TWO QUANTITATIVE FORECASTING METHODS FOR MACROECONOMIC INDICATORS IN CZECH REPUBLIC

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Abstract

Econometric modelling and exponential smoothing techniques are two quantitative forecasting methods with good results in practice, but the objective of the research was to find out which of the two techniques are better for short run predictions. Therefore, for inflation, unemployment and interest rate in Czech Republic some accuracy indicators were calculated for the predictions based on these methods. Short run forecasts on a horizon of 3 months were made for December 2011-February 2012, the econometric models being updated. For Czech Republic, the exponential smoothing techniques provided more accurate forecasts than the econometric models (VAR(2) models, ARMA procedure and models with lagged variables). One explication for the better performance of smoothing techniques would be that in the chosen countries the short run predictions more influenced by the recent evolution of the indicators.

Keywords: *accuracy, econometric models, forecasts, forecasting methods, smoothing exponential techniques*

JEL Classification: E_{21}, E_{27}, C_{51}, C_{53}

1. *Introduction*

In establishing the monetary policy, the deciders must take into account the possible future evolution of some important macroeconomic variables as inflation rate, unemployment rate or interest rate. This fact implies the knowledge of the predictions of these indicators. In econometrics we can build forecasts starting from a valid model. The real problem appears when we use two or more different forecasting methods and we must choose the one which generated the forecasts with the higher degree of accuracy.

In this article, we modelled the three selected variables and we made predictions for them. Using indicators of accuracy we demonstrated that the smoothing exponential techniques generated better forecasts than simple econometric models in Czech Republic.

2. *Literature review*

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 Jeon (2003) proposed a statistics. Another statistics is presented by Diebold and Mariano (1995) for comparison of other quantitative measures of errors. Diebold and Mariano 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 (2003), who developed a new statistics based on a bootstrap inference. Subsequently, Diebold and Christoffersen (1998) have developed a new way of measuring the accuracy while preserving the co-integrating relation between variables.

Armstrong and Fildes (1995) showed that the purpose of measuring an error of prediction is to provide information about the distribution of errors form and they proposed to assess the prediction error using a loss function. They showed that it is not sufficient to use a single measure of accuracy.

Since the normal distribution is a poor approximation of the distribution of a low-volume data series, Harvey, Leybourne, and Newbold (2003) improved the properties of small length data series, applying some corrections: the change of DM statistics to eliminate the bias and the comparison of this statistics not with normal distribution, but with the T-Student one. Clark (2006) evaluated the power of equality forecast accuracy tests, such as modified versions of the DM test or those used based on Bartlett core and a determined length of data series.

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 (2005) in their reference study in the field, *Another Look at Measures of Forecast Accuracy*:

- **Scale-dependent measures**

The most used measures of scale dependent accuracy are:

- ➢ Mean-Square Error (MSE) = average (e_t^2)
- ➢ Root Mean Square Error (RMSE) = $\sqrt{MSE}$
- ➢ Mean Absolute Error (MAE) = average ($|e_t|$)
- ➢ Median Absolute Error (MdAE) = median ($|e_t|$)

RMSE and MSE are commonly used in statistical modelling, although they are affected by outliers more than other measures.

- **Scale-independent errors**

➢ *Measures based on percentage errors*

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

The most common measures based on percentage errors are:

- Mean Absolute Percentage Error (MAPE) = average ($|p_t|$)
- Median Absolute Percentage Error (MdAPE) = median ($|p_t|$)
- Root Mean Square Percentage Error (RMSPE) = geometric mean (p_t^2)

- Root Median Square Percentage Error (RMdSPE) = median (p_t^2)

When X_t takes the value 0, the percentage error becomes infinite or it is not defined and the measure distribution is highly skewed, which is a major disadvantage. Makridakis (1984) introduced symmetrical measures in order to avoid another disadvantage of MAPE and MdAPE, for example, too large penalizing made to positive errors in comparison with the negative ones.

- Mean Absolute Percentage Error (sMAPE) = average ($\frac{|X_t - F_t|}{X_t + F} \cdot 200$)
- Symmetric Median Absolute Percentage Error (sMdAPE) = median ($\frac{|X_t - F_t|}{X_t + F} \cdot 200$), where F_t – forecast of X_t.

➢ *Measures based on relative errors*

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

- Mean Relative Absolute Error (MRAE) = average ($|r_t|$)
- Median Relative Absolute Error (MdRAE) = median ($|r_t|$)
- Geometric Mean Relative Absolute Error (GMRAE) = geometric mean ($|r_t|$)

A major disadvantage is the too low value for the error of benchmark forecast.

➢ *Relative measures*

For example, the relative RMSE is calculated:

$rel\_RMSE = \frac{RMSE}{RMSE_b}$, *where* $RMSE_b$ is the RMSE of “benchmark model”

Relative measures can be defined for MFA MdAE, MAPE. When the benchmark model is a random walk, it is used rel_RMSE, which is actually Theil’s U statistic. Random walk or naive model is used the most, but it may be replaced with naive2 method, in which the forecasts are based on the latest seasonally adjusted values according to Makridakis, Wheelwright and Hyndman (1998).

- **Free-scale error metrics (resulted from dividing each error at average error)**

Hyndman and Koehler (2005) introduce in this class of errors “Mean Absolute Scaled Error” (MASE) in order to compare the accuracy of forecasts of more time series.

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)

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

These measures of accuracy have some disadvantages. For example, RMSE is affected by outliers. Armstrong and Collopy (2000) stress that these measures are not independent of the unit of measurement, unless they are expressed as percentage. These measures include average errors with different degrees of variability. The purpose of using these indicators is related to the characterization of distribution errors. Clements and Hendry (1995) have proposed a generalized version of the RMSE based on errors inter-correlation, 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.

U Theil’s statistic is calculated in two variants by the Australian Tresorery 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

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

If U_1 is closer to one, the forecast 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

Other authors, like Fildes R. and Steckler H. (2000) use another criterion to classify the 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.

Clements and Hendry (2010) presented the most used accuracy measures in literature, which are described below.

1. *The specific loss function*

Diebold, Gunther and Tay (1998) started from a loss function $L(a_t, x_{t+1})$, where:

a_t − specific action

$x_{t+1} \rightarrow f(x_{t+1})$ − the future value of a random variable whose distribution is known

f (.) − density forecast

The optimal condition involves minimizing the loss function when the density forecast is

$$p_{t,1}(x_{t+1}): \; a^*_{t,1} = \underset{a_{t,1} \in A}{\arg\min} \int L(a_{t,1}, x_{t+1}) p_{t,1}(x_{t+1}) dx_{t+1}$$

The expected value of loss function is:

$$E[L(a^*_{t,1}, x_{t+1})] = \int L(a^*_{t,1}, x_{t+1}) f(x_{t+1}) dx_{t+1}$$

The density forecast will be preferred above any other density for a given loss function if the following condition is accomplished:

$$E[L(a^*_{t,1}(p_{t,1}(x_{t+1})), x_{t+1})] < E[L(a^*_{t,2}(p_{t,2}(x_{t+1})), x_{t+1})],$$

where $a^*_{t,i}$ – the optimal action for the following forecast: $p_{t,i}(x)$.

Making decisions based on forecast accuracy evaluation is important in macroeconomics, but few studies have focused on this. Notable achievements on forecasts performance evaluation were made in practical applications in finance and in metrology. Recent improvements refer to the inclusion of disutility that is presented in actions in the future states and take into account the entire distribution of forecast. Since an objective assessment of prediction errors cost cannot be made, only general absolute loss functions – loss or loss of error squares can be used.

2. *Mean square forecast error (MSFE) and the second error of the generalized forecast (GFESM)*

The most used measure to assess the forecasts accuracy is the mean square forecast error (MSFE). In case of a vector of variables, a MSFE matrix will be built: $V_h \equiv E[e_{T+h}e'_{T+h}] = V[e_{T+h}] + E[e_{T+h}]E[e'_{T+h}]$, where e_{T+h} – vector of errors with h steps-ahead-forecast.

The trace and the determinant of the mean square errors matrix are classical measures of forecast accuracy.

Generalized forecast error second moment (GFESM) is calculated according to Clements and Hendry (1993) as a determinant of the expected value of the forecast errors vector for future moments up to the horizon of interest. If forecasts up to a horizon of h quarters present interest, this indicator is calculated as:

$$GFESM = \left| E\left| \begin{pmatrix} e_{t+1} \\ e_{t+2} \\ \dots \\ e_{t+h} \end{pmatrix} \right| \cdot \left| \begin{pmatrix} e_{t+1} \\ e_{t+2} \\ \dots \\ e_{t+h} \end{pmatrix}^T \right| \right|.$$

e_{t+h} – n-dimensional forecast error of n variables model on horizon h

It is considered that GFESM is a better measure of accuracy, because it is invariant to elementary operations with variables, unlike the MSFE trace and it is also a measure that is invariant to basic operations of the same variables on different horizons of prediction, in contrast with MSFE matrix trace and determinant.

Clements and Hendry (1993) showed that the MSFE disadvantages related to invariance models are determined by the lack of invariance indicator non singular linear transformations, that preserves the scale. MSFE comparisons determined inconsistent ranks of forecast performance of different models with several steps along the variables transformations.

3. *Measures of relative accuracy*

Relative measure for assessing forecast accuracy suppose the comparison of forecast with one of reference, called in literature as "benchmark forecast" or "naïve forecast". However, the choice of forecast used for comparison remains a subjective approach. Problems that may arise in this case are related to: the existence of outliers or inappropriate choice of models on which forecasts are developed, and the emergence of shocks. A first measure of relative accuracy is Theil's U statistic, for which the reference forecast is the last observed value recorded in the data series. Collopy and Armstrong proposed a new indicator instead of U statistics similar (RAE). Thompson improved MSE indicator, proposing a statistically determined MSE (mean squared error log ratio).

Relative accuracy can also be measured by comparing predicted values with those based on a model built using data from the past. The tests of forecast accuracy compare an estimate of forecast error variance derived from the past residue and the current MSFE.

To check whether the differences between mean square errors corresponding to the two alternative forecasts are statistically significant the tests proposed by Diebold and Mariano, West, Clark and McCracken, Corradi and Swanson, Giacomini and White are used.

Starting from a general loss function based on predictive ability tests, the accuracy of two alternative forecasts for the same variable is compared. The first results obtained by Diebold and Mariano were formalized, as showed Giacomini and White (2006), by West, McCracken, Clark and McCracken, Corradi, Swanson and Olivetti, Chao, Corradi and Swanson. Other researchers started from the particular loss function (Granger and Newbold, Leitch and Tanner, West, Edison and Cho, Harvey, Leybourne and Newbold).

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 the introduction of a new statistical test is necessary.

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 et al. (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 generated 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 macroeconomic 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) 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.

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.

3. *The models used to make macroeconomic forecasts*

The variables used in models are: the inflation rate calculated starting from the harmonized index of consumer prices, unemployment rate and interest rate on short term. The last indicator is calculated as average of daily values of interest rates on the market. The data series are monthly ones and they are taken from

Eurostat website for the period from February 1999 to October 2011 for Czech Republic. The indicators are expressed in comparable prices, the reference base being the values from January 1999. We eliminated the influence of seasonal factors for the inflation rate using Census X11 (historical) method.

In Czech Republic only the date series for inflation and unemployment rate were transformed to become stationary.

Taking into account that our objective is the achievement of one-month-ahead forecasts for December 2011, January and February 2012, we considered necessary to update the models. We used three types of models: a VAR(2) model, an ARMA one and a model in which inflation and interest rate are explained using variables with lag. The econometric models used for Czech Republic are specified in **Appendix 1**.

We developed one-month-ahead forecasts starting from these models, then we evaluated their accuracy. The one-step-ahead forecasts for the 3 months were presented in **Appendix 2**.

4. *The assessment of accuracy for predictions based on econometric models*

A generalization of Diebold-Mariano test (DM) is used to determine whether the MSFE matrix trace of the model with aggregation variables is significantly lower than that of the model in which the aggregation of forecasts is done. If the MSFE determinant is used, according to Athanasopoulos and Vahid (2005), the DM test cannot be used in this version, because the difference between the two models MSFE determinants cannot be written as an average. In this case, a test that uses a bootstrap method is recommended.

The DM statistic is calculated as:

$$DM_t = \frac{\sqrt{T}\cdot[tr(MSFE_{VAR(2)\ \mathrm{mod}\,el})_h - tr(MSFE_{ARMA\,\mathrm{mod}\,el})_h]}{s} = \frac{1}{s}\cdot\sqrt{T}\cdot[\frac{1}{T}\sum_{t=1}^{T}(em_{1,1,t}^2 + em_{2,1,t}^2 + em_{3,1,t}^2 - er_{1,1,t}^2 - er_{2,1,t}^2 - er_{3,1,t}^2)] \quad (1)$$

T − number of months for which forecasts are developed

$em_{i,h,t}$ − the h-steps-ahead forecast error of variable i at time t for the VAR(2) model

$er_{i,h,t}$ − the h-steps-ahead forecast error of variable i at time t for the ARMA

s – the square root of a consistent estimator of the limiting variance of the numerator

The null hypothesis of the test refers to the same accuracy of forecasts. Under this assumption and taking into account the usual conditions of central limit theorem for weakly correlated processes, DM statistic follows a standard normal asymptotic distribution. For the variance the Newey-West estimator with the corresponding lag-truncation parameter set to $h-1$ is used.

On 3 months we compared in terms of accuracy the predictions for all the three variables, predictions made starting from VAR(2) models and ARMA models. Calculating DM statistics the accuracy of forecasts based on VAR models is higher than that based on ARMA models for all chosen countries.

In **Table 1** the accuracy indicators for the predictions are displayed.

Table 1

Indicators of forecasts accuracy for the inflation, unemployment and interest rate (Czech Republic)

Inflation rate	Models used to build the forecasts		
Indicators of accuracy	VAR(2)	ARMA	Models with lag
RMSE	0,17051339	0,8532325	3,6277209
ME	-0,6694	0,0955	-3,9449
MAE	1,3694	0,6045	4,6449
MPE	-0,0650	-0,0336	-0,2550
U1	0,051257	0,017019	0,151515
U2	1,388935	0,981571	2,980709
Unemployment rate	Models used to build the forecasts		
Indicators of accuracy	VAR(2)	ARMA	
RMSE	0,57231311	2,0922862	
ME	-0,51277	-2,09223	
MAE	0,512767	2,092233	
MPE	-0,07696	-0,31383	
U1	0,040086	0,186124	
U2	3,914625	15,89517	
Interest rate	VAR(2)	ARMA	
RMSE	0,03663478	0,3635292	
ME	0,0052	-0,3693	
MAE	0,0164	0,3693	
MPE	0,0100	-0,5302	
U1	0,014359	0,36058	
U2	0,761926	14,99092	

Source: own calculations using Excel.

In Czech Republic, when an econometric models was used to make forecasts, the ARMA procedure is the most suitable for the inflation rate, while the best results are given by VAR(2) models for unemployment and interest rate. However, only the predictions based on the ARMA models for inflation rate and on VAR for the interest rate are better than those that used the naïve model.

For Czech Republic only VAR and ARMA models could be built to explain the evolution of the interest rate. Best results for the interest rate in Czech Republic are given also by the VAR models.

5. ***The assessment of accuracy for predictions based on exponential smoothing techniques***

Exponential smoothing is a technique used to make forecasts as the econometric modelling. It is a simple method that takes into account the more recent data. In other words, recent observations in the data series are given more weight in predicting than the older values. Exponential smoothing considers exponentially decreasing weights over time.

4. *Simple exponential smoothing method (M1)*

The technique can be applied for stationary data to make short run forecasts. Starting from the formula of each rate $R_n = a + u_n$, where a is a constant and u_t – resid, s − seasonal frequency, the prediction for the next period is:

$$\hat{R}'_{n+1} = \alpha \times R'_n + (1-\alpha) \times \hat{R}'_n \text{ , } n = 1,2,...,t+k \tag{2}$$

α is a smoothing factor, with values between 0 and 1, being determined by minimizing the sum of squared prediction errors.

$$\min \frac{1}{n}\sum_{i=0}^{n-1}(R'_{n+1} - \hat{R}'_{n+1})^2 = \min \frac{1}{n}\sum_{i=0}^{n-1} e_{n+1}^2 \tag{3}$$

Each future smoothed value is calculated as a weighted average of the n past observations, resulting:

$$\hat{R}'_{n+1} = \alpha \times \sum_{i=1}^{n}(1-\alpha)^i \times \hat{R}'_{n+1-s} \text{ .} \tag{4}$$

5. *Holt-Winters Simple exponential smoothing method (M2)*

The method is recommended for data series with linear trend and without seasonal variations, the forecast being determined as:

$$R_{n+k} = a + b \times k \text{ .} \tag{5}$$

$$a_n = \alpha \times R_n + (1-\alpha) \times (a_{n-1} + b_{n-1}) \tag{6}$$

$$b_n = \beta \cdot (a_n - a_{n-1}) + (1-\beta) \cdot b_{n-1}$$

Finally, the prediction value on horizon k is:

$$\hat{R}_{n+k} = \hat{a}_n + \hat{b}_n \times k \tag{7}$$

6. *Holt-Winters multiplicative exponential smoothing method (M3)*

This technique is used when the trend is linear and the seasonal variation follows a multiplicative model. The smoothed data series is:

$$\hat{R}'_{n+k} = (a_n + b_n \times k) \times c_{n+k} \tag{8}$$

where a − intercept, b − trend, c − multiplicative seasonal factor

$$a_n = \alpha \times \frac{R'_n}{c_{n-s}} + (1-\alpha) \times (a_{n-1} + b_{n-1})$$
$$b_n = \beta \times (a_n - a_{n-1}) + (1-\beta) \times b_{n-1} \quad (9)$$
$$c_n = \gamma \times \frac{R'}{a_n} + (1-\gamma) \times c_{n-s}$$

The prediction is:

$$\hat{R}'_{n+k} = (\hat{a}_n + \hat{b}_n \times k) \times \hat{c}_{n+k} . \quad (10)$$

7. *Holt-Winters additive exponential smoothing method (M4)*

This technique is used when the trend is linear and the seasonal variation follows a multiplicative model. The smoothed data series is (14):

$$\hat{R}'_{n+k} = a_n + b_n \times k + c_{n+k}$$

a − intercept, b − trend, c − additive seasonal factor

$$a_n = \alpha \times (R'_n - c_{n-s}) + (1-\alpha) \times (a_{n-1} + b_{n-1})$$
$$b_n = \beta \times (a_n - a_{n-1}) + (1-\beta) \times b_{n-1} \quad (11)$$
$$c_n = \gamma \times (R'_n - a_n) + (1-\gamma) \times c_{n-s}$$

The prediction is:

$$\hat{R}'_{n+k} = \hat{a}_n + \hat{b}_n \times k + \hat{c}_{n+k} . \quad (12)$$

8. *Double exponential smoothing method (M5)*

This technique is recommended when the trend is linear, two recursive equations being used:

$$S_n = \alpha \times R_n + (1-\alpha) \times S_{n-1} \quad (13)$$

$D_n = \alpha \times S_n + (1-\alpha) \times D_{n-1}$, where S and D are simple, respectively double smoothed series.

In **Table 2** the accuracy indicators for predictions based on exponential smoothing techniques are presented for all the three countries. Analyzing the values of these indicators, the smoothing method is better than the econometric models for the mentioned countries.

Indeed, the exponential smoothing techniques provided the most accurate predictions for all indicators in Czech Republic. For the inflation rate the best method to be applied was additive exponential smoothing technique, while for unemployment and interest rate the simple exponential smoothing technique generated the best results due to the value of U1 that is very closed to zero. All the predictions for the unemployment rate based on the exponential smoothing techniques are more accurate than those based on the naïve model. All forecasts are overestimated on the chosen horizon, excepting those of the unemployment rate in case of Holt-Winters and double smoothing method and those of interest rate when the additive technique is used. The low values for RMSE imply a low variability in the data series.

Table 2

Measures of accuracy for forecasts based on exponential smoothing techniques for inflation, unemployment and interest rate (Czech Republic)

Inflation rate	RMSE	ME	MAE	MPE	U1	U2
M1	0,288386455	-1,73383	1,800501	-0,08296	0,056005	1,545809
M2	1,119007113	-1,50076	1,567428	-0,08027	0,049381	0,189913
M3	-	-	-	-	-	-
M4	0,859249004	-0,53664	0,603307	-0,03108	0,01775	0,947732
M5	1,039570357	-1,45292	1,519589	-0,0779	0,0475	0,228745
Unemployment rate						
M1	0,081731	-0,03343	0,033433	-0,00499	0,004345	0,43671
M2	0,058351	0,049443	0,049443	0,007421	0,00436	0,44044
M3	0,111016	-0,07804	0,09456	-0,01163	0,008375	0,836498
M4	0,116203	-0,0839	0,100421	-0,0125	0,00877	0,87466
M5	0,048776	0,01744	0,044912	0,002621	0,003653	0,365749
Interest rate						
M1	0,033121	-0,01294	0,022964	-0,01635	0,021484	1,125963
M2	0,045165	-0,01788	0,030232	-0,02586	0,02999	2,013734
M3	0,098583	-0,09484	0,094845	-0,13656	0,075181	4,417344
M4	0,076148	0,014587	0,094149	0,022764	0,068091	3,35745
M5	0,03487	-0,01772	0,023895	-0,02554	0,0225	1,657338

Source: own computations using Excel.

5. ***Conclusions***

In our research we proposed to check if the exponential smoothing techniques generate better short run predictions than the simple econometric models.

According to some recent researches, simple econometric models are recommended for forecasts due to the high degree of accuracy for predictions. For prognosis made for December 2011- February 2012 this hypothesis is not checked for Czech Republic.

In Czech Republic the recent values in the data series used for predictions have the biggest importance. Therefore, the exponential smoothing methods determined the best results in terms of forecasts accuracy. Simple and additive exponential smoothing techniques are recommended for Czech Republic.

To improve the policy we can use monthly forecasts based on the better method for that country. The policy is improved by choosing the most accurate forecast which will help the government or the banks in taking the best decisions. In our study we analyzed the results of only two quantitative methods, but the research could be extended by adding other quantitative forecasting methods or by using qualitative methods or predictions based on combinations of the two types of methods.

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APPENDICES

APPENDIX 1

Models used for one-month-ahead forecasts (Czech Republic)

Reference period of data series	VAR(2)
February 1999-November 2011	INTEREST_CR = 1.032955367*INTEREST_CR(-1) - 0.07435234854*INTEREST_CR(-2) + 0.01622901437*RI_CR(-1) - 0.02073687184*RI_CR(-2) - 0.2030556239*UR_CR(-1) + 0.1918379768*UR_CR(-2) + 0.1620812519 RI_CR = 0.07613664735*INTEREST_CR(-1) - 0.08479586276*INTEREST_CR(-2) + 1.091002306*RI_CR(-1) - 0.1006512028*RI_CR(-2) - 0.1904207202*UR_CR(-1) + 0.1284548155*UR_CR(-2) + 0.6752498405 UR_CR = - 0.1503567547*INTEREST_CR(-1) + 0.1438367589*INTEREST_CR(-2) - 0.01694177212*RI_CR(-1) + 0.0156354488*RI_CR(-2) + 1.616200903*UR_CR(-1) - 0.633750514*UR_CR(-2) + 0.1397074831
February 1999-December 2011	INTEREST_CR = 1.03212544*INTEREST_CR(-1) - 0.07367847639*INTEREST_CR(-2) + 0.01566704719*RI_CR1(-1) - 0.02030389812*RI_CR1(-2) - 0.2054864774*UR_CR1(-1) + 0.1938526614*UR_CR1(-2) + 0.1654661173 RI_CR1 = 0.08149977622*INTEREST_CR(-1) - 0.08915054128*INTEREST_CR(-2) + 1.094633835*RI_CR1(-1) - 0.103449154*RI_CR1(-2) - 0.1747121244*UR_CR1(-1) + 0.1154355747*UR_CR1(-2) + 0.6533762543 UR_CR1 = - 0.1495715212*INTEREST_CR(-1) + 0.143199176*INTEREST_CR(-2) - 0.01641006788*RI_CR1(-1) + 0.01522579148*RI_CR1(-2) + 1.61850085*UR_CR1(-1) - 0.6356567043*UR_CR1(-2) + 0.1365048988
February 1999-January 2011	INTEREST_CR = 1.031008851*INTEREST_CR(-1) - 0.07233575969*INTEREST_CR(-2) + 0.01671004085*RI_CR1(-1) - 0.02111360193*RI_CR1(-2) - 0.2024762562*UR_CR1(-1) + 0.1916516303*UR_CR1(-2) + 0.1588725354 RI_CR1 = 0.05833066638*INTEREST_CR(-1) -

	0.06128930788*INTEREST_CR(-2) + 1.116275846*RI_CR1(-1) - 0.1202504248*RI_CR1(-2) - 0.112250345*UR_CR1(-1) + 0.06976440581*UR_CR1(-2) + 0.5165601085 UR_CR1 = - 0.1488160438*INTEREST_CR(-1) + 0.1422907021*INTEREST_CR(-2) - 0.01711575102*RI_CR1(-1) + 0.01577363214*RI_CR1(-2) + 1.616464153*UR_CR1(-1) - 0.6341675*UR_CR1(-2) + 0.140966076

Reference period of data series	ARMA
February 1999-November 2011	$ri\_cr_t = 0{,}152 + 0{,}985 \cdot ri\_cr_{t-1} - 0{,}972 \cdot \varepsilon_{t-3} + \varepsilon_t$ $ur\_cr_t = -0{,}012 + 0{,}688 \cdot ur\_cr_{t-1} + \varepsilon_t$ $\text{int}\,erest\_cr_t = 1{,}662 + 0{,}958 \cdot \text{int}\,erest_{t-1} + \varepsilon_t$
February 1999-December 2011	$ri\_cr_t = 0{,}152 + 0{,}987 \cdot ri\_cr_{t-1} - 0{,}972 \cdot \varepsilon_{t-3} + \varepsilon_t$ $ur\_cr_t = -0{,}0127 + 0{,}689 \cdot ur\_cr_{t-1} + \varepsilon_t$ $\text{int}\,erest\_cr_t = 1{,}667 + 0{,}959 \cdot \text{int}\,erest_{t-1} + \varepsilon_t$
February 1999-January 2011	$ri\_cr_t = 0{,}153 + 0{,}988 \cdot ri\_cr_{t-1} - 0{,}973 \cdot \varepsilon_{t-3} + \varepsilon_t$ $ur\_cr_t = -0{,}013 + 0{,}689 \cdot ur\_cr_{t-1} + \varepsilon_t$ $\text{int}\,erest\_cr_t = 1{,}667 + 0{,}96 \cdot \text{int}\,erest_{t-1} + \varepsilon_t$

Reference period of data series	Models having variables with lags
February 1999-November 2011	$ri\_cr_t = 0{,}197 - 0{,}546 \cdot ur_{t-2} + \varepsilon_t$
February 1999-December 2011	$ri\_cr_t = 0{,}198 - 0{,}546 \cdot ur_{t-2} + \varepsilon_t$
February 1999-January 2011	$ri\_cr_t = 0{,}198 - 0{,}5463 \cdot ur_{t-2} + \varepsilon_t$

Source: own calculations using EViews.

One-month-ahead forecasts based on econometric models (Czech Republic)

Inflation rate	VAR(2) models	ARMA models	Models with lags
December 2011	16,6238	16,411	13,2974
January 2012	16,7299	16,9035	13,4066
February 2012	16,638	18,972	13,4612

Unemployment rate	VAR(2) models	ARMA models
December 2011	6,0388	4,5288
January 2012	6,2199	4,5969
February 2012	6,203	4,5976

Interest rate	VAR(2) models	ARMA models
December 2011	0,70482	0,34218
January 2012	0,67838	0,32302
February 2012	0,72238	0,31685

Source: own calculations using Excel.