on futures, choosing as a reference model a random walk and a random walk with drift.

Kurita (2010) showed that an ARFIMA model forecasts for Japan's unemployment rate outperformed the AR(1) model predictions in what concerns the performance.

Shittu and Yaya (2009) evaluated the performance of forecasts based on ARIMA and ARFIMA models for the exchange rate of England and USA. The authors recommended the ARFIMA models as a better tool of predicting the exchange rate in both countries.

Edge, Kiley and Laforte (2009) evaluated the performance of forecasts made by Federal Reserve staff and of those based by a time-series model and a DSGE model.

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.

Lam, Fung and Yu (2008) compared the predictions performance for the exchange rate when different forecasting methods are used: sticky price monetary model, uncovered interest rate parity model, Bayesian model and purchasing power parity model. The authors made also combined forecasts based on the mentioned models. The result was that combined predictions outperformed the ones based on a single model.

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.

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 macro-econometrics 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.

3. COMPARISONS BETWEEN UNEMPLOYMENT RATE FORECASTS MADE BY DIFFERENT INSTITUTIONS

3.1. The evaluation of forecasts accuracy

In this study we used the forecasted values of the annual registered unemployment rate made for USA by International Monetary Fund (IMF), Organization for Economic Co-operation and Development (OECD), Congressional Budget Office (CBO) and Blue Chips (BC) on the forecasting horizon 2001-2011. The objective is to assess the accuracy and the bias of these predictions and determine the best institution with the highest accuracy.

Armstrong and Fildes (1995) showed that it is not sufficient to use a single measure of accuracy. Therefore, more accuracy indicators were computed for the three types of forecasts on the specified horizon.

To make comparisons between forecasts we propose to determine the hierarchy of institutions according to the accuracy of their forecasts using multi-criteria ranking.

Two methods of multi-criteria ranking (ranks method and the method of relative distance with respect to the maximal performance) are used in order to select the institution that provided the best forecasts on the horizon 2001-2011 taking into account at the same time all computed measures of accuracy.

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: $e_t(t+k)$. This is the difference between the registered value and the predicted one.

The indicators for evaluating the forecasts accuracy that will be taken into consideration when the multi-criteria ranking is used are:

- Root Mean Squared Error (RMSE)

Equation 1 Formula for mean error $RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n} e_X^2(T_0 + j, k)}$

- Mean error (ME)

Equation 2 Formula for mean absolute error $ME = \frac{1}{n}\sum_{j=1}^{n} e_X(T_0 + j, k)$

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)

Equation 3 Formula for root mean squared error $MAE = \frac{1}{n}\sum_{j=1}^{n} \left| \; e_X(T_0 + j, k) \; \right|$

These measures of accuracy have some disadvantages. For example, RMSE is affected by outliers. Armstrong and Collopy stresses that these measures are not independent of the unit of measurement, unless if they are expressed as percentage. If we have two forecasts with the same mean absolute error, RMSE penalizes the one with the biggest errors.

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. Theil proposed the calculation of U statistic that takes into account both changes in the negative and the positive sense of an indicator:

U Theil's statistic can be computed in two variants, specified also by the Australian Tresorery.

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

Equation 4 Formula for U1 $$U_1 = \frac{\sqrt{\sum_{t=1}^{n}(a_t - p_t)^2}}{\sqrt{\sum_{t=1}^{n} a_t^2} + \sqrt{\sum_{t=1}^{n} p_t^2}}$$

A value close to zero for U_1 implies a higher accuracy.

Equation 5 Formula for U2 $$U_2 = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{p_{t+1} - a_{t+1}}{a_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{a_{t+1} - a_t}{a_t}\right)^2}}$$

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

Table 1. The accuracy of forecasts made by IMF, OECD, CBO and BC for the unemployment rate in USA (2001-2011)

ACCURACY MEASURE	INSTITUTION			
	IMF	OECD	CBO	BC
ME	0.0262	0.4664	1.0455	1.4818
MAE	0.0520	0.4973	1.3545	1.5909
RMSE	0.1120	0.8430	2.1564	2.3524
U1	0.0085	0.0654	0.1806	0.2047
U2	0.0551	0.6560	0.6560	1.4405

Source: own computations using Excel

According to all accuracy indicators for forecasts made on the horizon 2001-2011, the IMF provided the most accurate predictions for the unemployment rate. This institution is followed by OECD, CBO and BC. All the forecasts, excepting BC ones, outperformed the naïve predictions based on the random walk. The positive values of the mean error imply too low in average predicted values for all institutions. The less accurate forecasts are made by Blue Chips.

Ranks method application supposes several steps:

1. Ranks are assigned to each value of an accuracy indicator (the value that indicates the best accuracy receives the rank 1); The statistical units are the four institutions that made forecasts. The rank for each institution is denoted by: $(r_{i_{ind_j}})$, i=1,2,3,4 and ind_j –accuracy indicator j. We chose 5 indicators: mean error, mean absolute error, root mean squared error, U1 and U2.
2. If the ranks assigned to each institution are sum up, the score to each of them is computed. **Equation 6** Formula for the sum of ranks $S_{i}=\sum_{j=1}^{5}(r_{i_{ind_j}})$, i=1,2,3,4
3. The institution with the lowest score has the highest performance and it will get the final rank 1.

Table 2. The ranks of institutions according to the accuracy measures (ranks method)

ACCURACY MEASURE	INSTITUTION			
	IMF	OECD	CBO	BC
ME	1	2	3	44
MAE	1	2	3	44
RMSE	1	2	3	44
U1	1	2	3	44
U2	1	2	3	44
Sum of ranks	5	10	15	220
Final ranks	1	2	3	44

Source: own computations using Excel

The results of the ranks method are the same as those provided by all accuracy measures, especially U1 used in making comparisons between forecasts. Actually, if all the calculated accuracy indicators are taken into account at the same time, the following hierarchy was gotten: IMF, OECD, CBO and BC.

The method of relative distance with respect to the maximal performance is the second way of ranking.

For each accuracy indicator the distance of each statistical unit (institution) with respect to the one with the best performance is computed. The distance is calculated as a relative indicator of coordination:

Equation 7 Formula for the relative distance $d_{i_{ind_j}} = \frac{ind_i^j}{\{\min abs(ind_i^j)\}_{i=1,\dots,4}}$, i=1,2,3,4 and j=1,2,..,5

The relative distance computed for each institution is a ratio, where the denominator is the best value for the accuracy indicator for all institutions.

The geometric mean for the distances of each institution is calculated, its significance being the average relative distance for institution i.

Equation 8 Formula for the average relative distance $\overline{d_i} = \sqrt[5]{\prod_{j=1}^{5} d_{i_{ind_j}}}$, i=1,2,3,4

According to the values of average relative distances, the final ranks are assigned. The institution with the lowest average relative distance will take the rank 1. The position (location) of each institution with respect to the one with the best performance is computed as: its average relative distance over the lowest average relative distance.

Equation 9 Formula for the position of each statistical unit in the hierarchy $loc_i^{\%} = \frac{\overline{d_i}}{\min(\overline{d_i})_{i=\overline{1,4}}} \cdot 100$

Table 3. The ranks of institutions according to the accuracy measures (method of relative distance with respect to the best institution)

ACCURACY MEASURE	IMF	OECD	CBO	BC
ME	1	17.8125	39.9306	56.5972
MAE	1	9.5629	26.0490	30.5944
RMSE	1	7.5258	19.2519	21.0016
U1	1	7.7071	21.2832	24.1205
U2	1	11.9057	11.9057	26.1427
Average relative distance	1	10.3301	21.9317	29.6541
Ranks	1	2	3	4
Location (%)	100	10.3301	21.9317	29.6541

Source: own computations using Excel

The method of relative distance with respect to the best institution gave the same results as the previous methods. The lowest average relative distance was registered by IMF (the value 1).

The Diebold-Mariano test (DM test) is utilized to check if two forecasts have the same accuracy. The following steps are applied:

- The difference between the squared errors of forecasts (e^2) to compare and the squared errors of reference forecasts (e^{*2}): $d_{t,t} = (e^2_{t,t}) - (e^{*2}_{t,t})$
- The following model is estimated: $d_{t,t} = a + \varepsilon_t$
- We test if “a” differs from zero, where the null hypothesis is that a=0 (equal forecasts). A p-value less than 0.05 implies the rejection of the null hypothesis for a probability of 95% in guaranteeing the results.

The following variables are computed: d1, d2, d3, d4, d5 and d6 to make comparisons between all institutions predictions. The p-values are less than 0.05 for d1 and d6, fact that shows there are significant differences in accuracy between IMF and OECD predictions and CBO and BC predictions. The regression models are estimated in EViews and the results are presented in ***Appendix 1.*** The results are in accordance with the computed accuracy measures, IMF forecasts being more accurate than OECD ones, while CBO predictions outperform BC ones.

3.2. The forecasts bias

Corder (2003) shows that McNees (1978, 1987) and Fair and Schiller (1989) brought among the first contributions in the field of bias and efficiency of the individual forecasts made by consensus. Figlewski and Wachtel noted that early results showed that the projections of private sector are biased and uncorrelated with the rational expectations hypothesis. Batchelor R. (2007) detected the presence of systematic bias in the forecast of real GDP and inflation made by the private sector in the G7 countries during 1990-2005. The measuring and test of bias was based on regression models and nonparametric tests of accuracy of the ranks. Empirical researches have shown a conclusion already presented in the literature, namely, the discrepancy between rational expectations tests and the too pessimistic or too optimistic forecasts.

Bias in this context implies a zero mean forecast error series. In the literature rationality tests are used to check if the forecasts are optimal in relation to a certain criterion, if they are biased or ensure a good informational efficiency. The standard test of forecast bias-test-Mincer-Zarnowitz starts from this model: $A_t = a + b \cdot P_t + e_t$. A_t -Current values, P_t – predicted values

Holden and Peel proposed a modified version of the test, which is based on forecast errors by testing whether their mean (m) is zero: $A_t - P_t = m + e_t$.

Accuracy can be improved if it is known that there is autocorrelation between errors and other data available at the time the forecast is made. The correlation indicates an inefficient use of information from the past. If X_i are the observed variables that influence the forecast, then: $e_Y(t-k,k) = \gamma + \sum_i \sum_{j>k} \delta_{i,j} X_i(t-j) + e_t$.

If γ *and* $\delta_{i,j}$ are significantly different from zero, the forecasts can be improved if one takes into account the influence of X_i variables. However, Jeong and Maddie have demonstrated that tests of rationality are dependent on assumptions made for regression models. Pain shows that while the data series is non-stationary with unit roots, co-integration tests should be used. In the case of asymmetric loss functions the forecasts are rational, even if the errors mean is zero.

The unbiasedness of the forecasts is tested applying a simple t-test for the following regression: $e_{t+1} = a + \varepsilon_{t+1}$

We have to test if the parameter "a" differs or not significantly from zero.

A p-value or Prob. less than 0.05 for t test implies the existence of biasedness for those forecasts. The values of Prob. computed in EViews show that IMF, OECD and CBO predictions are unbiased, only the CB forecasts being biased.. The errors for each institution are denoted by e1, e2, e3 and e4 and the tests results are presented in ***Appendix 2***.

4. STRATEGIES TO IMPROVE THE ACCURACY OF UNEMPLOYMENT RATE PREDICTIONS

Bratu (2012) utilized some strategies to improve the forecasts accuracy (combined predictions, regressions models, historical errors method, application of filters and exponential smoothing techniques).

The combined forecasts are another possible strategy of getting more accurate predictions. The most utilized combination approaches are:

- optimal combination (OPT);
- equal-weights-scheme (EW);
- inverse MSE weighting scheme (INV).

Bates and Granger (1969) started from two forecasts f1;t and f2;t, for the same variable Xt, derived h periods ago. If the forecasts are unbiased, the error is calculated as: $e_{i,t} = X_{i,t} - f_{i,t}$. 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: $c_t = m \cdot f_{1t} + (1-m) \cdot f_{2t}$ .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}):

Equation 11 Formula for the optimal value of m $$m_{opt} = \frac{\sigma_2^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2 \cdot \sigma_{12}}$$

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:

Equation 12 Formula for the inverse weight $$m_{inv} = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$

Equally weighted combined predictions (EW) are gotten when the same weights are given to all models.

The U Theil's statistics were computed for the combined forecasts based on the three schemes, the results being shown in the following table (Table 4):

Table 4. The accuracy of combined forecasts for USA unemployment rate (2001-2011)

Accuracy indicator	IMF+OECD forecasts	IMF+CBO forecasts	IMF+BC forecasts	OECD+CBO forecasts	OECD+BC forecasts	CBO+BC forecasts
U1 (optimal scheme)	0.0523	0.1734	0.2073	0.1712	0.2058	0.2066
U2 (optimal scheme)	0.0551	0.6560	0.6560	1.4405	0.0551	0.6560
U1 (inverse MSE scheme)	**0.0269**	0.1738	0.2042	0.1758	0.2044	0.2030
U2 (inverse MSE scheme)	0.0534	0.6566	0.6567	1.4667	0.0556	0.6546
U1 (equally weighted scheme)	0.0459	0.1772	0.2044	0.1782	0.2045	0.2038
U2 (equally weighted scheme)	0.0534	0.6546	0.6545	1.4478	0.0544	0.6577

Source: Author's computations using Excel

0.0085	0.0654	0.1806	0.2047
0.0551	0.6560	0.6560	1.4405

All the combined predictions are better than the naïve ones, excepting those of OECD and CBO. We got improvements in accuracy by combining the OECD expectations with IMF ones, the highest improvement being brought by INV scheme. The biasedness of those forecasts was tested and these combined predictions based on all schemes are biased. If we take into account that accuracy is more important, these forecasts are better than the original ones.

We test the biasedness of the combined forecasts based on CB predictions. These combined predictions are biased. So, the combined predictions introduce bias to the original forecasts.

Another technique of improving the forecasts accuracy used by Bratu (Simionescu) (2013) is the application of filters to the predicted data. The author recommends also the use of exponential smoothing methods like Holts Winters.

Hodrick-Prescott filter and Holt-Winters exponential technique were applied to the original predictions and the accuracy of new forecasts was evaluated. *Holt-Winters*

Simple exponential smoothing method is recommended for data series with linear trend and without seasonal variations. The Hodrick–Prescott (HP) filter is very used in macroeconomics to extract the trend of the data series and separate the cyclical component of the time series. The smoothed data gotten are more sensitive to long term changes.

Table 5. The accuracy of filtered and smoothed forecasts of USA for unemployment rate (2001-2011)

Accuracy measure	Filtered IMF forecasts	Smoothed IMF forecasts	Filtered OECD forecasts	Smoothed OECD forecasts	Filtered CBO forecasts	Smoothed CBO forecasts	Filtered BC forecasts	Smoothed BC forecasts
U1	0.0886	0.0952	0.1001	0.1101	0.1837	0.1784	0.2045	0.2031

Source: Author's computations using Excel

The filtered and smoothed predictions using HP filter, respectively Holt-Winters technique are a good strategy only to improve the CB forecasts. For the other forecasts we got an increase of the degree of accuracy. The IMF, OECD and CBO forecasts are still unbiased and the BC ones are biased.

5. CONCLUSIONS

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 accuracy. The purpose of this evaluation is related to different aspects: the improvement of the model on which the forecast was based, adjustment of government policies, the planning of results. Basically, performance evaluation in this context refers directly to the degree of trust conferred 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 accuracy and biasedness.

In our study, we assessed the unemployment forecasts accuracy and bias for the predictions provided during 2001-2011 by four institutions: International Monetary Fund (IMF), Organization for Economic Co-operation and Development (OECD), Congressional Budget Office (CBO) and Blue Chips (BC). The best accuracy is provided by IMF, followed by OECD, CBO and BC. This hierarchy resulted from the application of the multi-criteria ranking, but also from the measurement of accuracy indicators, as U1, used in making comparisons between forecasts.

The combined forecasts using the three classical schemes are a good strategy of improving the accuracy for the combined forecasts of IMF and OECD. The combined forecasts are in all cases biased, but those of IMF, OECD and CBO are unbiased. Filtered forecasts based on HP filter or smoothed ones based on Holt-Winters technique succeeded in improving only the BC forecasts.

The forecasts accuracy should be a priority for the public that uses these predictions in underlying the decisional process. The combined forecasts and in some cases the filtered and smoothed predictions are a very good strategy of getting improvements in accuracy for some unemployment rate predictions.

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APPENDIX 1. The results of Diebold-Mariano test in EViews

Dependent Variable: D6
Method: Least Squares
Date: 11/24/12 Time: 14:05
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.883636	0.344872	-2.562214	0.0283

Dependent Variable: D2
Method: Least Squares
Date: 11/24/12 Time: 14:05
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.637454	2.345183	-1.977438	0.0762

Dependent Variable: D3
Method: Least Squares
Date: 11/24/12 Time: 14:05
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.521090	2.666494	-2.070543	0.0652

Dependent Variable: D4
Method: Least Squares
Date: 11/24/12 Time: 14:05
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.939427	2.520943	-1.562680	0.1492

Dependent Variable: D6
Method: Least Squares
Date: 11/24/12 Time: 14:05
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.883636	0.344872	-2.562214	0.0283

APPENDIX 2. Biasedness tests

Dependent Variable: E1
Method: Least Squares
Date: 11/24/12 Time: 14:22
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.026182	0.034439	0.760235	0.4647

Dependent Variable: E2
Method: Least Squares
Date: 11/24/12 Time: 14:22
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.466364	0.222054	2.100231	0.0621

Dependent Variable: E3
Method: Least Squares
Date: 11/24/12 Time: 14:23
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.045455	0.596408	1.752918	0.1102

Dependent Variable: E4
Method: Least Squares
Date: 11/24/12 Time: 14:23
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.481818	0.577741	2.564847	0.0281

The biasedness test for combined forecasts

Dependent Variable: C1
Method: Least Squares
Date: 11/24/12 Time: 15:01
Sample: 2001 2011
Included observations: 11

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	*6.678958*	*0.539466*	*12.38068*	*0.0000*

Dependent Variable: C2
Method: Least Squares
Date: 11/24/12 Time: 15:04
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.146983	0.607579	10.11717	0.0000

Dependent Variable: C3
Method: Least Squares
Date: 11/24/12 Time: 15:04
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.017582	0.641704	9.377502	0.0000

Dependent Variable: C4
Method: Least Squares
Date: 11/24/12 Time: 15:08
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.856279	0.026520	183.1166	0.0000

Dependent Variable: C5
Method: Least Squares
Date: 11/24/12 Time: 15:09
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.867313	0.027033	180.0511	0.0000

Dependent Variable: C6
Method: Least Squares
Date: 11/24/12 Time: 15:09
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.844737	0.026504	182.7940	0.0000