The Indicators' Inadequacy and the Predictions' Accuracy

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Abstract: In this article, we proposed the introduction in literature of a new source of uncertainty in modeling and forecasting: the indicators' inadequacy. Even if it was observed, a specific nominalization in the context of forecasting procedure has not been done yet. The inadequacy of indicators as a supplementary source of uncertainty generates a lower degree of accuracy in forecasting. This assumption was proved using empirical data related to the prediction of unemployment rate in Romania on the horizon 2011-2013. Four strategies of modeling and predicting the unemployment rate were proposed, observing two types of indicators' inadequacy: the use of transformed variables in order to get stationary data set (the difference between the unemployment rates registered in two successive periods was used instead of the unemployment rate) and the utilization of macro-regional unemployment rates whose predictions are aggregated in order to forecast the overall unemployment rate in Romania. The results put in evidence that the predictions of the total unemployment rate using moving average models of order 2 are the most accurate, being followed by the forecasts based on the predictions of active civil population and number of unemployed people. The strategies based on the aggregation of the predictions for the four macro-regional unemployment rates imply a higher inadequacy and consequently a lower degree of forecasts' accuracy.

Keywords: forecasts; accuracy; indicators' inadequacy; econometric model; uncertainty

JEL Classification: C12; C14; C180

1. Introduction

The objective of our research is related to the relationship between the inadequacy of the macroeconomic variables to predict and the precision of the forecasts. By its nature, the inadequacy of the indicators is a source of uncertainty, even it is not clearly specified in literature. This type of uncertainty affects at the same time two elements: the econometric model chosen as a quantitative method of forecasts and also the prediction itself. A problem very often met by researchers is the fact that

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an econometric model is used not to describe the evolution of the chosen variable, but the evolution of another variable gotten by making a transformation of the initial indicator. Usually the econometricians have to transform the data series in order to work with a stationary data set. The transformation supposes very often the differentiating of the data set, the use of the logged variables. On the other hand, we can use other variables in modeling because of the lack of same data. For example, the variables at the regional level could be used in constructing the econometric models. Then, the predictions of the regional indicators are aggregated using some empirical coefficients in order to elaborate the forecasts of the initial variable.

2. Literature

The uncertainty of the evolution of a phenomenon is a constant of any element to be studied. Even the presence of the observer in the process is a source of uncertainty. The predictions are also affected by uncertainty, the source of it being related to two major elements: the forecasting method and the forecasting process itself. It is interesting that none of the researchers in this domain presented in detail the problem of the inadequacy of the indicators in modeling and forecasting process. Cicarelli and Hubrich (2010) made a detailed presentation of the literature related to the sources of uncertainty in predictions. The authors made more classifications of the uncertainty sources, taking into account more perspectives that include the informational uncertainty, the model uncertainty (the imprecion of the model and of uncertainty of the forecast based on it) and the uncertainty in data measurement.

Clements and Hendry (1998) specified 5 uncertainty sources for predictions based on econometric models:

1. The estimators imprecision;
2. The incoorect specification of the model;
3. Errors in measuring the data;
4. Structural changes on the forecasting horizon;
5. Economic shocks on the forecasting horizon.

Many international institutions are specialized in providing their own macroeconomic appreciations. Some researchers were interested in evaluating the accuracy of those predictions (Timmermann for IMF Melander for European Commission, Vogel for OECD,), neglecting the comparison with government's expectations. Genrea, Kenny, Meylera and Timmermann (2013) made forecasts combinations starting from SPF predictions for ECB and using performance-based weighting, trimmed averages, principal components analysis, Bayesian shrinkage, least squares estimates of optimal weights. Only for the inflation rate there was a strong evidence of improving the forecasts accuracy with respect to the equally weighted average prediction. Hess and Orbe (2013) studied the association between analyst characteristics and the macroeconomic forecasts accuracy, noticing that the experience and the abilities of the analyst generate a better accuracy. Clarck and McCracken (2013) brought recent and important contribution in this domain: the assessment of point and density forecasts using the Vector Autoregression, direct and iterative forecasts with more steps, the application of accuracy tests on different samples of forecasts.Bratu (2012 a) assessed the accuracy of some macroeconomic predictions for Romania made by the Institute of Economic Forecasting and the National Commission of Prognosis, the last institution outperforming the forecasts for: inflation, unemployment, GDP deflator, export rate and exchange rate on the horizon 2004-2011. Novotny and Rakova (2012) assessed the accuracy of macroeconomic forecasts made by Consensus for the Czech Republic, observing an improvement in accuracy from a year to another on the horizon 1994-2009. The authors also proposed a regression for comparing the predictions. Abreu (2011) was interested in assessing the performance of macroeconomic predictions of IMF, European Commission and OECD and two private institutions (Consensus Economics and The Economist). The directional accuracy and the ability of predicting an eventual economic crisis were studied. 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. In general, the forecasts are biased and only a fraction of GDP forecasts are closer to the results registered in reality. 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. 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 analysed.

In literature, there are several traditional ways of measurement, which can be ranked according to the dependence or independence of measurement scale. The most utilized measures of forecasts accuracy, recalled by Fildes and Steckler (2000) are:

- Mean error (ME)

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

- Mean absolute error (MAE)

$$MAE = \frac{1}{n}\sum_{j=1}^{n} \left| \; e_X (T_0 + j, k) \; \right|$$

- Root Mean Squared Error (RMSE)

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

These measures of accuracy have some disadvantages. For example, RMSE is affected by outliers. If we have two forecasts with the same mean absolute error, RMSE penalizes the one with the biggest errors.

- Mean absolute percentage error

The percentage error is given by: $p_t = \frac{e_t}{X_t} \cdot 100$

The most common measures based on percentage errors is the mean absolute percentage error (MAPE), which is:

MAPE = average ($|p_t|$)

- Mean relative absolute error

It is considered that $r_t = \frac{e_t}{e_t^*}$, where e_t^* is the forecast error for the reference model.

The mean relative absolute error (MRAE) is computed as:

MRAE= average ($|r_t|$)

- The relative RMSE

The relative RMSE is calculated as: $rel\_RMSE = \frac{RMSE}{RMSE_b}$, *where* $RMSE_b$ is the RMSE of “benchmark model” U Theil’s statistic is calculated as U1 and U2 and it is used to make comparisons between forecasts.

Notations used:

r- the registered results

f- the forecasted results

t- reference time

e- the error (e=r-f)

n- number of time periods

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

A value of U_1 closer to zero implies a higher accuracy.

$$U_2 = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{f_{t+1} - r_{t+1}}{r_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{r_{t+1} - r_t}{r_t}\right)^2}}$$

If U_2 =1=> the same accuracy for the two predictions

If U_2 <1=> the prediction to compare more accurate than the naive one

If U_2 >1=> the prediction to compare more accurate than the naive one.

3. The Consequences of the Indicators' Inadequacy in Modeling and Forecasting. An Empirical Research for the Short-Run Predictions of the Overall Unemployment Rate in Romania

The indicators' inadequacy for describing a certain economic phenomenon has even at the level of forecasting process. Therefore, from this point of view we will try to assess the effects of using inadequate variables in econometric models regarding the precision of the forecasts based on this quantitative method. The data series refers to the registered unemployment rate for Romania and for the 4 main macroeconomic regions. The first macro-region includes the central region and the north-west one. The second major region groups north-east and south-east regions. The third macro-region refers to Bucharest-Ilfov and South-Muntenia. South-west Oltenia and the western part are included in the fourth macro-region. The data sets are provided by the National Institute of Statistics, using TEMPO-online facility. Our purpose is to predict the unemployment in Romania, using several strategies:

STRATEGY 1 (S1): Forecasting the total registered unemployment rate using an econometric model;

STRATEGY 2 (S2): Forecasting the unemployment for each region and then aggregate the predictions using some weighting coefficients;

STRATEGY 3 (S3): Forecasting the total number of unemployed people and the active civil population in order to get the total unemployment rate;

STRATEGY 4 (S4): Forecasting the numbers of unemployed people and the active population for each region, the calculation of the regional unemployment rate and the aggregation of the rates in order to get the total unemployment rate.

Another important aspect regarding the variables' inadequacy is related to the fact that in many cases, in order to work with stationary data series in econometric models, we have to transform the variables, more often applying a differentiation of the data series. What we have to predict using the econometric model is a transformed variable, whose forecast is then utilized to get the prediction of the main variable. It is clearly that a supplementary source of uncertainty was introduced in this way. The forecasting horizon is 2010-2012 and 2013. For the last year prediction, the accuracy assessment was done considering as benchmark the previous value of the indicator (the value from 2012). The total unemployment rate data set has a unit root, according to Phillips-Perron test (Appendix 1). The adjusted t-statistic is greater than the critical values for different levels (1%, 5% and 10%). The associate probability is greater than the threshold of 0.05, so the hypothesis that states the existence of unit root is not rejected. Therefore, it is necessary to stationarize the data. In this case the way to get a stationary data set is to difference it once (the new variable is d_ur). If the unemployment rate is denoted by ur and the error at time t is written as ε_t, then the following econometric models (moving average of order one MA(1)) is used to predict the indicator in one-step-ahead variant on the forecasting horizon 2011-2013.

Table 1. The moving average models used to forecast the overall unemployment rate in Romania on the predicting horizon 2011-2013

Forecasted years	MA(1) models
2011	$d\_ur_t = 0.1459 + 0.5706 \cdot \varepsilon_{t-1} + \varepsilon_t$
2012	$d\_ur_t = 0.6395 + 0.1805 \cdot \varepsilon_{t-1} + \varepsilon_t$
2013	$d\_ur_t = 0.1428 + 0.1713 \cdot \varepsilon_{t-1} + \varepsilon_t$

Source: Authors' computations

The unemployment rates for each macro-region are denoted by ur1, ur2, ur3 and, respectively, ur4. The data series are integrated of order 1, in the models being used the differentiated values.

Table 2. The moving average models used to forecast the macro-regional unemployment rates in Romania on the predicting horizon 2011-2013

Forecasted years	MA(2) models
2011	$d\_ur_{1t} = -0.2895 - 0.8924 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_ur_{1t} = -0.4885 - 0.9305 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_ur_{1t} = -0.2818 - 0.9096 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_ur_{1t} = -0.2843 - 0.8907 \cdot \varepsilon_{t-2} + \varepsilon_t$
2012	$d\_ur_{1t} = -0.2773 - 0.9227 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_ur_{1t} = -0.3251 - 0.9985 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_ur_{1t} = -0.1239 - 0.6716 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_ur_{1t} = -0.1057 - 0.6613 \cdot \varepsilon_{t-2} + \varepsilon_t$
2013	$d\_ur_{1t} = -0.2987 - 0.9352 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_ur_{1t} = -0.4179 - 0.9722 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_ur_{1t} = -0.2716 - 0.9492 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_ur_{1t} = -0.1114 - 0.6583 \cdot \varepsilon_{t-2} + \varepsilon_t$

Source: Authors' computations

For each macro-region the unemployment rate was computed and then the forecasts are aggregated in order to predict the total unemployment rate in Romania.

Table 3. The forecasts for macro-regional unemployment rate (%) in Romania

Forecasted years	Unemployment rate (%)			
	Macro-Region 1	Macro-Region 2	Macro-Region 3	Macro-Region 4
2011	3.73	6.47	3.008	4.19
2012	5.53	5.57	4.56	6.56
2013	3.77	5.69	3.21	6.06

Source: Authors' computations

The weighting coefficients are determined by solving a system of 4 equations, corresponding to the last 4 registered unemployment rates (2007-2010):

$$\begin{cases} a \cdot ur1_{2007} + b \cdot ur2_{2007} + c \cdot ur3_{2007} + d \cdot ur4_{2007} = ur_{2007} \\ a \cdot ur1_{2008} + b \cdot ur2_{2008} + c \cdot ur3_{2008} + d \cdot ur4_{2008} = ur_{2008} \\ a \cdot ur1_{2009} + b \cdot ur2_{2009} + c \cdot ur3_{2009} + d \cdot ur4_{2009} = ur_{2009} \\ a \cdot ur1_{2010} + b \cdot ur2_{2010} + c \cdot ur3_{2010} + d \cdot ur4_{2010} = ur_{2010} \end{cases}$$

After solving this system in Excel, we got the following values for coefficients: 0.95, 1.2, 0.85 and 1.05. After the aggregation of the regional predictions using these weighting coefficients, the forecasts were presented in final table.

Table 4. The forecasts for unemployment rate (%) in Romania (2011-2013)

Forecasted years	Type of strategy			
	S1	S2	S3	S4
2011	5.69	8.26	6.03	8.33
2012	5.77	7.3	7.12	7.98
2013	5.83	6.55	6.9	7.57

Source: Authors' computations

The fourth strategy supposes the use of MA(2) models to predict the variables used in the computation of the unemployment rate. The regional forecasts for unemployed people and active civil population are used to determine the macro-regional unemployment rates. The aggregation of these rates is made using the same coefficients used in the application of the second strategy.

Table 5. The moving average models used to forecast the number of unemployed people and the active civil population in Romania on the predicting horizon 2011-2013

Forecasted years	MA(2) models for unemployed people	MA(2) models for active civil population
2011	$d\_s_t = -44064.06 - 0.9095 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{1t} = -9152.386 - 0.898 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{2t} = -18675 - 0.936 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{3t} = -7750.126 - 0.9048 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{4t} = -7860 - 0.889 \cdot \varepsilon_{t-2} + \varepsilon_t$	$d\_acp_t = -88659.18 - 0.9238 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_acp_{1t} = -22694.469 - 0.905 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_acp_{2t} = -26.846 - 0.922 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_acp = -21967.559 - 0.924 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_acp_{4t} = -19658.668 - 0.915 \cdot \varepsilon_{t-2} + \varepsilon_t$
2012	$d\_s_t = -44778.06 - 0.9556 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{1t} = -9447.997 - 0.933 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{2t} = -18776 - 0.945 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{3t} = -7863.87 - 0.9138 \cdot \varepsilon_{t-2} + \varepsilon_t$	$d\_acp_t = -89679.49 - 0.9188 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_acp_{1t} = -23896.668 - 0.918 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_acp_{2t} = -26.846 - 0.922 \cdot \varepsilon_{t-2} + \varepsilon_t$

	$d\_s_{4t} = -7993 - 0.839 \cdot \varepsilon_{t-2} + \varepsilon_t$	$d\_acp = -21967.559 - 0.924 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_acp_{4t} = -19554.998 - 0.921 \cdot \varepsilon_{t-2} + \varepsilon_t$
2013	$d\_s_t = -44453.86 - 0.9126 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{1t} = -9152.386 - 0.898 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{2t} = -18887 - 0.954 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{3t} = -7896.584 - 0.9138 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_s_{4t} = -8560.69 - 0.893 \cdot \varepsilon_{t-2} + \varepsilon_t$	$d\_acp_t = -90467.45 - 0.9457 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_acp_{1t} = -23677.887 - 0.905 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_acp_{2t} = -26558.86 - 0.918 \cdot \varepsilon_{t-2} + \varepsilon_t$ $d\_acp = -21887.668 - 0.922 \cdot \varepsilon_{t-2} + \varepsilon_t d\_acp_{4t} = -19778.223 - 0.933 \cdot \varepsilon_{t-2} + \varepsilon_t$

Source: Authors' computations

For 2011-2012 ex-post assessment of the forecasts is made, while for 2013 an ex-ante evaluation is done. The predictions of the total unemployment rate based on the first proposed strategy (S1) are the most accurate, according to U1, outperforming even the naïve forecasts on both horizons 2011-2012 and 2011-2013.

Table 6. The accuracy of the forecasts for overall unemployment rate in Romania on the predicting horizon 2011-2012

Unemployment rate	Forecasts corresponding to the following strategies:			
Indicators of accuracy	S1	S2	S3	S4
RMSE	**0.3667**	2.4752	1.2246	2.7804
ME	**-0.3300**	-2.3800	-1.1750	-2.7550
MAE	**0.3300**	2.3800	1.1750	2.7550
MPE	**-0.0635**	-0.4577	-0.2260	-0.5298
U1	**0.0329**	0.1875	0.1020	0.2050
U2	**0.3029**	2.1346	1.2247	2.4967

Source: Authors' computations

For all the accuracy indicators the first strategy provided the most accurate forecasts on both horizons (2011-2012 and 2011-2013). In average the error was overestimated in 2011-2012 with 6.35% of the previous year registered value, when S1 procedure is applied. For all the strategies the tendency is to overestimate the real values, fact that shows that the shocks in the economy were not taken into account. The third strategy gave quite good results, but exactly as the first one it refers to the directly forecasting of the overall unemployment rate. The second and the fourth strategies bring a higher degree of uncertainty because the inadequacy of the indicators is higher. The total rate of unemployment is predicted starting from the components' predictions.

Table 7. The accuracy of the forecasts for overall unemployment rate in Romania on the predicting horizon 2011-2013

Unemployment rate	Forecasts corresponding to the following strategies:			
Indicators of accuracy	S1	S2	S3	S4
RMSE	**0.3276**	2.0941	1.2502	2.5392
ME	**-0.2967**	-1.9033	-1.2167	-2.4933
MAE	**0.2967**	1.9033	1.2167	2.4933
MPE	**-0.0571**	-0.3660	-0.2340	-0.4795
U1	**0.0292**	0.1627	0.1027	0.1890
U2	**0.3421**	2.2335	1.5194	2.8445

Source: Authors' computations

In the second case, when the ex-ante evaluation of the forecast made for 2013 is taken into account, the degree of accuracy for S1 is higher, because the assumption of the same effective value was considered. The tendency of overestimation of the unemployment is kept, but the error represents in average 5,71% of the previous registered value. For all the applied strategies the tendency of providing too large in average values is persistent, the indicators ME and MAE having the same absolute value.

4. Conclusions

The indicators' inadequacy should be considered an important and frequent source of uncertainty in econometric modeling and in forecasting process based on econometric models. In our empirical study regarding the predictions for the total unemployment rate in Romania we demonstrated that the inadequacy of the predicted indicators induces a growth of the degree of uncertainty. As a result, the degree of accuracy is lower. If the sources of uncertainty are more, the inadequacy being higher, the degree of accuracy is lower.

According to our empirical research, we should prefer modeling the total unemployment rate using a moving average model of order 2. The predictions based on this model are better than those gotten by the aggregation of the macro-regional predictions. On the other hand, it is preferable to predict the variables used to compute of the unemployment rate instead of forecasting the regional variables and aggregate the macro-regional unemployment rate for Romania.

This study recommends the introduction in literature of the inadequacy of the indicators as a source of uncertainty in modeling and forecasting. The relationship between the inadequacy and the forecasts accuracy is obvious, an increase in the degree of inadequacy by developing more phases in which unsuitable variables are used generating a decrease in predictions' precision.

5. References

Abreu, I. (2011). *International organizations' vs. private analysts' forecasts: an Evaluation*, Retrieved from http://www.bportugal.pt/en-US/BdP%20Publications%20Research/wp201120.pdf.

Bratu M. (2012a). Applying econometrics methods to improve the accuracy of the exchange rate forecasts in Romania. *Analele Universitatii "Eftimie Murgu" Resita, Fascicola II - Studii Economice/Annals of the University "Eftimie Murgu" Resita, Fascicle II - Economic Studies*, Year 2012, p. 611-616

Bratu, M. (2012 b). *Strategies to Improve the Accuracy of Macroeconomic Forecasts in USA*. LAP LAMBERT Academic Publishing.

Ciccarelli, M. & Hubrich, K. (2010). Forecast uncertainty: source, measure and evaluation. *Journal of applied econometrics*, Vol. 25, pp. 509-513.

Clarck T.E., McCracken M.W. (2013). Evaluating the accuracy of forecasts from Vector auto regression. Federal Reserve Bank of St. Louise, *Working Paper* 2013-010A.

Clements M.P. & Hendry D.F. (1998). Forecasting in co-integrated systems. Journal *of Applied Econometrics*, 10, pp. 127–146.

Dovern, J. & Weisser J. (2011). Accuracy, unbiasedness and efficiency of professional macroeconomic forecasts: An empirical comparison for the G7. *International Journal of Forecasting*, 27 (2), pp. 452-465.

Fildes R. & Steckler H. (2000). The State of Macroeconomic Forecasting. Lancaster University EC3/99, George Washington University, Center for Economic Research, *Discussion Paper* No. 99-04.

Genrea V., Kenny G., Meylera A. & Timmermann A. (2013). Combining expert forecasts: Can anything beat the simple average?. *International Journal of Forecasting*, 29(1), pp. 108–121.

Gorr, W.L. (2009). Forecast accuracy measures for exception reporting using receiver operating characteristic curves. *International Journal of Forecasting*, 25 (1), pp. 48-61.

Heilemann, U. and Stekler, H. (2007). Introduction to "The future of macroeconomic forecasting". *International Journal of Forecasting*, 23(2), pp. 159-165.

Hess D. & Orbe S. (2013). *Idiosyncratic predictability and analyst characteristic*. University of Cologne papers, 30(1), pp. 3-20.

Novotny F. & Rakova M.D. (2012). Assessment of Consensus forecasts accuracy: The Czech National Bank perspective. *Economic Research Bulletin*, 10(2), pp. 10-13.

Ruth, K. (2008). Macroeconomic forecasting in the EMU: Does disaggregate modeling improve forecast accuracy ?. *Journal of Policy Modeling*, 30 (3), pp. 417-429.

APPENDIX 1

The Phillips-Perron test

Null Hypothesis: UR has a unit root

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-0.457010	**0.5048**
Test critical values:	1% level	-2.679735	
	5% level	-1.958088	
	10% level	-1.607830	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(UR) has a unit root

Exogenous: None

Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-5.729595	0.0000
Test critical values:	1% level	-2.685718	
	5% level	-1.959071	
	10% level	-1.607456	

Null Hypothesis: D(UR) has a unit root Test equation with trend and intercept

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.797518	0.0001
Test critical values:	1% level	-4.498307	
	5% level	-3.658446	
	10% level	-3.268973	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(UR) has a unit root

Test equation with intercept

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.119033	0.0000
Test critical values:	1% level	-3.808546	
	5% level	-3.020686	
	10% level	-2.650413	

*MacKinnon (1996) one-sided p-values.