IS THE PRECISION OF THE EX POST FORECAST ERRORS HELPFUL TO CHOOSE A GOOD FORECASTING MODEL?

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Abstract

In this paper we show possible ways of obtaining some information about applicability of forecasting model and its probable accuracy in computing ex ante forecasts using accuracy of ex post forecast errors, which are made at the same time when the extrapolative model is looking for. We will use the Theil coefficient of inequality to show how well the model fits the data during the time period for which the ex post forecasts are computed. The Theil decomposition of mean square of ex post forecast errors will be used to show sources of possible bias in their means or variances. Six months ex post forecasts will be computed for the unemployment rate in Slovakia using the SARIMA model in repeating mode to analyze its stability after adding six new observations and computing six months ex post forecasts.

Keywords

ex post and ex ante forecasts, Theil coefficient of inequality, Theil decomposition of mean square of ex post forecast errors, unemployment rate

I. Introduction

Our experience in Box-Jenkins ARIMA modelling and creating extrapolative forecasts for monthly unemployment variables (Institute for Forecasting CSPS SAS, 2012 - 2018) showed us various precision of ex ante forecasts computed with the horizont of six months ahead, from the last known observation of the series (six-period forecast). Variability of ex ante forecasts could be explain partially herewith using the Box-Jenkins methodology, which could offer more than one model "quite good" for extrapolative purposes based on the analysis of residuals of the estimated model that fits the past data very well, but the outcomes of forecast are different. The question is - why is there such variability? Is it because the model has not been chosen correctly or because there are other reasons, which have been started to influence the outcomes of forecasted variable?

To get answer about the correctness of forecasting model, it is necessary to provide a quantitative and the qualitative evaluation of the ex-ante forecast errors in order to know whether the same model would be possible to use in a repeating mode.

Ex ante evaluation is rarely done because it needs to wait for several time periods (for example six months) to get the actual values and ex ante forecast errors to evaluate their real accuracy. For this causation, forecasters want to visualize the precision of its forecasting model in advance, before he or she could evaluate ex ante forecasts accurately.

In this paper, we show one possible way of obtaining some information about applicability of forecasting model and its probable accuracy in future, using ex post forecast errors at the same time as when the extrapolative model is looking for accuracy.

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II. Time series, training set and test set

Assume time series data y_t , t = 1, 2, ..., T, with T observations of the variable Y we want to forecast to the horizont h = 1, 2, ..., H beyond the last observation y_T . The values $\hat{y}_{T+1}(T), \hat{y}_{T+2}(T), \ldots, \hat{y}_{T+H}(T)$ are called ex ante forecast or m-period forecast with the starting period T. The differences $fe_{T+h}(T) = y_{T+h} - \hat{y}_{T+h}(T)$ are called ex ante forecast errors for horizont h = 1, 2, ..., H. Our aim is to look for an extrapolative model, which we assume that would forecast future values of variable Y with the smallest ex ante forecast errors.

To get an idea how precise the model will produce ex ante forecasts before the actual values are known, we will use the technique of splitting the series to two samples called the training set (with N = T – m observations) and the test set (with m observations). The training set is usually called in the sample period or estimation period. The test set is also called out of the sample period or validation period.

The training set is used to look for the model, to make its estimation and verification by means of its residuals using tests for independence, homoscedasticity and normality. All these tests are mentioned in Rublíková's (2007) research.

Sometimes several models are verified in the estimation period, and then the Akaike information criterion (1976) could be used to choose the best model with the smallest value. This criterion is mostly used with the computer automatic building model.

The descriptive statistics of residuals like RSME, MAE, MPE, and MAPE give us an idea how good the model fits the data in the training set and these measures we could treat as the measures of future forecast accuracy in one time period ahead. If these measures are small, the verified model is suggested as the forecasting model to produce extrapolative m – period forecast (ex post forecast $\hat{y}_{N+j}(N)$, j = 1, 2, ..., m), in the test set (validation period). Because the data of the test set together with their ex post forecast are known, we can statistically evaluate the ex post forecast errors $e_{N+j}(N) = y_{N+j} - \hat{y}_{N+j}(N)$ for j = 1, 2, ..., m, to make an idea, how well the model used forecasts known values. These m – period ex post forecast errors are summarised by means of RMSE, MAE, MAPE, ME, MPE, which could be larger in comparison with the same statistics of residuals in the training set. The values of ME and MPE need not be close to zero so they are counted as the measures of bias. If they are positive, the model systematically underestimates actual values or if they are negative the model systematically over estimate actual values. The bias and its sources would be explained by the Theil decomposition of MSEex-post published in 1961 (Theil, 1961).

Other useful statistics is the Theil inequality coefficient U, which indicates the model goodness of fit in the test set (validation period or out of sample set). Both Theil formulas are taken from Pindyck and Rubenfeld (1981: 364 - 365).

Quantitative evaluation of ex post forecast errors would be used to inform the forecaster how close the forecast came to describing the outcome of variable forecasted beyond the last observation in estimation period.

III. Measures of ex post forecast accuracy

Assume we have m-values of the test set (validation period) in time series y_t for t = 1, 2, ..., T, where T is the number of observations of the series. Assume the estimated and verified model on the training set N (estimation period) shows small measures of residuals RMSE, MAE, MAPE, ME, MPE, so the model is used to compute the *m-period* ex post forecast in the test set. Because the last m values of the time series are known, we can compute ex post forecast errors:

$$e_{N+j}(N) = y_{N+j} - \hat{y}_{N+j}(N) \qquad j = 1, 2, ..., m \qquad (1)$$

Where y_{N+j} actual value of the series taken from the test set (validation period);

$\hat{y}_{N+j}(N)$ ex post forecast in the test set (validation period);

m number of observations in the test set (validation period).

Descriptive measures of ex post forecast errors provide a single and easily interpreted measure of model´s usefulness or reliability.

The ex post mean absolute error measures forecast accuracy in the same units as the original series by averaging the magnitude of the forecast errors. The formula is:

$$MAEex-post = \frac{1}{m}\sum_{j=1}^{m} \left| y_{N+j} - \hat{y}_{N+j}(N) \right| \qquad (2)$$

The ex post RMSE forecast error (root mean square error), a very important criterion for model performance, is defined as:

$$RMSEex-post = \sqrt{\frac{1}{m}\sum_{j=1}^{m}(y_{N+j} - \hat{y}_{N+j}(N))^2} \qquad (3)$$

The mean absolute percentage ex post forecast error MAPEex-post is defined as:

$$MAPEex-post = \frac{1}{m}\sum_{j=1}^{m}\frac{\left| y_{N+j} - \hat{y}_{N+j}(N) \right|}{y_{N+j}} 100\,\% \qquad (4)$$

and gives us an indication of how large the forecast errors are in comparison to the actual values of the series.

The last two measures are measures of bias, which the model could perform in the future.

The mean ex post forecast error is given by the formula:

$$MEex-post = \frac{1}{m}\sum_{j=1}^{m} \left(y_{N+j} - \hat{y}_{N+j}(N) \right) \qquad (5)$$

and used to inform us whether the model overestimate (underestimate) actual values.

The mean percent error, MPEex post error is defined as:

$$MPEex-post = \frac{1}{m}\sum_{i=1}^{m}\frac{y_{N+J} - \hat{y}_{N+j}(N)}{y_{N+j}} 100\,\% \qquad (6)$$

Other useful criterion is Theil´s inequality coefficient, defined as:

$$U = \frac{\sqrt{\frac{1}{m}\sum_{j=1}^{m}(y_{N+j} - \hat{y}_{N+j}(N))^2}}{\sqrt{\frac{1}{m}\sum_{j=1}^{m} y_{N+j}{}^2} + \sqrt{\frac{1}{m}\sum_{j=1}^{m}\hat{y}^2{}_{N+j}(N)}} \qquad (7)$$

If U = 0 *the model forecasts perfectly*. The smallest the U is, the forecasting performance of the model is better.

U = 1 the forecasting performance of the model is as bad as it possibly could be.

Theil also developed a decomposition of the MSEex-post into three components, each addressing a different aspect of forecast accuracy.

$$MSEex-post = (\bar{\hat{y}} - \bar{y})^2 + (s_{\hat{y}} - s_y)^2 + 2(1-r)s_{\hat{y}}s_y$$

$$1 = \frac{(\bar{\hat{y}} - \bar{y})^2}{MSEex-post} + \frac{(s_{\hat{y}} - s_y)^2}{MSEex-post} + \frac{2(1-r)s_{\hat{y}}s_y}{MSEex-post}$$

$$1 = U_M + U_V + U_C \qquad (8)$$

where:

$$MSEex-post = \frac{1}{m}\sum_{j=1}^{m}(y_{N+j} - \hat{y}_{N+j}(N))^2$$

y_{N+j} $j = 1, 2, ..., m$ actual value of the series from the test set (validation period)

$\hat{y}_{N+j}(N)$ $j = 1, 2, ..., m$ ex post forecast in the test set, started in the period N

$\bar{\hat{y}} = \frac{1}{m}\sum_{j=1}^{m}\hat{y}_{N+j}(N)$ the average of ex post forecasts

$\bar{y} = \frac{1}{m}\sum_{j=1}^{m}y_{N+j}$ the average of actual values in the test set

$s_{\hat{y}} = \sqrt{\frac{1}{m}\sum_{j=1}^{m}(\hat{y}_{N+j}(N) - \bar{\hat{y}})^2}$ the standard deviation of the ex post forecasts in the test set

$s_y = \sqrt{\frac{1}{m}\sum_{j=1}^{m}(y_{N+j} - \bar{y})^2}$ the standard deviation of the actual values in the test set

$$r = \frac{\frac{1}{m}\sum_{j=1}^{m}(y_{N+1} - \bar{y})(\hat{y}_{N+j}(N) - \bar{\hat{y}})}{s_{\hat{y}}.s_y} \in <-1, 1>$$ the Pearson´s coefficient of correlation between actual and forecasted series

Each of the three components in formula (8), called U_M, U_V, and U_C, can be interpreted as a proportion or percentage of the MSEex-post.

The bias proportion U_M (M stands for the difference in the means) is an indication of systematic error, since it measures the extent to which the average values of the ex post forecasts and actual series deviate from each other. Whatever the value of the inequality coefficient, we would hope that U_M would be close zero. A large value of U_M (above 0.1 - 0.2 or above 10 - 20 percent) would be quite troubling since it would mean that systematic bias is present, so that a revision of the model is necessary.

The variance proportion U_V (V stands for variance) indicates the ability of the model to replicate the degree of variability in the variable of interest. It is desirable to have $U_V = 0$. If U_V is large, it means that the actual values has fluctuated considerably while the ex post forecast values shows little fluctuation, or vice versa. Such a model is also troubling and it might lead us to revise the model.

The covariance proportion U_C measures unsystematic forecast error, i.e. it represents the remaining error after deviations from average values and average variabilities have been accounted for. Since it is unreasonable to expect forecasts that are perfectly correlated with actual values, this component of error is less worrisome.

The ideal distribution of inequality over the three sources is $U_M = U_V = 0$ and $U_C = 1$.

The RMSEex-post statistics is a very useful criterion for forecast performance of the model. When we are ready to forecast the future in real time, because we are satisfied with the ex-post forecast characteristics, then we use *all* the available data for estimation (whole time series with T observations), which means that the most recent data is used and the test set (validation period) is zero time periods.

Forecasts into the future are "true" forecasts that are made for time periods beyond the end of the time series T for horizont *h* = 1, 2, ..., H, or for the observations in time periods T + 1, T + 2. ..., T + H. The ex ante forecast errors $fe_{T+h}(T) = y_{T+h} - \hat{y}_{T+h}(T)$ for horizont *h* = 1, 2, ..., H time periods ahead may be evaluated only when the real values are available.

Most forecasting software is capable of performing ex ante forecasts automatically with 95% confidence intervals. The confidence intervals typically *widen* as the forecast horizont increases, due to the expected build-up of error in the bootstrapping process: first a one-period-ahead forecast is made, then the one-period-ahead forecast is treated as a data point and the model is cranked ahead to produce a two-period-ahead forecast, and so on as far as we wish. The rate at which the confidence intervals widen is in general a function of the type of forecasting model selected.

IV. Data

The unemployment rate in Slovakia is a very important indicator of the labour market activity; hence, our interest is focused upon preparing the forecasts as precise as they could be. We will work with the monthly time series of unemployment rate from January 2001 till December 2017. The data explains the registered unemployment rate at the end of month published by the Central Office of Labour (2018), Social Affairs and Family in Bratislava. This series will be spliced to the training set and to the test set two times in such a way, that six new observations will be added to previous training set and six new observations will create the test set in order to analyse not only the stability of the estimated model but also to find out whether the descriptive statistics of ex post forecast errors are changing as well.

We will start to work with the time series from January 2001 to June 2017, with the length T = 198 observations. We will split the series to the training set (estimation period) with N = 192 observations (January 2001 to December 2016) and the test set (validation period) with *m* = 6 observations (January 2017 to June 2017).

On the training set (January 2001 to December 2016) model SARIMA will be selected, estimated and tested for statistical significance of its parameters, independence, homoscedasticity and normality of residuals. The verified model will be used to compute ex post forecast in the test set (validation period) for the six months ahead $j = 1, 2, ..., 6$, for January 2017 to June 2017, starting in December 2016. Hence, the descriptive characteristics of residuals with the ex post forecast errors will be computed and interpreted together with the Theil coefficient of inequality.

If the identified, estimated and tested SARIMA model shows good statistical results of ex post forecast errors, then the same model SARIMA will be applied again and estimated on the training set with N = 198 observations (January 2001 to June 2017). The test set will create the next six observations (July 2017 to December 2017) for which six months ex post forecasts will be computed, starting with period N = 198 (June 2017).

The results ex post forecast errors from both test sets will be compared to see how they could be changed if the series are expanded with the next six new observations.

In the end, the same model SARIMA will be applied for whole time series with T = 204 observations (from January 2001 to December 2017) to compute the ex ante 6–period forecast (January 2018 to June 2018), started in December 2017.

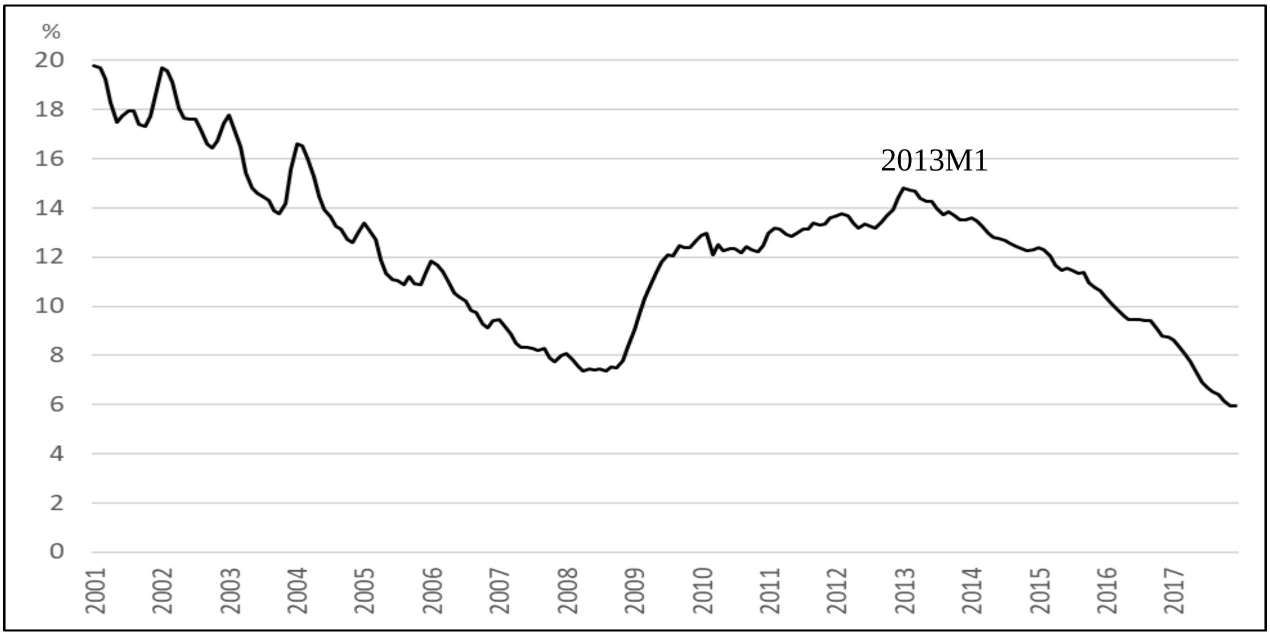
The series is used to observe two aims:

1. *Whether the Theil decomposition of MSE ex-post is useful tool for explaining bias of the forecasting model?*
2. *How well the verified model would compute 6-months ex ante forecasts after repeating it two times.*

V. Forecasting unemployment rate in Slovakia

In Figure 1 is realized the development of the unemployment rate in Slovakia during the period January 2001 to December 2017.

Figure 1: **Monthly time series of unemployment rate in Slovakia (January 2001 – December 2017)**

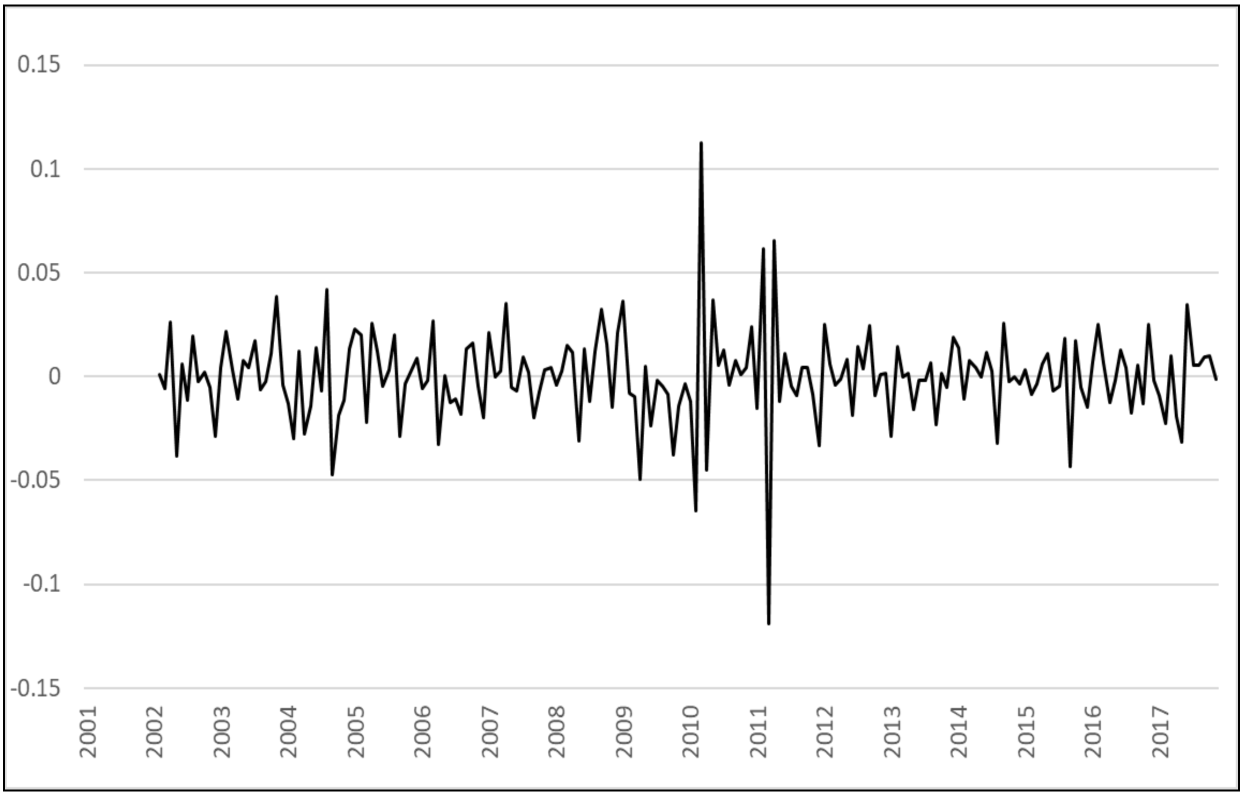


Source: Own computations; Central Office of Labour (2018)

As we can see form Figure 1 the development of unemployment rate (UR) is stochastic, nonstationary, changing the mean and variance, with stochastic seasonality. From January 2013 there is long time decreasing trend.

To stabilize variance the logarithmic transformation was used. To adjust the series from stochastic trend the second order of non-seasonal difference is applied. Stochastic seasonality was adjusted by the first order seasonal difference. The transformed time series $z_t = (1-B)^2(1-B^{12})\log(UR_t)$ for t = 15, 16... 204 is stationary and depicted in Figure 2.

Figure 2: The stationary unemployment rate (March 2002- December 2017)



Source: Own computations

The sample of N = 192 observations will create the training set (estimation period) and *m* = 6 observations will be the test set (out-of sample period or validation period V = 6 months) for which ex post forecast from January 2017 to June 2017 will be computed.

According to the properties of autocorrelation and partial autocorrelation function applied on transformed variable $z_t = (1-B)^2(1-B^{12})\log(UR)_t$, t = 15, 16, ..., 192, model SARIMA(0,2,1)(0,1,1)12 was selected, estimated and tested for independence, homoscedasticity and normality of its residuals with the results summarised as follows:

Estimation of the model SARIMA (0, 2, 1)(0, 1, 1)12 is:

$$(1-B)^2(1-B^{12})\log(UR_t) = (1-0.457874B)(1-0.565732B^{12})a_t \qquad (9)$$

(0.066992) (0.061146)

t = 15, 16, ..., 192

The parameters are statistically significant at 5 % level of significance (standard deviations of parameters are in parentheses), fulfilling invertibility conditions.

According to the *Box-Pierce test* based on the first 24 autocorrelations, with large statistic Q_{24} = 20.1708 and its P – value = 0.572359, the residuals form a random sequence of numbers. The condition of homoscedasticity for residuals is fulfil by the F–test and the normality was confirmed by the Shapiro-Wilk test with P–value = 0.15727.

The estimated model (9) was used to compute dynamic ex post forecast in the test set (validation period) with descriptive statistics of residuals and ex post forecast errors summarised in Table 1.

Table 1: The mean measures of residuals and 6-months ex post forecast errors for unemployment rate given by model (9)

Mean statistics model (9)	Estimation period	Validation period
	2001M01-2016M12	2017M01-2017M6
	Residuals	6 months ex post forecast errors
RMSE	0.218	0.126
MAE	0.157	0.104
MAPE	1.305	1.412
ME	–0.007	–0.087
MPE	–0.022	–1.198

Source: Own computations

It is evident from Table 1 that model overestimate actual values systematically, measures of bias (ME and MPE) are negative. Dynamic ex post forecasts of the unemployment rate for January 2017 to June 2017 are depicted in Table 2.

Table 2: Actual and ex post forecast of unemployment rate using model (9)

Period	Unemployment rate		
	Actual value	Ex post forecast	Ex post absolute error (%)
January 2017	8.64	8.66	0.231
February 2017	8.39	8.42	0.358
March 2017	8.04	8.14	1.244
April 2017	7.74	7.69	0.646
May 2017	7.35	7.5	2.041
Jun 2017	6.9	7.17	3.913

Source: Own computations

Theil inequality coefficient U = 0.00853 shows almost perfect fit in the test set, but Theil decomposition of MSEex-post (8) indicate systematic error, since 100 % = 41 % + 28 % + 31 % means that there is large proportion $U_M = 0.41$ or large bias (systematic overestimation of the actual values). Percentage errors in Table 2 are small for the first two months, but with increasing horizont, the percentage errors are growing. The reason is that dynamic forecasts are linear extrapolation of the previous forecasts.

In spite of the fact that the means of actual values and ex post forecasts are different inductive of proportion U_M larger than 20 %, it is possible to conclude that the model is good and would give precisions forecasts for short horizont of two months ahead.

To see whether the same model will give similar results in repeating mode, we will use the same model SARIMA(0,2,1)(0,1,1)12 with log unemployment rate for the estimation period (training set) January 2001 to June 2017 and the test set (validation period) from July 2017 to December 2017. The new model and its changes in parameters, descriptive statistics of residuals and 6 months ex post forecast errors together with Theil U and the decomposition of MSEex-post are as follows:

Estimation of the model SARIMA(0, 2, 1)(0, 1, 1)12 is:

$$\underset{}{(1-B)^2(1-B^{12})\log(UR_t) = (1-\underset{(0.06755)}{0.448275}B)(1-\underset{(0.05999)}{0{,}576166}B^{12})a_t} \qquad (10)$$

t = 15, 16, ..., 198

The parameters are statistically significant at the 5 % level of significance (standard deviations of parameters are in parentheses), fulfilling invertibility conditions. The values of estimated parameters are not changed considerably.

According to the *Box-Pierce test* based on the first 24 autocorrelations, with large statistic Q_{24} = 20.1326 and its P – value = 0.574745, we determine that the residuals form a random sequence of numbers. The condition of homoscedasticity for residuals is fulfilled by the F–test and the normality was confirmed by the Shapiro-Wilk test with P–value = 0.15192.

The estimated model (10) was used to compute dynamic ex post forecasts in the test set (validation period, July 2017 to December 2017) with the following results of their descriptive statistics depicted in Table 3.

Table 3: The mean measures of residuals and 6-months ex post forecast errors for unemployment rate given by model (10)

Mean statistics model (10)	Estimation period	Validation period
	2001M01-2017M06	2017M07-2017M12
	Residuals	6 months ex post forecast errors
RMSE	0.216	0.091
MAE	0.155	0.078
MAPE	1.307	1.219
ME	– 0.009	0.078
MPE	– 0.060	1.220

Source: Own computations

Again, the mean measures of residuals and 6 months forecast errors are very similar, but there is change in measures of bias. Whereas ME and MPE for residuals show overestimation, ME and MPE for 6 months ex post forecast errors show underestimation. How the actual values are underestimated by the model (10) is depicted in Table 4.

Table 4: Actual and ex post forecast for unemployment rate using model (10)

Period	Unemployment rate		
	Actual value	Ex post forecast	Ex post absolute error (%)
July 17	6.70	6.54	2.388
August 17	6.54	6.42	1.835
September 17	6.42	6.39	0.467
October 17	6.14	6.11	0.489
November 17	5.95	5.90	0.840
December 17	5.94	5.86	1.347

Source: Own computations

The Theil inequality coefficient U = 0.00735 again shows perfect fit in the test set, but Theil decomposition of MSEex-post by the formula (8) indicate systematic error, since 100 % = 74 % + 2.10 % + 23.90 %, which is interpreted that there is large proportion of U_M = 0.74 or large bias (systematic underestimation of the actual values). From Table 4 is possible to see percentage errors are for the first two months large. With increasing horizont the percentage errors are also slowly increasing.

In comparing the results of model (9) and (10) we can conclude, that absolute percentage errors have changed. There is larger bias in means and also some instability because of changing signs not only in ME and MPE for residuals but for ex post forecast errors as well.

Ex ante forecasts of unemployment rate

In spite of the previous facts we will use the same model SARIMA(0,2,1)(0,1,1)12 with Log transformation of unemployment rate in the estimation period with T = 204 observations (January 2001 to December 2017) to compute 5-months ex ante forecasts for January 2018 to May 2018. The test set (validation period) will have zero observations. The reason is that at the time of writing the paper we got from the Central Office of Labour (2018), Social Affairs and Family these five new actual values, so we can also analyse the precision of ex ante forecasts.

Estimation of the third model SARIMA(0, 2, 1)(0, 1, 1)12 is:

$$(1-B)^2(1-B^{12})\log(UR_t) = (1-0.45699B)(1-0{,}573084B^{12})a_t \qquad (11)$$

$$\qquad\qquad (0.0652) \qquad (0.05959)$$

t = 15, 16, ..., 204

As in previous cases, the parameters are statistically significant at the 5 % level of significance (standard deviations of parameters are in parentheses), fulfilling invertibility conditions.

According to the *Box-Pierce test* based on the first 24 autocorrelations, with large statistic Q_{24} = 21.10 and its P – value = 0.5083 we determine that the residuals form a random sequence of numbers. The condition of homoscedasticity for residuals is fulfilled by the F–test and the normality was confirmed by the Shapiro-Wilk test with P–value = 0.13704.

Published actual values of unemployment rate for the forecasted period and the ex ante forecasts for January 2018 to May 2018 are summarised in Table 5.

Table 5: Actual and ex ante forecast for unemployment rate using model (11)

Period	Unemployment rate		
	Actual value	Ex ante forecast	Ex ante absolute error (%)
January 2018	5.88	5.85	0.51
February 2018	5.72	5.73	0.17
March 2018	5.55	5.53	0.36
April 2018	5.42	5.36	1.11
May 2018	5.37	5.26	2.05

Source: Own computations

The mean measures of residuals and 5-months ex ante forecast errors for unemployment rate given by model (11) are presented in Table 6.

Table 6: The mean measures of residuals and 5-months ex ante forecast errors for unemployment rate given by model (11)

Mean statistics model (11)	Estimation period	Forecasted period
	2001M01-2017M12	2018M01-2018M05
	Residuals	5 months ex ante forecast error
RMSE	0.213	0.057
MAE	0.153	0.044
MAPE	1.306	0.811
ME	– 0.007	0.041
MPE	– 0.019	0.749

Source: Own computations

From Table 6, it is evident that ME and MPE have changed their signs, there is some instability of the model (in the past model overestimated actual values, but in the forecasting period the model underestimated actual values). The mean absolute percentage error is less than 1 %, so the model is acceptable.

VI. Conclusion

We have performed simple analysis of accuracy of 6-months ex post forecasts for unemployment rate computed by means of SARIMA model. We have found out that model SARIMA (0,2,1)(0,1,1)12 applied with logarithmic transformation of unemployment rate is a good forecasting model. The MAPEex-post for the model (9) was 1.412% and for the model (10) was 1.219 %. From these results we would expect that ex ante forecasts will be computed with similar results, not greater than 1.50 %. Mean absolute percentage error of 5-months ex ante forecast errors give us the result 0.811 %, which is less than 1.219 %. The reason may be hidden in that we have only 5-months forecast errors but not 6-months forecast errors.

Moreover, we have found that repeating the same SARIMA model three times for various length of estimation period gives us very similar results of estimated parameters, so the chosen model could be used for forecasting unemployment rate in a repeating mode at least two times.

We are aware of the temporality of our results because extrapolative forecasts may be correct only when based on the assumption that the development of the series will not change qualitatively.

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Literature

Central Office of Labour, Social Affairs and Family (2018). *Statistics*. Retrieved from http://www.upsvr.gov.sk/statistiky.html?page_id=1247. (5.1.2018).

Pindyck, R. S. & Rubenfeld, D. L. (1981). *Econometric Models and Economic Forecasts*. United States: McGraw-Hill.

Institute for Forecasting CSPS SAS (2012 - 2018). *Bulletin Prognostického ústavu SAV*. Retrieved from http://www.prog.sav.sk/bulletin. (5.1.2018).

Rublíková, E. (2007). *Analýza časových radov*. Bratislava: Iura Edition.

Theil, H. (1961). *Economic Forecasts and Policy*. Amsterdam: North Holand.

Willis, R. E. (1987). *A Guide to Forecasting for Planners and Managers*. New Jersey: Prentice-Hall.