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Unemployment Rates Forecasts – Unobserved Component Models Versus SARIMA Models In Central And Eastern European Countries

Abstract

In this paper we compare the accuracy of unemployment rates forecasts of eight Central and Eastern European countries. The unobserved component models and seasonal ARIMA models are used within a rolling short-term forecast experiment as an out-of-sample test of forecast accuracy. We find that unemployment rates present clear unconditional asymmetry in three out of eight countries. Half the cases there is no difference between forecasting accuracy of the methods used in the study. In the remaining, a proper specification of seasonal ARIMA model allows to generate better forecasts than from unobserved component models. The forecasting accuracy deteriorates in periods of rapid upward and downward movement and improves in periods of gradual change in the unemployment rates.

Keywords: *unemployment rate, unobserved component, SARIMA models, forecasting accuracy*

JEL: *E23, E2*

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1. Introduction

For more or less forty years autoregressive moving average (ARMA) models have been used for modelling and forecasting a variety of economic time series. The ARMA forecasting equation for a stationary time series is a linear equation in which the predictors consist of lags of the dependent variable and lags of the forecast errors. This approach has a certain feature: all shocks, coming either from the cycle or from other sources, are included in model's innovations. Therefore, in the last years the unobserved component models have become a very promising tool in forecasting different economic series. Structural time series models (or unobserved component models, UC) are constructed in terms of components, such as trend, seasonal and cycle, that have a direct interpretation (Harvey 1989). In this paper we compare the forecasting performance of structural time series models with seasonal autoregressive integrated moving average (SARIMA) models. The latter may be perceived as a reduced form of the linear unobserved component models. As Harvey (2006) points out one of the drawbacks of ARIMA models in comparison to UC is that the former may not grasp some sophisticated characteristics of a time series. In this study the issue is whether the restrictions placed on the ARIMA models have an impact on forecasting accuracy of unemployment rate series in several Central and Eastern European (CEE) countries.

A number of research papers have used time series models for forecasting unemployment rates. These works are devoted either to single unemployment rate, where clearly the most popular is the US unemployment rate (e.g. Montgomery et al. 1998, Altissimo and Violante 2001, Caner and Hansen 2001, Proietti 2003, Koop and Potter 1999) or a comparison of models used in forecasting unemployment rates from different economies, eg. OECD countries (Skalin and Teräsvirta 2002), US, UK, Canada, and Japan (Milas and Rothman 2005), G7 countries (Teräsvirta et al. 2005) and the Baltic States (Będowska-Sójka 2015).

Many works are devoted to comparison of different models. Montgomery, Zarnowitz, Tsay and Tiao (1998) in a rolling forecasts experiment for the US quarterly unemployment rates show that non-linear models performed better than the linear ARMA model in terms of forecasting errors when the unemployment increased rapidly but not elsewhere. Stock and Watson (1999) use a large data set of US macroeconomic time series, including the monthly unemployment rate, and show that linear models have better forecasting accuracy than nonlinear ones. Oppositely, Teräsvirta et al. [2005] find that the nonlinear LSTAR model turns out to be better than the linear or neural network models when modelling unemployment rates in G7 countries.

There is a strong evidence of the asymmetric behaviour of unemployment rates: these rates tend to rise suddenly, but fall gradually. This phenomena is strictly related to the state of the business cycle (Koop and Potter 1999, Belaire-

Franch and Peiró 2015). Proietti (2003) finds that linear models of the seasonally adjusted US unemployment rate perform significantly better than nonlinear models, but a nonlinear specification outperforms the selected linear model in periods of slowly decreasing unemployment rate. Hamilton (2005) argue that the different dynamics in recessions and expansions are to be modelled within the time-varying approach.

The main purpose of this paper is to compare an accuracy of unemployment rate forecasts obtained from different linear models, namely structural time series models and SARIMA models. Our approach is much in the same spirit of Proietti (2003) as it concentrates on the comparison of forecasting models on the basis of the short-term forecasts. Our sample data consists of seasonally unadjusted monthly unemployment rates of the eight CEE countries that joined European Union in 2004 in the so called first-wave accession. These countries are: Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia. The forecasts of unemployment rates are generated from the rolling forecasts experiment where seasonality effects are built directly into the forecasting procedure. In order to compare forecasts from different models, we use forecasting error measures and Diebold-Mariano statistic.

Our contribution is as follows: first, only in three out of eight countries unemployment rates present signs of unconditional asymmetry. In case of Estonia, Latvia and Lithuania for one month horizon the forecasting accuracy provided by the unobserved component models is greater than for airline model, but not significantly different from the AR(2) model. In Poland the greater forecasting accuracy is provided by seasonal ARIMA models. In the remaining cases the forecasting performance of seasonal ARIMA and UC models is not statistically different. In case of twelve months horizon more parsimonious ARIMA models perform better or as good as the unobserved component models. Second, when comparing models across all countries in the sample, there are substantial differences between their forecasting abilities; the lowest mean percentage forecasting error for 12-month horizon is 1.82% in case of Slovakian unemployment rate and the highest is 8.67% for the Estonian one. Third, we also examine if there are the differences of the unemployment rates' forecasts accuracy at the time of increase and decrease in these rates. In case of Estonian, Latvian and Slovenian unemployment rates shocks that increase unemployment rate tend to have greater negative impact on the model's forecasting ability than shocks that lower unemployment rate. Finally, the forecasting accuracy scores better in periods of gradual decrease or increase in unemployment rates and deteriorates in the beginning of the periods of rapid increase or decrease in the series.

The plan of the paper is as follows. Next section describes the methodology used in the study. The data are presented in Section 3, whereas the empirical results of the comparison of forecasts are shown in Section 4. The conclusions are presented in Section 5.

2. Methodology

Our paper aims to compare forecasts from two alternative specifications that are used to represent the dynamic properties of time series, namely unobserved component models (UC) and seasonal ARIMA models. When the disturbances are independent, identically distributed and Gaussian, an ARIMA model with restrictions in the parameters is the reduced form of an unobserved component model (Harvey 1989). There is one aggregated disturbance within the specification of ARIMA models, whereas unobserved component models include usually several component disturbances. Thus, the latter may allow to discover the features, that are not observed in the reduced form of ARIMA model. In this paper we try examine which of these two classes of the models is more appropriate when forecasting the unemployment rates.

We forecast the unemployment rates with ARIMA models, with the general specification for y_t, $y_t \sim \mathrm{ARIMA}(p,d,q)$, written as:

$$\phi(L)\Delta^d y_t = \theta_0 + \theta(L)\xi_t \tag{1}$$

where L is a lag operator, $\phi(L) = 1 - \phi_1 L - ... - \phi_p L^p$ and $\theta(L) = 1 - \theta_1 L - ... - \theta_q L^q$.

Two specifications of ARIMA models are used in the study. As we model the series that are unadjusted seasonally, we consider seasonal ARIMA models in the following specifications:

I. Seasonal ARIMA(0,1,1)(0,1,1) – henceforth SARIMA1 (airline model)

II. Seasonal ARIMA(2,1,0)(0,1,1) – henceforth SARIMA2 (AR(2) model).

In unobserved component models the general structural model is written as (Harvey 1989):

$$y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{NID}(0,\ \sigma_\varepsilon^2) \quad t = 1,...,T \tag{2}$$

where y_t represents the time series to be modelled and forecasted, μ_t is the trend component, γ_t is the seasonal component, ψ_t is the cyclical component, ε_t represents the irregular component and N denotes Normally and Independently Distributed. All of these components are assumed to be unobserved. Thus the simple specification of the local level model that consists of a random walk plus noise,

$$\begin{aligned} y_t &= \mu_t + \varepsilon_t & \varepsilon_t &\sim NID(0,\ \sigma_\varepsilon^2) & t &= 1,\dots,T \\ \mu_t &= \mu_{t-1} + \eta_t & \eta_t &\sim NID(0,\ \sigma_\eta^2) \end{aligned} \tag{3}$$

where the irregular and level disturbances, ε_t and η_t respectively, are mutually independent, might be perceived as a reduced form of ARIMA(0,1,1) (Harvey 2006).

In the study we use two specifications of UC models:

III. Basic Structural Model (BSM)

$$\begin{aligned} y_t &= \mu_t + \gamma_t + \varepsilon_t \\ \mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t \qquad \eta_t \sim NID(0, \sigma_\eta^2) \\ \beta_t &= \beta_{t-1} + \zeta_t \qquad \zeta_t \sim NID(0,\ \sigma_\zeta^2) \end{aligned} \tag{4}$$

where μ_t represents the stochastic level of the trend and β_t represents the stochastic slope of the trend. It is also assumed that ε_t, η_t and ζ_t are independent variables. Additionally, γ_t is trigonometric seasonal component described as:

$$\gamma_t = \sum_{j=1}^{s/2} \gamma_{j,t} \tag{5}$$

with *s* standing for the number of seasons, *s* = 12 in our case. Each $\gamma_{j,t}$ is generated by:

$$\begin{bmatrix} \gamma_{j,t} \\ \gamma_{j,t}^* \end{bmatrix} = \begin{bmatrix} \cos\lambda_j & \sin\lambda_j \\ -\sin\lambda_j & \cos\lambda_j \end{bmatrix} \begin{bmatrix} \gamma_{j,t-1} \\ \gamma_{j,t-1}^* \end{bmatrix} + \begin{bmatrix} \omega_{j,t} \\ \omega_{j,t}^* \end{bmatrix}, \qquad j = 1,\dots\dots,[s/2],\ t = 1,\dots\dots,T \tag{6}$$

where $\lambda_j = 2\pi j/s$ is the frequency and $\omega_{j,t}$, $\omega_{j,t}^*$, the seasonal disturbances, are mutually uncorrelated $(\omega_{j,t} \sim NID(0,\sigma_{\omega_j}^2),\ \omega_{j,t}^* \sim NID(0,\sigma_{\omega_j^*}^2))$ and uncorrelated with ε_t.

As the unemployment rate tends to move in a countercyclical way (Montgomery et al. 1998), we expect that a cyclical component might improve unemployment rates forecasts.

Therefore we consider:

IV. Structural Model Plus Cycle (SMC)

$$y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t, \quad \mu_t = \mu_{t-1} + \eta_t$$

In the SMC the statistical specification of a cycle, ψ_t, is defined by:

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \rho \begin{bmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix}, \qquad t = 1,...T \tag{7}$$

where: λ_c is the frequency (in radians), $0 < \lambda_c < \pi$, ρ is a damping factor, $0 \le \rho \le 1$, κ_t, κ_t^* are mutually uncorrelated white noise disturbances with zero means and common variance denoted as σ_κ^2.

We use out-of-sample forecasts to assess which model gives the better accuracy. These forecasts are generated in a rolling forecasts window: for the given origin the model is estimated and forecasts are generated. Next, this step is repeated for each model and each series – hence we obtain 75 forecasts for each series from one-step till twelve-step ahead. For all series we calculate different forecasting errors, identify the models with the lowest errors and verify with Diebold-Mariano test if the models have similar forecasts performance. We also divide whole forecasts origin into periods of increases and decreases in unemployment rates and examine if there are any differences between forecasting errors in these two states.

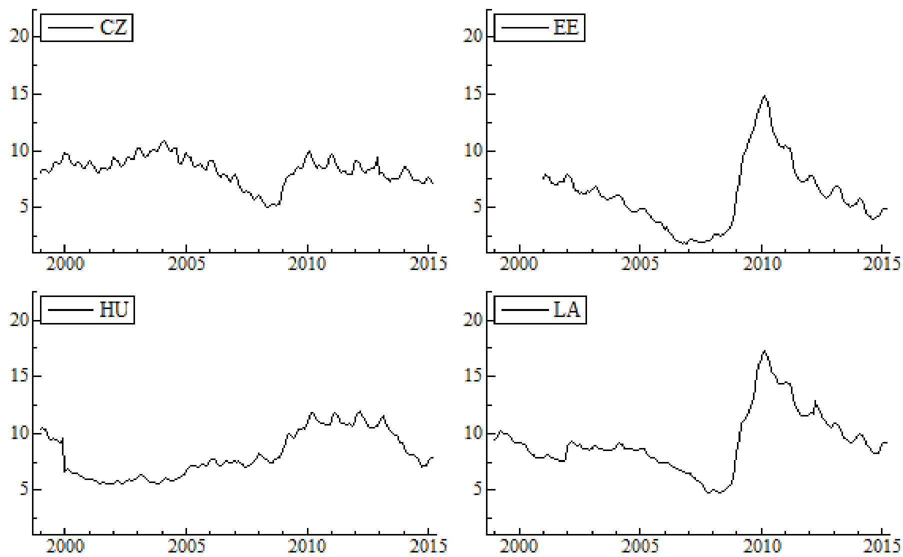
3. Data

Our sample data consists of monthly unemployment rates from eight first-wave accession Central and Eastern European countries that joined European Union in May 2004. There are (in alphabetical order): Czech Republic (CZ), Estonia (EE), Hungary (HU), Latvia (LA), Lithuania (LIT), Poland (PL), Slovenia (SI) and Slovakia (SK). We consider logarithms of monthly seasonally unadjusted series. The seasonality is included in the models: in the unobserved component models seasonal component is modelled as a stochastic one.

The data source is CEIC database (www.ceic.com).The sample starts in January 1999 and ends in March 2015 with some minor exceptions. The data for Estonian unemployment rate starts in 2001, for Slovenia starts in 2000, and for Slovakia in 2006 (in all cases the first month of the available data is January). In case of the series that are available since January 1999 starting from that date each model is estimated and forecasts from one month till twelve months are computed. The process is repeated until the end of sample is reached. In case of Estonian and Slovenian unemployment rate the pre-forecasts period is extended until it reaches 108 observations and then the rolling window procedure is applied. The experiment provides in total 75 forecasts for horizons from one-month to one-year for each model and each series. For unemployment rate of Slovakia the data starts in 2006, therefore the model is reestimated on the extended estimation window.

Figure 1 and Figure 2 show the unemployment rates of eight CEE countries within the sample period. There is no single tendency for the unemployment rates in the region at that time. The forecast origin consists of the period of increase in the unemployment rates as well as the decrease. Starting from 2001 the unemployment rates in the region are decreasing in all cases but one, Hungary. In all time series but Slovenia unemployment rates increase sharply in the beginning or the mid of 2008 and decrease since the mid of 2010. In the whole sample the highest unemployment rate is observed in Poland in March 2003 and the lowest in Estonia in December 2006.

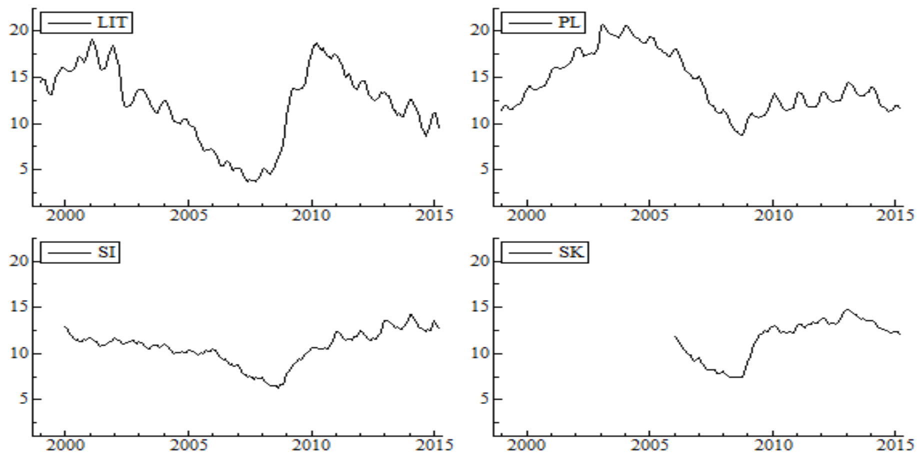
Figure 1. Unemployment rates in Czech Republic, Estonia, Hungary and Latvia in 1999.01–2015.03



CZ stands for Czech Republic, EE for Estonia, HU for Hungary, LA for Latvia.

Source: own calculations based on the data from www.ceic.com

Figure 2. Unemployment rates in Lithuania, Poland, Slovenia and Slovakia within 1999.01–2015.03



LIT stands for Lithuania, PL for Poland, SI for Slovenia and SK for Slovakia.

Source: own calculations based on the data from www.ceic.com. The graphics through the paper are done in OxMetrics (Doornik and Hendry 2005).

A few unemployment rates display visible dynamic asymmetry in the series, therefore to confirm this preliminary evidence, the unconditional symmetry of the variations in the unemployment rates is formally examined with the test proposed by Racine and Maasoumi (2007). We consider the increments of series corrected for seasonal component estimated with basic structural model, BSM (eq. 4), within the whole forecast period. Table 2 presents evidence against the null of symmetry in the increments of seasonally adjusted unemployment rates: it is found for Estonian, Latvian and Lithuanian unemployment rates. The hypothesis of symmetry in the increments of the remaining unemployment rates cannot be rejected.

Table 1. The unconditional symmetry test

unemployment rates	CZ	EE	HU	LA	LIT	PL	SI	SK
$\hat{S}\rho$	0.07	**0.31**	0.04	**0.33**	**0.15**	0.00	0.04	0.13
p-value	(0.31)	(0.02)	(0.29)	(0.01)	(0.01)	(0.88)	(0.36)	(0.13)

Source: own calculations.

The values of $\hat{S}\rho$ statistics is calculated as of Maasoumi and Racine (2009), for the increments of seasonally adjusted unemployment rates, together with *p*-values in italics. Bolded values are statistically significant at $\alpha = 0.05$. The value of the statistics are computed using 1,000 bootstrap replications (Hayfield, Racine 2008).

4. Empirical results

This section consists of three parts: in the first a comparative performance of a rolling forecast experiment is provided based on the out-of-sample test of forecast accuracy. In the second, we compare the forecasts errors from the periods of increase and decrease of the unemployment rate series. In the third step, the errors are depicted together with the increments of the unemployment rates in order to illustrate if and how the errors differ within the sample period.

We report comparative performance of the rolling forecasts in the models used in the study. Table 2 presents the different forecasting errors for each series whereby: $\tilde{y}_{t+l|t}$ is the *l*-ahead forecast for a given model, the Mean Error (ME) is obtained as an average of forecasts errors, $y_t - \tilde{y}_{t+l|t}$, the Mean Square Forecast Error (MSFE) is calculated as square root of averages of $(y_t - \tilde{y}_{t+l|t})^2$, and the Mean Absolute Percentage Error, MAPE, is obtained as an average of $\left| y_t - \tilde{y}_{t+l|t} \right| / y_t * 100\%$. These errors are reported for 1-month and 1-year horizon.

As presented in Table 2 the forecasting errors differ substantially across the countries, with the lowest value of Mean Absolute Percentage Error which is 0.3698 for one-month horizon in Poland and the highest value, three times larger (1.1983) in Estonia. For twelve months horizon the lowest MAPE is observed in Slovakia (1.8284) and the highest, almost five times larger, in Estonia (8.6889). The important observation is that the Mean Square Forecast Error or Mean Absolute Percentage Error both indicate the same model in a given horizon for a given country to have the lowest forecasts errors, except LIT in twelve months horizon. Mean Error indicates different models to have the lowest forecasts errors.

In order to examine if the forecasting precision differs significantly across the methods used in the study, we employ modified Diebold-Mariano (henceforth *mDM*) statistic for comparing predictive accuracy (Harvey et al. 1997). This modified statistic is found to perform much better than the original Diebold-Mariano test for different forecast horizons, as well as in cases when the forecast errors are autocorrelated or have non-normal distribution. As our purpose is to compare ARIMA models with UC models, we calculate *mDM* statistic in pairs, in which forecast errors come from one of seasonal ARIMA models and the other from one of UC component models. In table 3 we show the results of the *mDM* test for each country and two forecasting horizons, one month and twelve months. We reject the null of equal predictive accuracy at the 5% level.

Table 2. Comparison of forecasts performance in the test period 2008.1–2015.3 for unemployment rates CEE countries

	CZ			EE			HU			LA		
1 month	ME	MSFE	MAPE	ME	MSFE	MAPE	ME	MSFE	MAPE	ME	MSFE	MAPE
SARIMA1	0.0058	**0.0206**	**1.0120**	0.0080	0.0364	2.1943	**-0.0020**	0.0151	0.6683	0.0022	0.0272	1.1926
SARIMA2	0.0020	0.0210	1.0257	0.0043	0.0211	1.3709	-0.0029	**0.0151**	**0.6684**	0.0002	**0.0183**	**0.8225**
BSM	-0.0029	0.0220	1.0781	-0.0009	**0.0206**	**1.1983**	0.0021	0.0157	0.6962	-0.0011	0.0192	0.8552
SMC	**-0.0019**	0.0228	1.1146	**-0.0001**	0.0223	1.2923	0.0025	0.0152	0.6728	**0.0001**	0.0203	0.9006
12 months												
SARIMA1	0.0831	**0.1100**	**4.5645**	-0.0411	0.3245	13.8566	-0.0518	0.0911	3.4156	0.0210	0.2244	7.9093
SARIMA2	0.0309	0.1270	5.2363	**0.0248**	0.2329	9.8575	-0.0558	0.0880	3.2697	0.0085	**0.1793**	**6.3304**
BSM	-0.0327	0.1716	7.0297	0.0556	**0.2197**	**8.6889**	**0.0251**	0.0904	3.4197	**-0.0035**	0.1885	6.6558
SMC	**-0.0007**	0.1798	7.3484	0.1326	0.2729	10.9082	0.0366	**0.0840**	**3.1354**	0.0151	0.2016	7.0545

	LIT			PL			SI			SK		
1 month	ME	MSFE	MAPE	ME	MSFE	MAPE	ME	MSFE	MAPE	ME	MSFE	MAPE
SARIMA1	0.0052	0.0326	1.4241	0.0044	0.0116	0.4765	0.0034	0.0133	0.5862	-0.0030	0.0110	0.4269
SARIMA2	0.0046	0.0276	1.1976	0.0008	**0.0091**	**0.3698**	0.0006	**0.0111**	**0.4842**	-0.0006	**0.0097**	**0.3759**
BSM	**0.0002**	0.0274	1.1946	-0.0008	0.0103	0.4230	**-0.0003**	0.0126	0.5497	0.0003	0.0115	0.4695
SMC	0.0007	**0.0261**	**1.1086**	**-0.0008**	0.0099	0.4051	-0.0008	0.0124	0.5364	**-0.0001**	0.0113	0.4369
12 months												
SARIMA1	**0.0002**	0.2193	7.5631	0.0669	0.0805	2.8133	0.0461	**0.0927**	**3.4312**	-0.0504	0.0544	1.8580
SARIMA2	0.0301	**0.1992**	7.0236	0.0267	**0.0612**	**2.1209**	0.0129	0.0962	3.4656	-0.0319	**0.0542**	**1.8284**
BSM	0.0721	0.2190	7.3663	-0.0179	0.0821	2.8268	-0.0086	0.1122	4.0394	**-0.0079**	0.1210	4.0687
SMC	0.0677	0.2000	**6.5930**	**-0.0176**	0.0761	2.6076	**0.0010**	0.1138	4.0938	0.0227	0.0699	2.3577

Note: The bolded values are the lowest errors in a given horizon for a given country.
CZ stands for Czech Republic, EE for Estonia, HU for Hungary, LA for Latvia, LIT for Lithuania, PL for Poland, SI for Slovenia and SK for Slovakia.
The calculations are done in OxMetrics, modules STAMP7 and X12-ARIMA (Koopman et al. 2006, Doornik and Hendry 2005).

Source: own calculations.

Based on the results of *DM* statistics presented in Table 3, with respect to one month horizon in three out of four cases, Estonia, Latvia and Lithuania, with respect to airline model (SARIMA1) the greater forecasting accuracy is provided by the unobserved component models – the asymmetric feature observed in unemployment rates of the Baltic States is better picked up by BSM or SMC model. With respect to SARIMA2 model that contains AR(2) part there is no statistical difference between forecasting errors from either BSM or SMC. In case of Poland the greater forecasting accuracy is provided by seasonal ARIMA models. In the remaining four cases the predictive performance of these two groups of models is similar. When twelve month forecasts horizon are considered, in case of four unemployment rates from Czech Republic, Latvia, Slovenia and Slovakia better accuracy is provided by one of seasonal ARIMA models. For the remaining unemployment rates forecast errors are not statistically different meaning that both approaches have similar forecasting performance. The seasonal ARIMA models, although more parsimonious, seem to outperform unobserved component models in the longer forecast horizon.

Table 3. Test for comparing predictive accuracy in one-month and 12-months forecasting horizons

	1 month horizon	12 months horizon
CZ	no difference	SARIMA1←BSM (0.011), SARIMA1←SMC (0.001) SARIMA2←BSM (0.015)
EE	BSM←SARIMA1 (0.001) SMC←SARIMA1 (0.001)	no difference
HU	no difference	no difference
LA	BSM←SARIMA1 (0.025) SMC←SARIMA1 (0.021)	SARIMA2←BSM (0.043) SARIMA2←SMC (0.023)
LIT	BSM←SARIMA1 (0.021) SMC←SARIMA1 (0.003)	no difference
PL	SARIMA1←SMC (0.031) SARIMA2←BSM (0.020) SARIMA2←SMC (0.041)	no difference
SI	no difference	SARIMA1←BSM (0.014) SARIMA1←SMC (0.017) SARIMA2←BSM (0.031) SARIMA2←SMC (0.041)
SK	no difference	SARIMA1←BSM (0.006) SARIMA2←BSM (0.000) SARIMA2←SMC (0.035)

Note: In the table the summary of the results of mDM test is presented (Hyndman and Khandakar 2008). CZ stands for Czech Republic, EE for Estonia, HU for Hungary, LA for Latvia, LIT for Lithuania, PL for Poland, SI for Slovenia and SK for Slovakia. "no difference" means that forecasts accuracy from ARIMA models and UC models is the same. The direction of the arrow shows errors from which model are smaller, e.g. "SARIMA1←BSM" means that forecast errors from BSM model are greater than forecast errors from SARIMA1 model. The numbers in italics are p-values of mDM statistics in one-sided tests. If the p-values are bigger than 0.05, the results are not presented in the table.

Source: own calculations.

In the next step we examine if forecasting performance differs in the time of increase and decrease of the unemployment rates. Therefore we divide the forecasting origin into two subsamples and calculated the means of forecasting errors separately for increase/decrease case. Table 4 presents the results of *t*-test of equality of two sample means (Snedecor and Cochran 1989). Table 4 presents evidence against the null that forecasting errors are the same when increase and decrease of unemployment rates is observed in case of Estonian, Latvian and Slovenian unemployment rates. The hypothesis of equality of two sample means of the remaining unemployment rates cannot be rejected.

Table 4. Two-sample *t*-test for equal means of errors in time of unemployment rates' increase or decrease

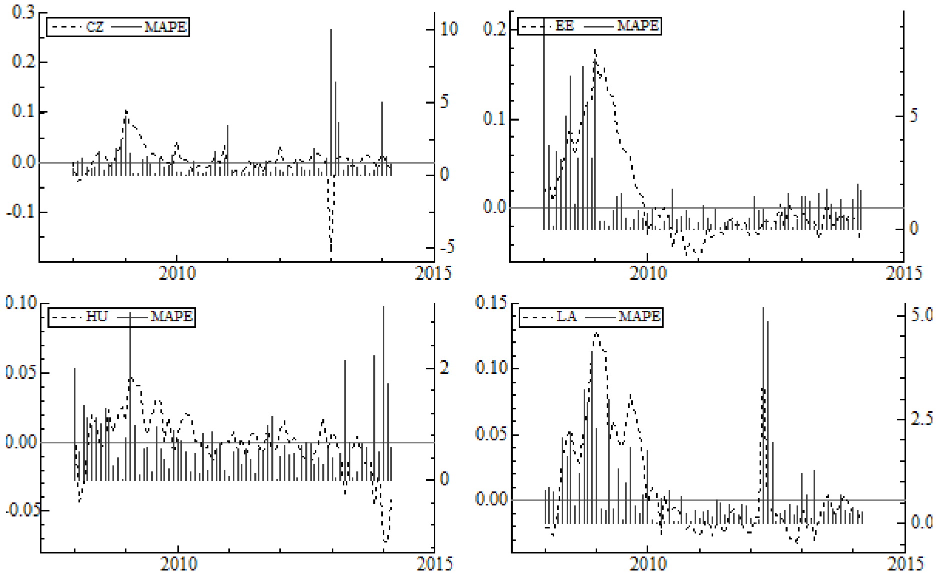
	CZ	EE	HU	LA	LIT	PL	SI	SK
1 month	-0.6726	**-3.0655**	1.1359	**-2.4533**	-1.1712	-1.6840	**-3.3242**	-0.4870
12 months	-1.8739	**-4.8674**	0.7862	**-2.9217**	-1.7194	0.2594	-1.4220	-0.2920

Source: own calculations.

This table presents statistics of two-sample *t*-test. The alternative hypothesis states that the mean forecasting errors in time of increase of unemployment rates is different from the mean in the time of decrease of unemployment rate. Bolded values are statistically significant at significance level $\alpha = 0.05$. The statistics are presented for seasonal ARIMA(2,1,0)(0,1,1) model and MAPE errors, however the results of the statistical interference are the same for other models as well as for ME or MSFE.

According to the results presented in Table 4, in case of one-month forecasts of unemployment rates in Estonia, Latvia and Slovenia, errors coming from the forecasts generated for the time of increase in unemployment rates that might correspond to cyclical contractions, are systematically higher than errors obtained in case of decrease in unemployment rates usually observed in the time of expansions (Belaire-Franch and Peiró 2015). This result holds also for Estonian and Latvian 12-month forecasts. It suggests that in case of those three countries the effect of cyclical contractions in terms of weakening forecasting accuracy is much stronger than that of expansions. In the remaining cases the forecast errors are not statistically different.

Figure 3. Unemployment rate increments and one month MAPE within forecast period 2008.01–2014.03

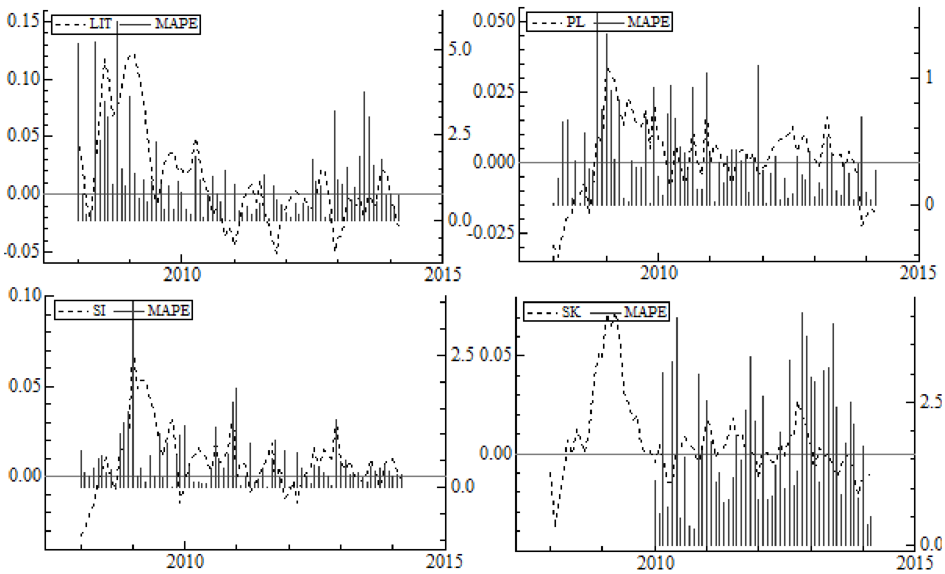


CZ stands for Czech Republic, EE for Estonia, HU for Hungary, LA for Latvia.

Source: own calculations based on the data from www.ceic.com

Figure 3 and 4 show the increments in the unemployment rates together with the forecast errors. Because in case of forecasts for one month horizon the errors from SARIMA2 model are not statistically different from any errors from UC model, we compare one-step ahead Mean Absolute Percentage Error from this model in 75 consecutive periods together with the increments of the seasonally adjusted unemployment rate series (the latter is obtained again from BSM model). The most extreme values of increments of seasonally adjusted unemployment rates are positive. The highest value of MAPE is observed in periods of rapid increase (e.g. in case of Estonia, Hungary, Latvia, Lithuania, Poland or Slovenia from 2008 to 2009, Latvia in the late 2012) or rapid decrease (e.g Czech Republic in 2013, Hungary in the middle of 2013, Lithuania in 2013). In fact, forecasting accuracy scores better in periods of gradual decrease or increase in unemployment rates and deteriorates in the beginning of the periods of rapid increase or decrease in the series. This can be visually assessed by observing relatively calm period starting in 2010 and lasting for at least two years. Similar phenomenon, although not presented here, characterizes this relationship for multistep forecasts.

Figure 4. Unemployment rate increments and one month MAPE within forecast period 2008.01–2014.03



LIT stands for Lithuania, PL for Poland, SI for Slovenia and SK for Slovakia.

Source: own calculations based on the data from www.ceic.com

5. Conclusion

In this paper we have examined the out-of-sample performance of two alternative specifications that are used to represent the dynamic properties of time series, seasonal ARIMA and unobserved component models. We present the results of an empirical exercise with forecasts for unemployment rates of eight CEE countries that have accessed European Union in May 2004. As the main interest is to select the best forecasting models according to their post-sample performance, we have used rolling forecasts experiment and examine, which model generates better forecasts. Starting in January 1999 and ending in March 2015 our sample consists of the periods of dynamic changes in the unemployment rates.

We find that for the monthly horizon in case of Czech Republic, Hungary, Slovenia and Slovakia there is no difference between forecasting accuracy of the methods used in the study. In the remaining countries in three out of four cases forecast errors from unobserved component models are significantly lower than from one of the SARIMA model (the airline model), but no statistical difference is found when the forecasts errors from the AR(2) model are considered. For twelve months horizon in case of Estonia, Hungary, Lithuania and Poland both, seasonal ARIMA and unobserved component models, generate similar forecast errors. In the remaining cases seasonal ARIMA model generate forecasts with significantly lower errors. It means that in our sample parsimonious and well-fitted specification of SARIMA model may give as good forecasts as the unobserved component models or even better.

Altogether the forecasting ability across examined series differs substantially, with mean average percentage error MAPE ranging from 0.37 to 1.2 in case of one month horizon and from 1.8 to 8.7 in case of twelve month horizon. When sample is divided into periods of increase and decrease of the unemployment rates, mean forecasting errors are significantly different only in three countries: Estonia, Latvia and Slovenia, where forecasting errors generated for the time of increase in unemployment rates are systematically higher than errors obtained in case of decrease. Last but not least, we find graphical evidence that the forecasting accuracy deteriorates in periods of rapid upward and downward movement and improves in periods of gradual change in the unemployment rates.

References

Altissimo F., Violante G.L. (2001), *The Non-Linear Dynamics of Output and Unemployment in the U.S.*, 'Journal of Applied Econometrics' 16: 461–486.

Belaire-Franch J., Peiró A. (2015), *Asymmetry in the relationship between unemployment and the business cycle*, 'Empirical Economics' 48, 2: 683–697.

Będowska-Sójka B. (2015), *Unemployment Rate Forecasts. The Evidence from the Baltic States*, 'Eastern European Economics' 53: 57–67.

Caner M., Hansen B.E (2001), *Threshold Autoregression with a Unit Root*, 'Econometrica' 69: 1555–1596.

Diebold F.X., Mariano R.S (1995), *Comparing predictive accuracy,* 'Journal of Business and Economic Statistics' 13: 253–263.

Doornik J.A., Hendry D.F. (2005), *Empirical Econometric Modelling. PcGive^{TM}11*, Timberlake Consultants, London.

Hamilton J.D. (2005), *What's real about the business cycle?*, Federal Reserve Bank St. Louis Review 2005:425–452.

Harvey A.C. (1989), *Forecasting Structural Time Series Models and the Kalman Filter*, Cambridge: Cambridge University Press.

Harvey A.C. (2006), *Forecasting with Unobserved Component Time Series Models*, in: Elliott G., Granger C.W.J., Timmermann A., *Handbook of Economic Forecasting*, vol. I, North-Holland, Elsevier.

Harvey D., Leybourne S.J., Newbold P. (1997), *Testing the Equality of Prediction Mean Squared Errors*, 'International Journal of Forecasting', vol. 13: 281–291.

Hayfield T., Racine J.S. (2008), *Nonparametric Econometrics: The np Package*. Journal of Statistical Software 27(5), URL http://www.jstatsoft.org/v27/i05/.

Hyndman R.J., Khandakar Y. (2008), *Automatic time series forecasting: the forecast package for R*, 'Journal of Statistical Software' 26(3): 1–22.

Koop G.S., Potter M. (1999), *Dynamic Asymmetries in U.S. Unemployment*, 'Journal of Business and Economic Statistics' 17 (3): 298–312.

Koopman S.J., Harvey A.C., Doornik J.A,. Shephard N (2006), *Structural Time Series Analyser and Modeller and Predictor STAMP 7*, Timberlake Consultants, London.

Marcellino M. (2002), *Instability and non-linearity in the EMU*, Discussion Paper No. 3312, Centre for Economic Policy Research.

Maasoumi E., Racine J.S. (2009), *A robust entropy-based test of asymmetry for discrete and continuous processes*, 'Econometric Reviews', 28: 246–261.

Milas C., Rothman P. (2005), *Multivariate STAR Unemployment Rate Forecasts*, 'Econometrics' 0502010, EconWPA.

Montgomery A.L., Zarnowitz V., Tsay R.S., Tiao G.C (1998), *Forecasting the U.S. Unemployment Rate*, 'Journal of the American Statistical Association' 93, no. 442: 478–493.

Proietti, T. (2003), *Forecasting the US unemployment rate*, 'Computational Statistics and Data Analysis' 42: 451–476.

Racine J.S., Maasoumi E. (2007), *A versatile and robust metric entropy test of time-reversibility, and other hypotheses*, 'Journal of Economics' 138:547–567.

Skalin J., Teräsvirta T. (2002), *Modeling asymmetries and moving equilibria in unemployment rates*, Macroeconomic Dynamics 6: 202–241.

Snedecor G.W., Cochran W.G. (1989), *Statistical Methods*, Eighth Edition, Iowa State University Press.

Stock J.H., Watson M.W. (1999), *Business cycle fluctuations in us macroeconomic time series*, in: Taylor, J. B., M., Woodford (ed.) *Handbook of Macroeconomics*, volume 1: 3–64, Elsevier.

Teräsvirta T., van Dijk D., Medeiros M.C. (2005), *Smooth transition autoregressions, neural networks, and linear models in forecasting macroeconomic time series: A reexamination*, International Journal of Forecasting 21: 755–774.

Streszczenie

PROGNOZOWANIE STOP BEZROBOCIA – PORÓWNANIE MODELI SARIMA I MODELI NIEOBSERWOWANYCH KOMPONENTÓW DLA WYBRANYCH KRAJÓW EUROPY ŚRODKOWEJ I WSCHODNIEJ

W artykule porównano prognozy wskaźników stóp bezrobocia w ośmiu krajach Europy Środkowej i Wschodniej. Zastosowano modele nieobserwowanych komponentów i sezonowe modele ARIMA w przesuwanym oknie i postawiono prognozy krótkoterminowe weryfikowane na podstawie trafności prognozy spoza próby. Wykazano, że w przypadku trzech krajów stopa bezrobocia charakteryzuje się bezwarunkową asymetrią. Generalnie w przypadku stosowanych metod, dla połowy badanych szeregów nie znaleziono statystycznie istotnej różnicy w dokładności stawianych prognoz. W pozostałych przypadkach odpowiednio dobrany sezonowy model ARIMA pozwalał na postawienie lepszych prognoz. Ponadto wykazano, że trafność prognoz pogarsza się w okresach gwałtownych wzrostów i spadków stóp bezrobocia, a poprawia się w okresach nieznacznych zmian wielkości tego wskaźnika.

Słowa kluczowe: *stopa bezrobocia, modele nieobserwowanych komponentów, modele SARIMA, trafność prognoz*