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EVALUATING FORECASTING MODELS FOR UNEMPLOYMENT RATES BY GENDER IN SELECTED EUROPEAN COUNTRIES

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ABSTRACT

The unemployment can be considered as one of the main economic problems. The aim of this article is to examine the differences in male and female unemployment rates in selected European countries and to predict their future trends by using different statistical forecasting models. Furthermore, the impact of adding a new data point on the selection of the most appropriate statistical forecasting model and on the overall forecasting errors values is also evaluated. Male and female unemployment rates are observed for twelve European countries in the period from 1991 to 2014. Four statistical forecasting models have been selected and applied and the most appropriate model is considered to be the one with the lowest overall forecasting errors values. The analysis has shown that in the period from 1991 to 2014 the decreasing trend of unemployment rates in the short-run is forecasted for more Eastern Balkan than the EU-28 countries. An additional data point for male and female unemployment rates in 2014 led to somewhat smaller forecasting errors in more than half of the observed countries. However, the additional data point does not necessarily improve forecasting performances of the used statistical forecasting models.

KEY WORDS

Balkan countries, forecasting error criteria, unemployment rates by gender, statistical forecasting methods, unemployment

CLASSIFICATION

JEL: C53, E27, J29

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INTRODUCTION

The aim of this article is to emphasize the differences between male and female unemployment rates and to forecast their future trends in selected European countries. Namely, two research questions arise. The first research question is if the decreasing trend of male and female unemployment rates expected to be more pronounced in the European Union member states or in the Eastern Balkan countries. The second research question is if adding a new data point result in smaller overall forecasting errors.

Thus, male and female unemployment rates are examined for twelve European countries in the period from 1991 to 2014. Also, the analysed countries were divided into two groups: Austria, Croatia, Greece, Portugal, Slovenia and Spain were grouped in the EU-28 member states group, whereas Albania, Bosnia and Herzegovina, the Former Yugoslav Republic of Macedonia, Montenegro, Serbia and Turkey were classified as the Eastern Balkan countries. In the empirical analysis, the average unemployment rate concerning all the EU-28 member states was used as a benchmark for comparison of male and female unemployment rates. After a basic descriptive statistical analysis of male and female unemployment rates, forecasting methods and models were employed. The selection of the most appropriate forecasting method and the model was based on the smallest overall forecasting error criteria, more precisely: mean squared error (MSE), mean absolute deviation (MSD) and mean absolute percentage error (MAPE).

The empirical analysis has shown that the linear trend model was the best forecasting model when forecasting male and female unemployment rates for a vast majority of countries in the sample. The forecasted unemployment rates from previous relevant research have been used in this article for comparison of forecasted and actual unemployment rates in the sampled countries in 2014. Furthermore, the impact of an additional real data point on the forecasting error was also examined.

The reminder of this article is as follows. After the short introduction, the section two presents the literature review. The section three describes data and methods while the section four presents the results of the empirical analysis. Finally, the section five concludes.

LITERATURE REVIEW

The forecasts construction is an important element for developing macroeconomic activities and for economic analysis in general. However, the prediction should be followed by an evaluation of its accuracy. There is a rich empirical literature related to the prediction methods, but only a few studies are dedicated to the accuracy assessment and ways to improve it. Since in our study we aim to test the accuracy of conducted forecasts of female and male unemployment rates in selected European countries, this section provides a brief literature review related to forecasting accuracy assessment.

In the recent article of [1], a valuation of alternative unemployment rate predictions for the Romanian economy is given and the best strategy to improve the forecasts accuracy is to combine forecasts of forecasters' predictions. In their initial study [2] present the most suitable model for forecasting the unemployment rate in Malaysia and make comparisons in order to see how well the historical and forecasted data match and correlate. According to their analysis the Holt's method is the most suitable model for forecasting quarterly unemployment rates in Malaysia. Furthermore, according to another study by [3], the evaluation and the improvement of forecasts accuracy generate growth in the quality of decisional process. Therefore, the Monte Carlo method is not used to simulate the forecasted unemployment rate in Romania, which proved to be the best way to increase the prediction accuracy. In addition, [4] presented a research in which different forecasts for the unemployment rate in the USA are analysed by four diverse institutions. The multi-criteria ranking is applied and five significant measures of accuracy are simultaneously used. Even though the recommended strategies to improve the precision of forecasts did not solve the problem of biasness, it is concluded that the valuation and enhancement of forecasts accuracy have an essential impact on improving the quality of the decision making process. According to the research by [5], the key phase in forecasting is the selection of a prediction method with the maximum extent of precision. In that sense in their article they made short-term forecasts for macroeconomic variables such as the inflation rate, the unemployment rate and the interest rate for Romania using various techniques. With the aim of improving the accuracy of forecasts the authors combined two empirical approaches. Namely, they made a joined prediction and constructed the forecasts founded on historical indicators of accuracy. Accordingly, the highest degree of accuracy was found in the case of predictions constructed on the basis of the exponential smoothing technique. Furthermore, [6] applied quarterly data on unemployment rates in Nigeria. The study evaluated the forecasting performance of four competing models using various forecast accuracy criteria. Accordingly, the results have shown that the mixed ARIMA/ARCH model could be used to forecast unemployment rates in Nigeria in the short-run. In [7] authors emphasize the need for high-quality statistics for labour policy. Namely, their study is aimed at presenting the method used for repeatedly creating the estimation of monthly unemployment directly from the Labour Force Survey (LFS) results. Accordingly, the improved Holt's model has shown to be the most appropriate for predicting the monthly unemployment rate in Romania. Finally, the recent study by [8] proposes the best forecasting model for unemployment rates for each gender in selected European countries using yearly official time series data. The study shows a cross-country comparison of the forecasting models efficiency for short-term forecasts for both genders. Accordingly, the linear trend forecasting model has shown to be the most accurate for some countries, while for other countries the double exponential smoothing forecasting appeared to be the most precise.

Our study contributes to the existing empirical literature by using the most recent data set on male and female unemployment rates in selected European countries and by comparing the trend of male and female unemployment rates in the EU-28 member states and in the Eastern Balkan countries which has not been explored yet. Also, our study reveals whether adding a new data point results in smaller overall forecasting errors.

DATA AND METHODS

In order to collect the data for the analysis, the World Development Indicators database provided by [9] was used. For the purpose of this article only data for two variables were collected. The first variable is the male unemployment rate *(% of male labour force, modelled ILO estimate)* whereas the second one is the female unemployment rate *(% of female labour force, modelled ILO estimate)* [9]. Male unemployment rates are calculated by dividing the total number of males who are without work but available for and seeking employment with the total number of male labour force. Similarly, female unemployment rates are calculated by taking into account the total number of females who are without work but available for and seeking employment and the total number of female labour force.

Male and female unemployment rates are going to be analysed for a certain number of European countries. Namely, in the Eastern Balkan countries, male and female unemployment rates are going to be compared to the corresponding unemployment rates in some of the EU-28 member states. The countries selected among the Eastern Balkan countries include Albania, Bosnia and Herzegovina, the Former Yugoslav Republic of Macedonia, Montenegro, Serbia and Turkey. By selecting these countries the vast majority of Eastern Balkan countries were included in the analysis. On the other side, among the EU-28 member states the following countries were selected: Austria, Croatia, Greece, Portugal, Slovenia and Spain. These countries were selected either because they have really low unemployment rates, i.e. Austria, or high unemployment rates with certain problems with unemployment, i.e. Greece, Portugal and Spain. Croatia and Slovenia can be considered as the Western Balkan countries but here they are placed in the group of the EU-28 member states. So, in the analysis, twelve European countries are observed.

The male and female unemployment rates are observed for the selected European countries in the period from 1991 to 2014. Only yearly data were considered in the analysis. The data before 1991 were missing for some countries and because of that previous periods were not analysed. On the other hand, the newest data is available for 2014. Consequently, the period of 24 years is observed.

Descriptive statistics methods were used to compare male and female unemployment rates among the observed European countries. Furthermore, male and female unemployment rates of all the EU-28 member states together were used as a benchmark to get a better insight into the position of unemployment in the observed countries.

After descriptive statistical analyses, forecasting models were used to forecast male and female unemployment rates in the selected countries. It is assumed that unemployment rates are not stable and that they have some trend movements depending on the leading party in a country, economic crisis, investment cycle, and similar. Consequently, it is assumed that all observed time series of male and female unemployment rates have the trend component. Furthermore, this assumption will be checked by analysing line charts of actual values. Since yearly data are observed, the seasonal component cannot be identified. So, the following four statistical forecasting models were selected: trend polynomial of the first degree (linear trend) model, trend polynomial of the second degree (quadratic trend) model, exponential trend polynomial of the first degree (exponential trend) model and Holt's two-parameter model of linear exponential smoothing (double exponential smoothing).

The estimated linear trend model is given by the following expression:

$$F_t = \hat{\beta}_0 + \hat{\beta}_1 x_t, \quad t = 1,2,\ldots,n, \tag{1}$$

$$F_{n+\tau} = \hat{\beta}_0 + \hat{\beta}_1 \cdot x_{n+\tau}, \quad \tau = 1,2,3,\ldots, \tag{2}$$

where F_t is the estimated (forecasted) value of the time series at time *t*, $\hat{\beta}_0$ is the estimated constant term, $\hat{\beta}_1$ is the estimated slope coefficient, x_t is the value of the time variable at time *t*, $F_{n+\tau}$ is the estimated (forecasted) value of the time series at time $n+\tau$, $x_{n+\tau}$ is the value of the time variable at time $n+\tau$, n is the total number of values in the time series, and τ is the time horizon (forecast horizon). The constant term and the slope coefficient are estimated by using the ordinary least squares (OLS) approach. The equation (1) is used to calculate forecasts for periods in which actual values are known whereas the equation (2) is used to calculate forecasts for periods in which actual values are unknown.

The trend polynomial of the second degree model or quadratic trend is given by:

$$F_t = \hat{\beta}_0 + \hat{\beta}_1 \cdot x_t + \hat{\beta}_2 \cdot x_t^2, \quad t = 1,2,\ldots,n, \tag{3}$$

$$F_{n+\tau} = \hat{\beta}_0 + \hat{\beta}_1 \cdot x_{n+\tau} + \hat{\beta}_2 \cdot x_{n+\tau}^2, \quad \tau = 1,2,3,\ldots, \tag{4}$$

where F_t is the estimated (forecasted) value of the time series at time *t*, $\hat{\beta}_0$ is the estimated constant term, $\hat{\beta}_1$ and $\hat{\beta}_2$ are estimated coefficients, x_t is the value of the time unit variable at time *t*, x_t^2 is the squared value of the time variable at time *t*, $F_{n+\tau}$ is the estimated (forecasted) value of the time series at time $n+\tau$, $x_{n+\tau}$ is the value of the time variable at time $n+\tau$, n is the total number of values in the time series, and τ is the time horizon (forecast horizon). The parameters here are also estimated by the OLS approach and the difference between performing forecasts in periods where actual values are known equation (3)) and are not known (equation (4)) is presented also.

In order to use the OLS approach, in the exponential trend polynomial of the first degree or exponential trend, first the model must be transformed using logarithms. The exponential model is given by:

$$F_t = \hat{\beta}_0 \cdot \hat{\beta}_1^{x_t}, \quad t = 1,2,...,n, \tag{5}$$

$$F_{n+\tau} = \hat{\beta}_0 \cdot \hat{\beta}_1^{x_{n+\tau}}, \quad \tau = 1,2,3,..., \tag{6}$$

where F_t is the estimated (forecasted) value of the time series at time *t*, $\hat{\beta}_0$ is the estimated constant term, $\hat{\beta}_1$ is the estimated slope coefficient, x_t is the value of the time variable at time *t*, $F_{n+\tau}$ is the estimated (forecasted) value of the time series at time $n+\tau$, $x_{n+\tau}$ is the value of the time variable at time $n+\tau$, n is the total number of values in the time series, and τ is the time horizon (forecast horizon). In order to calculate forecasts for periods in which actual values are known, the equation (5) is used, whereas the equation (6) is used to calculate forecasts when actual values are unknown.

The last statistical forecasting model which is going to be used in the analysis is the Holt's two-parameter model of linear exponential smoothing or double exponential smoothing. The double exponential smoothing is given by:

$$F_{t+1} = \hat{y}_t + T_t, \quad 0 < \alpha < 1,\ 0 < \beta < 1,\ t = 1,2,...,n, \tag{7}$$

$$F_{n+\tau} = \hat{y}_n + \tau T_n, \quad \tau = 1,2,3, \tag{8}$$

where F_{t+1} is the forecast at time *t+1*, $\hat{y}_t$ is the estimated value of the time series at time *t* and is calculated as $\hat{y}_t = \alpha y_t + (1-\alpha)(\hat{y}_{t-1} + T_{t-1})$, T_t is the estimated value of the trend at time *t* and is calculated as $T_t = \beta(\hat{y}_t - \hat{y}_{t-1}) + (1-\beta)T_{t-1}$, α is the level smoothing constant, β is the trend smoothing constant, y_t is the value of the time series at time *t*, n is the total number of values in the time series, $F_{n+\tau}$ is the forecast at time $n+\tau$, $\hat{y}_n$ is the estimated value of the time series at time *n*, T_n is the estimated value of the trend at time *n*, and τ is the time horizon (forecast horizon). Equations (7) and (8) are used to calculate forecasts in periods in which actual values are known and in which actual values are not known, respectively.

The four statistical forecasting models are used to calculate forecasts for male and female unemployment rates at each of the observed countries. The selection of the best forecasting model was conducted by looking at overall forecasting error values. The analysis took into consideration mean absolute percentage error (MAPE), mean absolute deviation (MAD) and mean squared error (MSE). These overall forecasting errors are calculated as follows:

$$MAPE = \frac{\sum_{t=1}^{T} \left| \frac{y_t - F_t}{y_t} \right| \cdot 100}{T}, \quad y_t \neq 0, \tag{9}$$

$$MAD = \frac{\sum_{t=1}^{T} \left| y_t - F_t \right|}{T}, \tag{10}$$

$$MSE = \frac{\sum_{t=1}^{T} \left(y_t - F_t \right)^2}{T}, \tag{11}$$

where $MAPE$ is the mean absolute percentage error, y_t is the value of the time series at time *t*, F_t is the forecast at time *t*, T is the number of pairs of actual values and forecasts, MAD is the mean absolute deviation, MSE is the mean squared error. According to equations (9-11), it can be concluded that each of the observed overall forecasting errors has certain unique properties and characteristics in comparison to the others. Consequently, it is possible that according to one overall forecasting error, one forecasting model is better than the other one because it has a lower value of that overall forecasting error. However, it could happen that according to another forecasting error the second forecasting model is better than the first one. In that case, a forecasting model which has more overall forecasting errors with lower values is considered to be the best one and it is chosen for further analysis.

According to the selected forecasting models, further trends in male and female unemployment rates are forecasted in the observed European countries. It has been decided that the two-period forecast horizon is going to be analysed. In other words, only two periods after the period for which the last actual value exists will be forecasted. Forecasting in the long-run is not recommended because many factors which can have an impact on unemployment can change in the long-run. Consequently, the forecasting errors tend to be very high in the long-run. Thus only short-run forecasts are performed. However, forecasting in the short-run can also provide misleading forecasts. In order to illustrate that and to emphasize that researchers should be careful about their conclusion when forecasting in the short-run, the recent research by [8] has been used with the aim of comparing the results with actual values and with results gained in this article.

ANALYSIS OF MALE AND FEMALE UNEMPLOYMENT RATES

DESCRIPTIVE STATISTICS ANALYSIS OF MALE AND FEMALE UNEMPLOYMENT RATES

In this article male and female unemployment rates of twelve selected European countries are observed. In this chapter, first male and then female unemployment rates are examined. At the end of this section, the differences between male and female unemployment rates are studied.

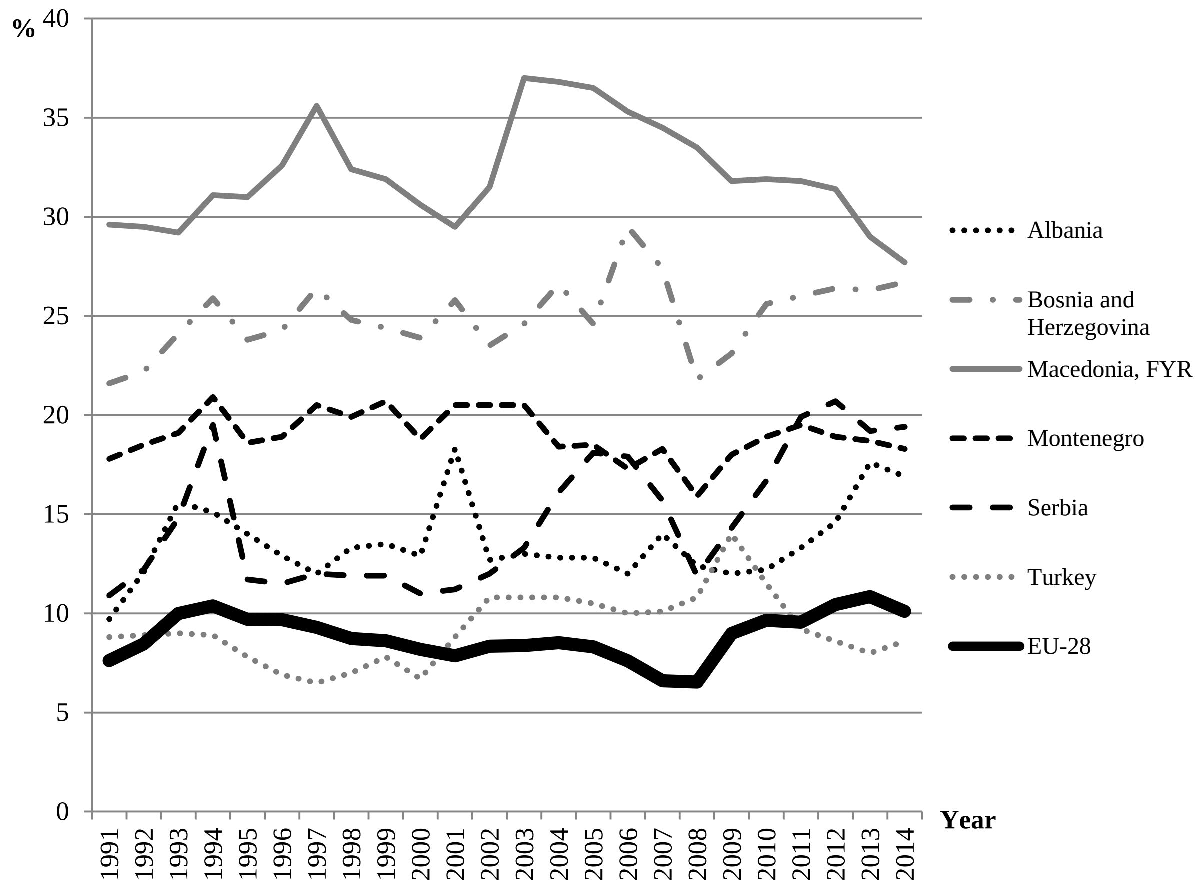

Figure 1. Male unemployment rates in selected Eastern Balkan countries, in the period from 1991 to 2014, in % [9].

In Figure 1 male unemployment rates in the selected Eastern Balkan countries in the period from 1991 to 2014 are presented. In order to make comparisons and to get an insight into whether male unemployment rates are low or high, the average male unemployment rate for the whole EU-28 area is used as a benchmark in Figure 1. It can be concluded that almost all the observed Eastern Balkan countries, except Turkey, have higher male unemployment rates than the EU-28 countries in the whole observed period. Only male unemployment rates in Turkey are close to the (average) EU-28 levels. The worst situation is in the Former Yugoslav Republic of Macedonia. In the whole observed period, the male unemployment rate in the Former Yugoslav Republic of Macedonia was not lower than 27,7 % which was achieved in 2014. After the Former Yugoslav Republic of Macedonia the next country with very high male unemployment rates is Bosnia and Herzegovina. Considering male unemployment rates, the best situation in Bosnia and Herzegovina was in 1991 (21,6 %) and in 2008 (21,8 %). The other three Eastern Balkan countries, Albania, Montenegro and Serbia, had male unemployment rates between 10 % and 20 % in the analysed period.

Figure 2 presents male unemployment rates for the selected six EU-28 member states in the period from 1991 to 2014. Again, the average male unemployment rate for EU-28 is included in Figure 2, in the same way as in Figure 1.

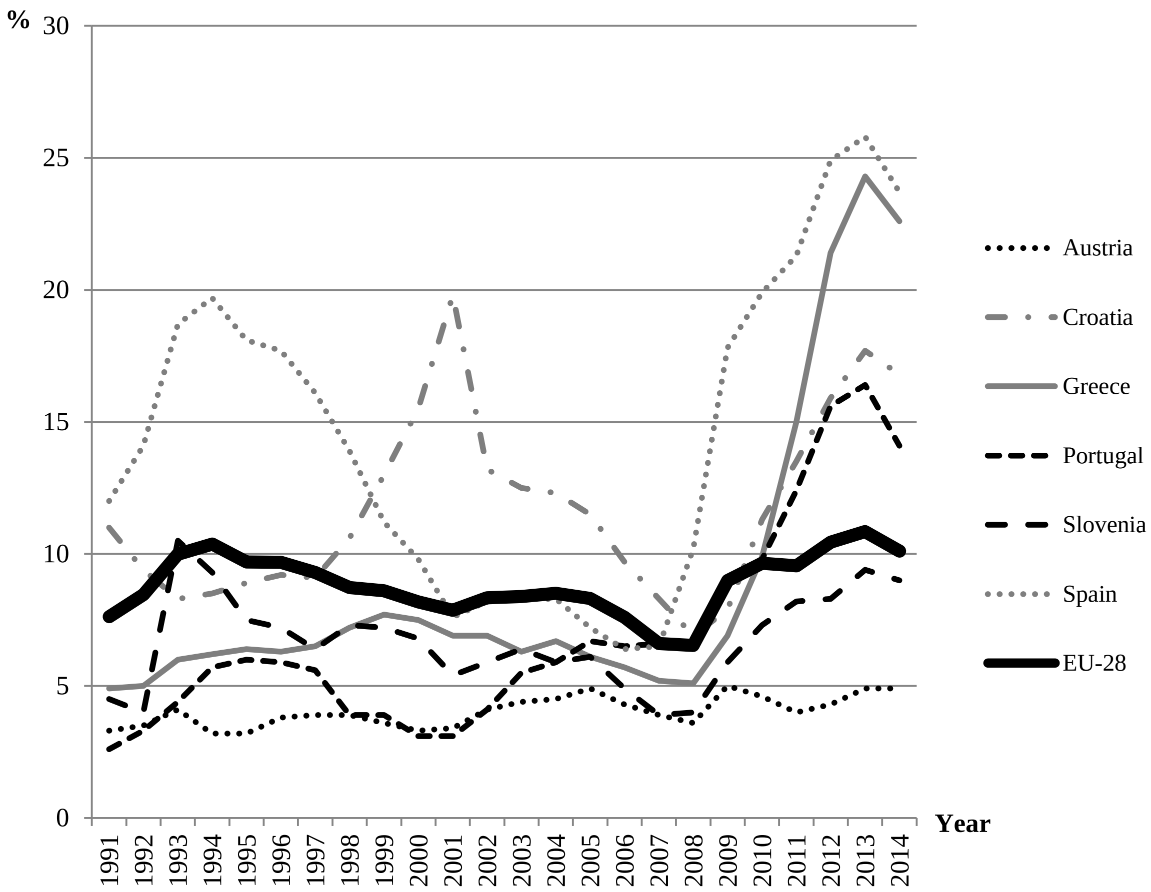

Figure 2. Male unemployment rates in the selected EU-28 member states in the period from 1991 to 2014, in % [9].

By far the best country with the lowest male unemployment rates in the observed periods is Austria. Namely, Austria did not have the lowest male unemployment rates in each observed period but it had male unemployment rates undoubtedly lower than the EU-28 benchmark. After Austria, Slovenia seems to have the lowest male unemployment rates. However, male unemployment rates are much closer to the EU-28 benchmark values. The male unemployment rates in other four countries had a strong increase from 2007 or 2008. That increase stopped in 2014. It is obvious that these Croatia, Greece, Portugal and Spain are above the EU-28 benchmark, especially since 2008. According to the recent male unemployment rates, Spain and Greece seem to have the same male unemployment rate levels whereas Croatia and Portugal also have similar male unemployment rate levels.

The most recent analysed year was 2014. According to Figure 3, in 2014 the Former Yugoslav Republic of Macedonia and Bosnia and Herzegovina had the highest male unemployment rates, both with the value above 25 %. These Eastern Balkan countries are followed by two EU-28 member states – Spain and Greece. Both countries had male unemployment rates above 20 %. The next five countries, Serbia (19,4 %), Montenegro (18,3 %), Albania (16,9 %), Croatia (16,8 %) and Portugal (14.1 %) had male unemployment rates around 5,3 %. Figure 3 reveals that 9 countries had their male unemployment rates above the EU-28 benchmark whereas only 3 countries had male unemployment rates under the benchmark value of 10.1 %. Out of these three countries two of them, Slovenia (9,0 %) and Austria (4,9 %), are the EU-28 member states. Turkey (8,6 %) is the only Eastern Balkan country with its male unemployment rate lower than the EU-28 benchmark.

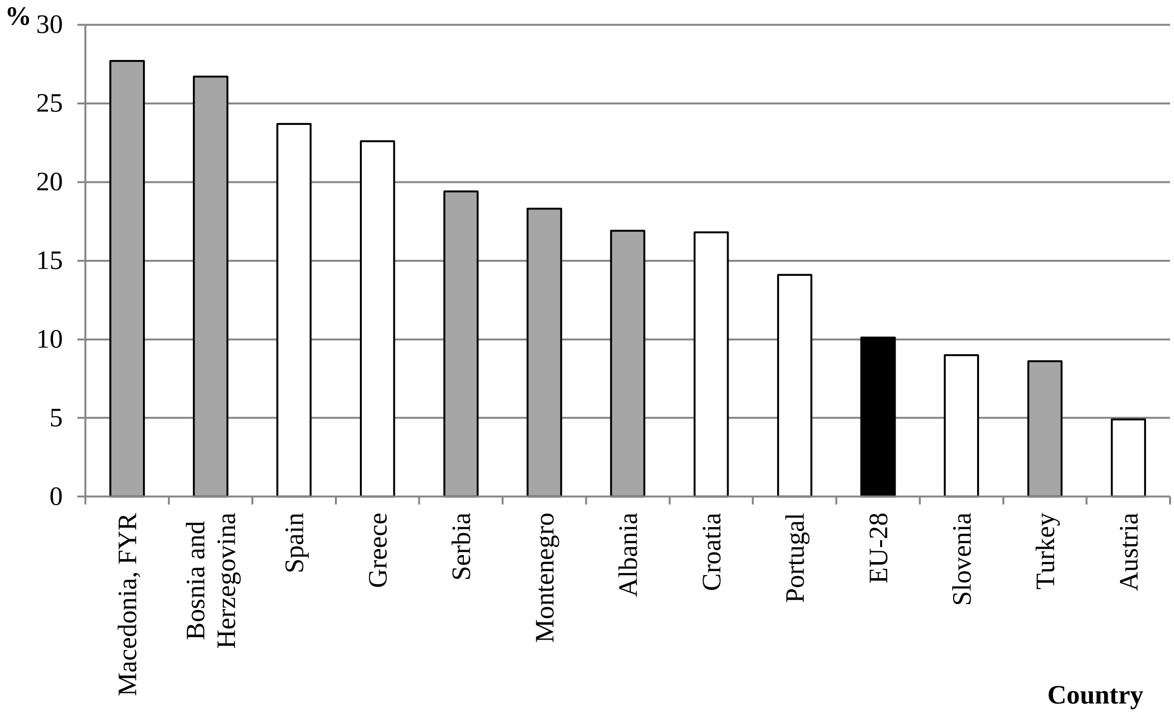

Figure 3. Male unemployment rates in the selected European countries in 2014, in % [9].

Figure 4 shows female unemployment rates in selected Eastern Balkan countries in the period from 1991 to 2014. The conclusions are almost the same as in the case of male unemployment rates in the selected Eastern Balkan countries in the same period. The Former Yugoslav Republic of Macedonia and Bosnia and Herzegovina have the highest female unemployment rates in the analysed period. On the other side, Turkey has the lowest female unemployment rates in the same period in comparison to the other selected Eastern Balkan countries. The female unemployment rates in Turkey tend to be very close to the average female unemployment rates in the EU-28. It has to be emphasized that Montenegro seems to have a very low variability level of female unemployment rates in comparison to the other countries whose variability levels are much higher.

According to Figure 5, Austria has the lowest female unemployment rates in comparison to the other observed EU-28 member states. Slovenia is found to be under the EU-28 benchmark values as well. However, the values of female unemployment rates of the observed EU-28 countries, except Austria, have shown a strong increase in values since 2008. Consequently, Slovenia came very close to the average EU-28 level. The female unemployment rates in Greece were almost at the EU-28 level but since 2008 the difference has been becoming greater and greater. Consequently, Greece has become the EU-28 member state with the highest female unemployment rate in the most recent period (2014). Considering female unemployment rates in recent years, Spain is very close to Greece. Croatia and Portugal also tend to have similar female unemployment rates in the recent years.

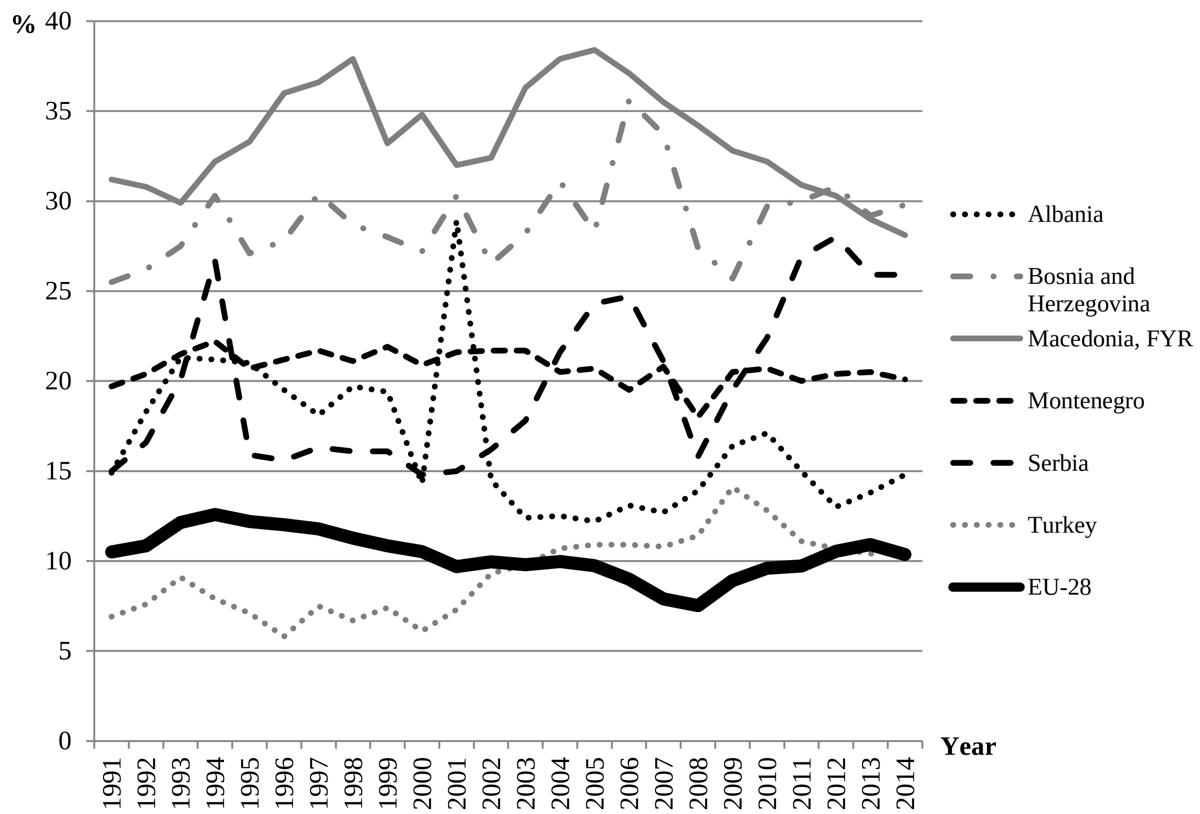

Figure 4. Female unemployment rates in the selected Eastern Balkan countries in the period from 1991 to 2014, in % [9].

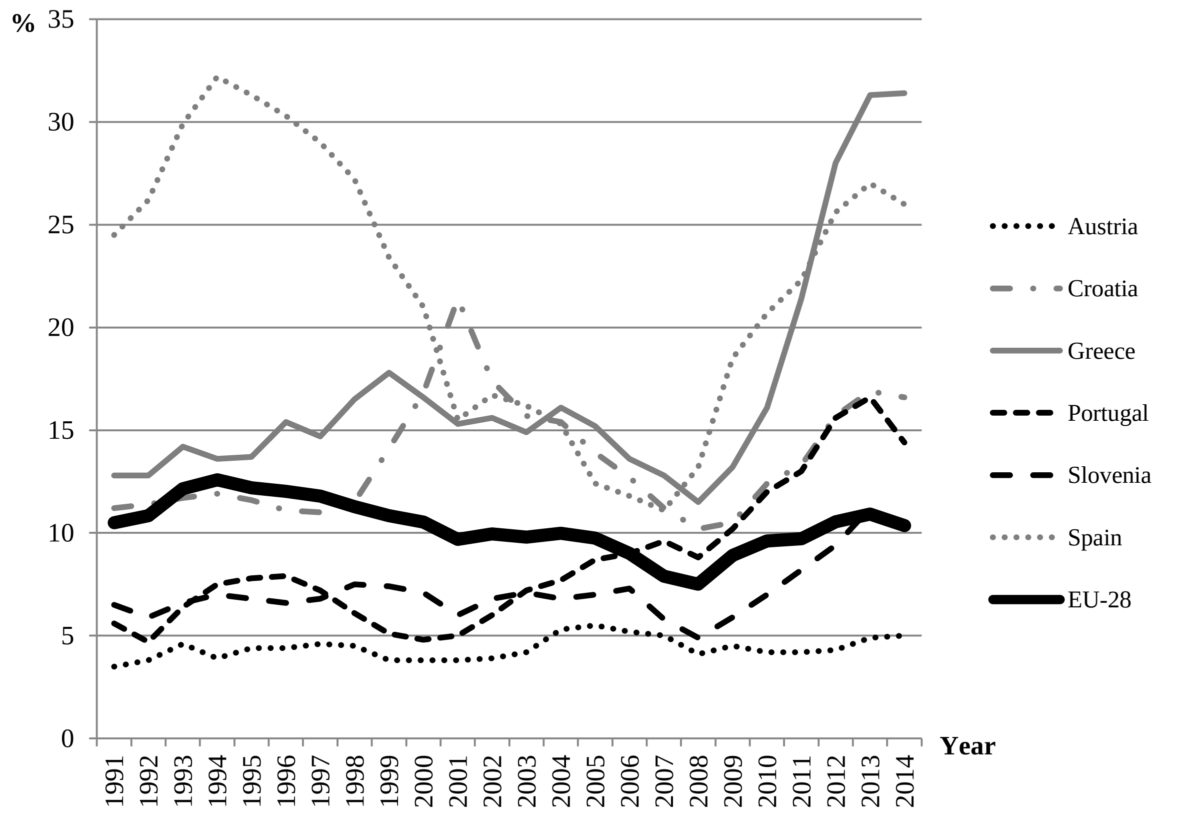

Figure 5. Female unemployment rates in the selected EU-28 member states in the period from 1991 to 2014, in % [9].

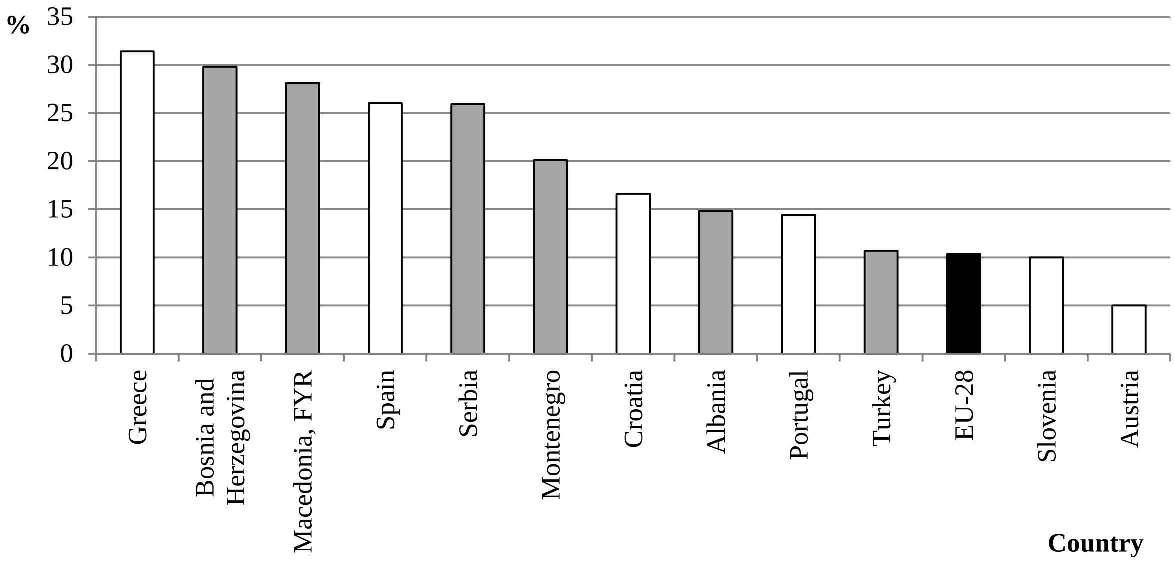

Figure 6. Female unemployment rates in the selected European countries in 2014, in % [8].

Figure 6 shows female unemployment rates for selected European countries in the year 2014. Surprisingly, Figure 6 reveals that Greece (31,4 %) had the highest female unemployment rate among all the observed European countries in 2014. However, Bosnia and Herzegovina and the Former Yugoslav Republic of Macedonia with female unemployment rates of 29,8 % and 28.1 %, respectively, are following Greece closely. Spain (26,0 %) and Serbia (25,9 %) had almost the same female unemployment rates in 2014. Croatia having the female unemployment rate of 16,6 % follows after Montenegro with the female unemployment rate of 20,1 %. Albania (14,8 %) had a slightly higher female unemployment rate than Portugal (14,4 %) in 2014. Turkey with the female unemployment rate of 10,7 % is slightly above the EU-28 benchmark level (10,4 %). The only two countries which had female unemployment rates in 2014 below the EU-28 benchmark level are Slovenia (10,0 %) and Austria (5,0 %).

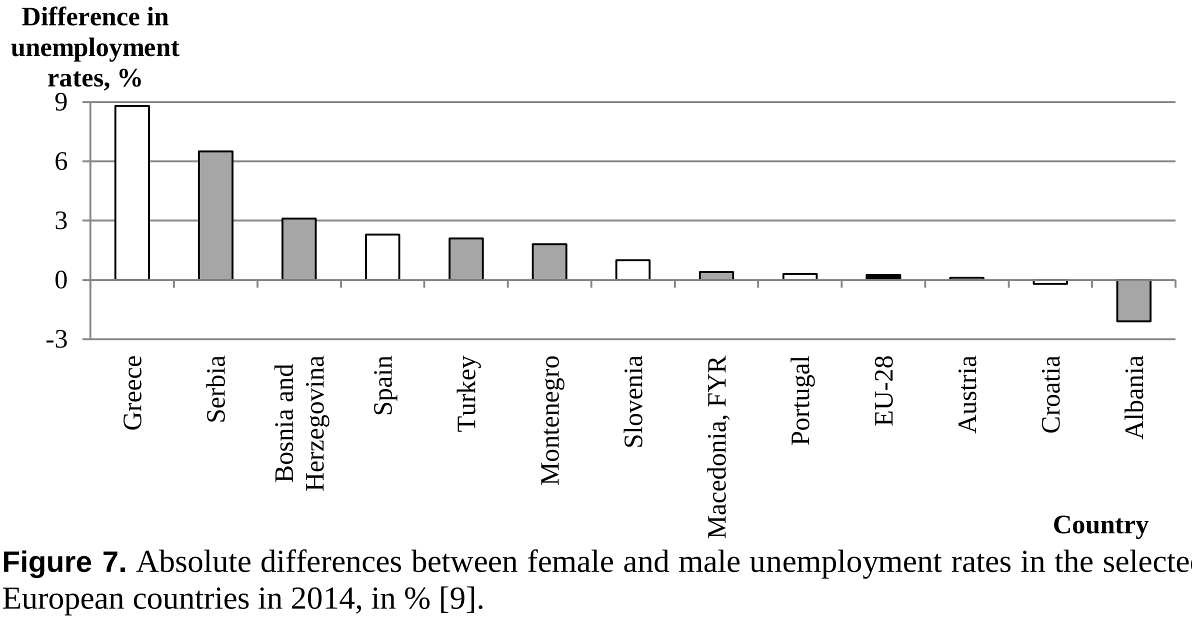

Figure 7. Absolute differences between female and male unemployment rates in the selected European countries in 2014, in % [9].

The absolute differences between female and male unemployment rates in 2014 are calculated and presented in Figure 7. It has to be emphasized that the differences were calculated by subtracting female and male unemployment rates for each observed European country and the differences are given in percentages.

Figure 7 shows that the highest difference between female and male unemployment rates in 2014 was in Greece. Namely, in Greece the female unemployment rate was 8,8 %, which is higher than the male unemployment rate in 2014. In Serbia, the female unemployment rate was 6,5 % higher than the male unemployment rate in 2014. Serbia is following countries with moderately high female unemployment rates: Bosnia and Herzegovina (3,1 %), Spain (2,3 %), Turkey (2,1 %), Montenegro (1,8 %) and Slovenia (1,0 %). The Former Yugoslav Republic of Macedonia (0,4 %), Portugal (0,3 %) and Austria (0,1 %) had slightly higher female unemployment rates than male unemployment rates in 2014. If all the EU-28 member states are taken into account, it can be concluded that the female unemployment rate in the EU-28 member states was 0,3 % higher than the male unemployment rate in 2014. Only in Croatia and Albania the male unemployment rate was higher than the female unemployment rate in 2014. So, in Croatia the male unemployment rate was 0.2 % higher than the female unemployment rate whereas the difference in Albania was 2,1 % in favour of the higher male unemployment rate.

FORECASTING MALE AND FEMALE UNEMPLOYMENT RATES

In further analysis male and female unemployment rates in twelve observed European countries are forecasted by using four selected statistical trend forecasting models. In order to select the most precise and the best forecasting statistical model the overall forecasting error approach is used. The forecasting models with the smallest MAPE, MAD and MSE are chosen. However, in some cases there was no forecasting model which was the best according to all the three overall forecasting errors. In that case, a model which was the best at least for two overall forecasting errors was chosen. The selected forecasting models for male unemployment rates based on data for the period 1991-2014 are shown in Table 1 whereas the selected forecasting models for female unemployment rates are shown in Table 2.

Table 1. Forecasting male unemployment rates: Selected statistical forecasting models for 12 European countries with overall forecasting errors, based on data for the period 1991-2014.

Country	Forecasting model	Equation / Smoothing constants	Overall forecasting errors		
			MAPE	MAD	MSE
Albania	Quadratic trend	$F_t=13{,}43 - 0{,}1 \cdot t+0{,}008 \cdot t^2$	9,88	1,35	3,31
Austria	Linear trend	$F_t=3{,}30+0{,}06 \cdot t$	8,51	0,34	0,16
Bosnia and Herzegovina	Linear trend	$F_t=23{,}47+0{,}12 \cdot t$	4,71	1,16	2,65
Croatia	Double exponential smoothing	α=1,1611; β=0,0641	12.22	1,47	4,78
Greece	Double exponential smoothing	α=0,0474; β=59,6001	10,40	0,81	1,35
Macedonia, FYR	Double exponential smoothing	α=1.2187; β=0,0078	4.29	1,39	3,56
Montenegro	Exponential trend	$F_t=19{,}60 \cdot (0{,}9973^t)$	4,93	0,93	1.28
Portugal	Double exponential smoothing	α=1,3484; β=0,0965	14,94	0,92	1,39
Serbia	Quadratic trend	$F_t=13{,}78 - 0{,}35 \cdot t+0{,}026 \cdot t^2$	12.28	1,80	5.28
Slovenia	Double exponential smoothing	α=0,9970; β=0,0100	15,81	1,08	2,74
Spain	Double exponential smoothing	α=1,6284; β=0,0781	14,88	1,94	5,14
Turkey	Double exponential smoothing	α=1.2189; β=0,0372	8,70	0,83	1,55

According to results from Table 1, the linear trend and the quadratic trend were the best forecasting models for forecasting male unemployment rates in two countries, the exponential trend in just one country, and the double exponential smoothing was the best forecasting model for forecasting male unemployment rates in seven countries. In case of forecasting female unemployment rates only two forecasting models seem to be the best choice. So, according to the results from Table 2, the quadratic trend was the best forecasting model for forecasting female unemployment rates in five countries whereas the double exponential smoothing was the best forecasting models for forecasting female unemployment rates in seven countries.

Table 2. Forecasting female unemployment rates: Selected statistical forecasting models for 12 European countries with overall forecasting errors, based on data for the period 1991-2014.

Country	Forecasting model	Equation / Smoothing constants	Overall forecasting errors		
			MAPE	MAD	MSE
Albania	Quadratic trend	F_t=20,38 – 0,32 · t+0,001 · t^2	14,98	2,48	11,42
Austria	Double exponential smoothing	α=0,9699; β=0,0100	8,04	0,35	0.21
Bosnia and Herzegovina	Quadratic trend	F_t=26,02+0,43 · t–0,012 · t^2	5.27	1,55	4,45
Croatia	Double exponential smoothing	α=1.2606; β=0,0698	7,98	1,17	3,00
Greece	Double exponential smoothing	α=1,5745; β=0,1229	9,42	1,52	3.23
Macedonia, FYR	Quadratic trend	F_t=28,57+1.26 · t–0,053 · t^2	3,92	1,34	3,11
Montenegro	Quadratic trend	F_t=20,80+0,09 · t–0,006 · t^2	2,86	0,58	0,62
Portugal	Double exponential smoothing	α=1,5546; β=0,0873	11.20	0,90	1,52
Serbia	Quadratic trend	F_t=18,87–0,51 · t+0,036 · t^2	12,51	2,48	10,09
Slovenia	Double exponential smoothing	α=1.2896; β=0,0702	9,73	0,69	0,77
Spain	Double exponential smoothing	α=1,0519; β=0,5419	9,12	1,78	4,95
Turkey	Double exponential smoothing	α=0,9924; β=0,0442	11,31	0,98	1,40

Table 3. Forecasted male unemployment rates in 12 European countries in 2015 and 2016 (time horizon τ=2).

Country	Actual values		Forecasted values		Recent forecast tendency
	2013	2014	2015	2016	
Albania	17,6	16,9	15,34	15,61	Increase
Austria	4,9	4,9	4,75	4,81	Increase
Bosnia and Herzegovina	26,3	26,7	26,47	26,59	Increase
Croatia	17,7	16,8	16,98	17,43	Increase
Greece	24,3	22,6	15,99	8.26	Decrease
Macedonia, FYR	29,0	27,7	27.29	27,00	Decrease
Montenegro	18,7	18,3	18,34	18.29	Decrease
Portugal	16,4	14,1	13,61	14,15	Increase
Serbia	19.2	19,4	21,39	22,37	Increase
Slovenia	9,4	9,0	9,05	9,10	Increase
Spain	25,8	23,7	22,93	23,65	Increase
Turkey	8,0	8,6	8,66	8,54	Decrease

It has to be emphasized that overall forecasting errors are not directly comparable neither among different countries, nor male and female unemployment rates overall errors in a country because different forecasting models and/or different parameters in forecasting models were used. Thus, trends in male and female unemployment rates in the observed European countries are analysed. The last actual male and female unemployment rates are officially available for 2014. Because of that, forecasts for 2015 and 2016, developed using the models from Table 1 and Table 2 and the forecast time horizon τ=2, are observed to determine the short-run tendencies in male and female unemployment rates. It has been decided to forecast only two periods in the future because unemployment rates are influenced by different factors. In Table 3, the forecasts and determined trends in male unemployment rates are shown, whereas in Table 4, the forecasts and determined trends in female unemployment rates are presented.

Unfortunately, the results from Table 3 and Table 4 are not as positive as one might expect because Gross Domestic Product per capita is rising on the World level since 2010 [10]. Namely, only in four countries (Greece, the Former Yugoslav Republic of Macedonia, Montenegro and Turkey) there is a decrease of male unemployment rates. So, according to Table 3, only in four countries the decrease in male unemployment rates is expected. It is interesting that out of these four countries, three are the Eastern Balkan countries whereas just one is the EU-28 member state. The results from Table 4 show that the female unemployment rate decrease is forecasted in only four countries. All countries in which a decrease of the female unemployment rate is expected are the Eastern Balkan countries (Albania, Bosnia and Herzegovina, the Former Yugoslav Republic of Macedonia, Montenegro and Turkey). The only two countries in which a decrease in both, male and female, unemployment rates is forecasted are the Former Yugoslav Republic of Macedonia and Montenegro. Consequently, it is expected that in these two countries the overall unemployment rate will also decrease in the future periods.

Table 4. Forecasted female unemployment rates in 12 European countries in 2015 and 2016 (time horizon τ=2).

Country	Actual values		Forecasted values		Recent forecast tendency
	2013	2014	2015	2016	
Albania	13,8	14,8	13,06	12,80	Decrease
Austria	4,9	5,0	5,03	5,07	Increase
Bosnia and Herzegovina	29.2	29,8	29,34	29,17	Decrease
Croatia	16,9	16,6	16,75	17,10	Increase
Greece	31,3	31,4	31,98	33,43	Increase
Macedonia, FYR	29,0	28,1	26,80	25,34	Decrease
Montenegro	20,5	20,1	19,49	19.29	Decrease
Portugal	16,6	14,4	13,40	13,76	Increase
Serbia	25,9	25,9	28,83	30,17	Increase
Slovenia	11.2	10,0	9,64	9,85	Increase
Spain	27,0	26,0	26,16	26,48	Increase
Turkey	10,4	10,7	10,77	10,84	Increase

DISCUSSION AND COMPARISONS OF MALE AND FEMALE UNEMPLOYMENT RATES

As it was mentioned earlier, forecasting is easy to perform but it is hard to rely on forecasts. As a consequence, conducting forecasts in a long-run should be avoided because the future is very unpredictable, especially when economy is observed. Furthermore, often forecasts in the long-run do not have meaningful interpretation. Therefore, it is highly recommended to conduct only short-term forecasts. In this article only two periods in the future were forecasted. That was the minimal number of forecasts to determine future trends in male and female unemployment rates developments in the observed countries. It has to be emphasized that little or no care was given to the exact forecasts values. The reason for that is very simple. Namely, with a high reliability level it can be concluded that the calculated point forecasts are going to be different from the real values in the future. In other words, it can be concluded that no matter which statistical forecasting approach is used, there would always be a certain forecasting error. However, by using the most appropriate statistical forecasting model these forecasting errors in the future should be minimal. In order to select the most appropriate statistical forecasting model it is necessary that enough data points are available. If there are not enough data points available, the development of the observed variable cannot be described very well by any statistical forecasting model. Consequently very high values of overall forecasting errors are present. Of course, in case of a small number of available data points there is a danger of choosing the wrong statistical forecasting model which seems to be the best by observing only a small number of data points. However, the question is whether an additional data point necessarily leads to smaller overall forecasting errors or the impact of an additional data point can be neglected.

In this article male and female unemployment rates were forecasted for the observed European countries by using data from 1991 to 2014. Based on performed forecasts and calculated overall forecasting errors the best statistical forecasting models were chosen and presented in Table 1 and Table 2. In order to examine the impact of additional data points on the overall forecasting errors and the precision of the selected statistical forecasting models, additional forecasting was conducted. Again, male and female unemployment rates will be forecasted for the observed European countries but by using data from 1991 to 2013. So, in the process of forecasting, one data point less will be used in comparison to the previously conducted forecasting. In order to make overall forecasting errors comparable, forecasting is conducted only by using previously selected statistical forecasting models which had the smallest overall forecasting errors based on data from 1991 to 2014. After the overall forecasting errors were calculated based on data points from 1991 to 2013, their values have been compared to the overall forecasting errors values which have been calculated based on data points from 1991 to 2014. The differences between overall forecasting errors have been observed in an absolute and in a relative sense. In order to calculate absolute differences between overall forecasting errors, the simple subtraction of overall forecasting errors based on data points from 1991 to 2013 from overall forecasting errors values based on data points from 1991 to 2014 was conducted. The relative differences were calculated by using the following expression:

$$\Delta DIFF = \frac{OFE_t - OFE_{t-1}}{OFE_{t-1}} \cdot 100, \tag{12}$$

where $\Delta DIFF$ is the relative difference between two overall forecasting errors, OFE_t is the overall forecasting error value based on data points from 1991 to 2014, OFE_{t-1} is the overall forecasting error value based on data points from 1991 to 2013. As overall forecasting errors in the analysis *MAPE*, *MAD* and *MSE* were used. The absolute and relative differences are shown in Table 5 for male unemployment rates and in Table 6 for female unemployment rates in the analysed European countries.

Opposite to the expected, the results from Table 5 and Table 6 have shown that adding a new data point for 2014 does not necessarily lead to smaller overall forecasting errors. If the male unemployment rates forecasts are observed, it can be concluded that an additional data point resulted in smaller overall forecasting errors in 9 countries by using *MAPE*, in 7 countries by using *MAD* and in 7 countries by using *MSE*. So, for the majority of countries an additional data point led to smaller overall forecasting errors. The largest decrease in overall forecasting errors by adding a new data point is achieved in Slovenia. In case of Slovenia, the additional male unemployment rate data for 2014 resulted in the 28,12 % decrease of *MAPE*, in the 21.24 % decrease of *MAD* and in the 30,15 % decrease in *MSE*. On the other side, in Portugal the additional male unemployment rate data for 2014 resulted in the 10,78 % increase of *MAPE*, in the 15,00 % increase of *MAD* and in the 38,06 % increase in *MSE*. In Albania and in the Former Yugoslav Republic of Macedonia adding an additional data point resulted in an increase of all the three observed forecasting errors, also.

According to results from Table 6, if female unemployment rates forecasts are observed, it can be concluded that an additional data point resulted in smaller overall forecasting errors for 8 countries by using *MAPE*, in 7 countries by using *MAD* and in 7 countries by using *MSE*. So, again an additional data point resulted in lower overall forecasting errors in the majority of the observed European countries. However, the improvements of overall forecasting errors are much less expressed in the case of female unemployment rates than in the case of male unemployment rates. The best improvements of overall forecasting errors are present in the case of Turkey. Namely, in Turkey, the additional female unemployment rate data for 2014 resulted in the 4,73 % decrease of *MAPE*, in the 4,76 % decrease of *MAD* and in the 7,12 % decrease in *MSE*. On the other side, in four European countries (Croatia, Greece, Slovenia, Spain) all the three observed overall forecasting errors increased because a new female unemployment rate from 2014 was included in the analysis. The largest increase of overall forecasting errors is present in Slovenia where *MAPE* increased by 9,50 %, *MAD* increased by 12,89 % and *MSE* increased by 21,56 %.

Table 5. Differences in overall forecasting errors values when male unemployment rates in the period from 1991 to 2014 and in the period from 1991 to 2013 are compared in 12 considered European countries.

Country	Forecasting model	Overall forecasting error					
		MAPE (difference)		MAD (difference)		MSE (difference)	
		Absolute	Relative (%)	Absolute	Relative (%)	Absolute	Relative (%)
Albania	Quadratic trend	0,14	1,39	0,02	1,43	0,07	2,04
Austria	Linear trend	-0.20	-2,34	-0,01	-2,10	-0,00	-2,85
Bosnia and Herzegovina	Linear trend	-0,16	-3.25	-0,04	-3.23	-0,11	-3,95
Croatia	Double exponential smoothing	-0,11	-0,86	0,01	0,59	-0,08	-1,56
Greece	Double exponential smoothing	-1,15	-9,97	-0,12	-12,39	0,00	0,18
Macedonia, FYR	Double exponential smoothing	0,05	1,18	0,01	0,40	0.21	6.24
Montenegro	Exponential trend	-0,19	-3,65	-0,04	-3,64	-0,06	-4,11
Portugal	Double exponential smoothing	1,45	10,78	0,12	15,00	0,38	38,06
Serbia	Quadratic trend	-0.22	-1,73	-0,02	-1.20	-0,16	-2,92
Slovenia	Double exponential smoothing	-6,19	-28,12	-0.29	-21.24	-1,18	-30,15
Spain	Double exponential smoothing	-0.29	-1,93	0,03	1,45	0,17	3,47
Turkey	Double exponential smoothing	-0,18	-2,08	-0,02	-2,33	-0,10	-5,95

The main reason why in some countries all the three overall forecasting errors have increased by adding a new data point could be in statistical forecasting model misspecification. In other words, it could happen that if data from 1991 to 2013 are observed, one statistical forecasting model is the most appropriate but if data from 1991 to 2014 are observed, another statistical forecasting model should be chosen because of lower overall forecasting errors. In order to take this fact into account, the list of selected statistical forecasting models from recent research by [8] was taken and presented in Table 7.

In [8] the author also forecasted male and female unemployment rates, but by using data from 1991 to 2013. Table 7 summarizes statistical forecasting models which appeared to be the best to perform forecasts of male and female unemployment rates for the observed European countries according to [8] and according to the research presented in this article. According to Table 7, an additional data point of the male unemployment rate in 2014 led to a change of the best statistical forecasting model in the case of 5 countries (Albania, Montenegro, Portugal, Serbia, and Spain). Similarly, an additional data point of the female unemployment rate in 2014 led to a change of the most appropriate statistical forecasting model in 5 countries also (Albania, Bosnia and Herzegovina, the Former Yugoslav Republic of Macedonia, Montenegro, Serbia).

However, if these lists of countries are compared to the lists of countries in which all the three overall forecasting errors increased only one match can be found. Only when male

Table 6. Differences in overall forecasting errors values when female unemployment rates in the period from 1991 to 2014 and in the period from 1991 to 2013 are compared in 12 observed European countries.

Country	Forecasting model	Overall forecasting error					
		MAPE (difference)		MAD (difference)		MSE (difference)	
		Absolute	Relative, %	Absolute	Relative, %	Absolute	Relative, %
Albania	Quadratic trend	–0,40	-2,62	-0,07	-2,66	-0,36	-3,03
Austria	Double exponential smoothing	–0.28	-3,35	-0,01	-3.27	-0,01	-4.22
Bosnia and Herzegovina	Quadratic trend	–0,18	-3.23	-0,05	-3.26	-0,19	-4,04
Croatia	Double exponential smoothing	0,03	0,38	0,01	0,61	0,00	0,14
Greece	Double exponential smoothing	0,06	0,62	0,00	0,31	0.26	8,87
Macedonia, FYR	Quadratic trend	–0,17	–4,17	–0,06	–4,18	–0,13	–4,16
Montenegr o	Quadratic trend	–0,07	–2.27	–0,01	–2,34	–0,02	–2,41
Portugal	Double exponential smoothing	–0,02	–0,15	0,07	8,48	0.21	15,94
Serbia	Quadratic trend	–0,17	–1,33	–0,02	–0,76	–0.26	–2,54
Slovenia	Double exponential smoothing	0,84	9,50	0,08	12,89	0,14	21,56
Spain	Double exponential smoothing	0,01	0,14	0,04	2.27	0,18	3,67
Turkey	Double exponential smoothing	–0,56	–4,73	–0,05	–4,76	–0,11	–7,12

unemployment rate forecasts for Albania is observed it can be concluded that an additional data point for 2014 resulted in an increase of all the three observed overall forecasting errors and resulted in the change of the most appropriate statistical forecasting method. Thus, it can be concluded that the increase of overall forecasting errors by including a new data point in the analysis does not have support in the misspecification and choosing the wrong statistical method. The reason for the increase of the overall forecasting error therefore should be in adding a new data point. It is possible that a new data point has a strong impact on the model parameters which lead to a different shape of the forecasted model. Consequently, the forecasting errors also change.

Table 7. Comparison of the selected statistical forecasting model for forecasting male and female unemployment rates by using data from 1991 to 2013 (approach developed in [8]), and by using data from 1991 to 2014 (longer period approach) in the 12 observed European countries.

Country	Male unemployment rate – selected statistical forecasting models		Female unemployment rate – selected statistical forecasting models	
	1991 to 2013 based forecasts	1991 to 2014 based forecasts	1991 to 2013 based forecasts	1991 to 2014 based forecasts
Albania	Linear trend	Quadratic trend	Linear trend	Quadratic trend
Austria	Linear trend	Linear trend	Double exponential smoothing	Double exponential smoothing
Bosnia and Herzegovina	Linear trend	Linear trend	Linear trend	Quadratic trend
Croatia	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing
Greece	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing
Macedonia, FYR	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing	Quadratic trend
Montenegro	Linear trend	Exponential trend	Double exponential smoothing	Quadratic trend
Portugal	Quadratic trend	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing
Serbia	Double exponential smoothing	Quadratic trend	Double exponential smoothing	Quadratic trend
Slovenia	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing
Spain	Linear trend	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing
Turkey	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing	Double exponential smoothing

CONCLUSIONS

In this article short-run forecasts of male and female unemployment rates for the selected group of European countries using historic time series data for 1991 to 2013 is performed, and to the unemployment rates in the group of the Eastern Balkan countries are compared.

The accuracy of predictions by adding a new data point, for 2014, and by comparing our estimates with relevant research by [8], which was developed for the period from 1991 to 2013 only, is evaluated.

According to the empirical analysis and 1991 to 2014 based forecasts, the linear trend and the quadratic trend were the best forecasting models for forecasting male unemployment rates in only two observed countries, the exponential trend in only one country, and the double exponential smoothing was the best forecasting model for forecasting male unemployment rates in seven observed countries. In the case of forecasting female unemployment rates, only two forecasting models seem to be the best choice. Namely, the quadratic trend was the best forecasting model for forecasting female unemployment rates in five countries whereas the double exponential smoothing was the best forecasting model for unemployment rates in seven countries. Adding a new data point has a strong impact on the model parameters which may lead to a different shape of the best forecasting model and, as a result, to the changed forecasting errors.

This research raised a number of questions that still have to be answered, offering a good basis for further research. Thus, future research might focus on the impact of a new data point on the forecasting model shape. In that way the exact change of trend values and forecasts as a consequence of adding new data points can be estimated. Furthermore, in order to select the best statistical forecasting model to perform forecasts the believability criteria instead of the smallest overall forecasting error criteria should also be taken into account.

REFERENCES

[1] Simonescu, M.: *The improvement of unemployment rate predictions accuracy.* Prague Economic Papers **24**(3), 274-286, 2015, http://dx.doi.org/10.18267/j.pep.519,

[2] Nasir, M.N.M.; Hwa, K.M. and Mohammad, H.: *An Initial Study on the Forecast Model for Unemployment Rate.* Statistics Malaysia – Journal of the Department of Statistics **1**(1), 27-43, 2008,

[3] Simonescu, M.: *The Performance of Unemployment Rate Predictions in Romania. Strategies to Improve the Forecasts Accuracy.* Review of Economic Perspectives – Národohospodářský Obzor **13**(4), 161-175, 2013,

[4] Simonescu, M.: *The Accuracy and Bias Evaluation of the USA Unemployment Rate Forecasts. Methods to Improve the Forecasts Accuracy.* Annals of the University of Petroşani, Economics **12**(4), 17-32, 2012,

[5] Bratu, M. and Marin, E.: *Short run and alternative macroeconomic forecasts for Romania and strategies to improve their.* Journal of International Studies **5**(2), 30-46, 2012, http://dx.doi.org/10.14254/2071-8330.2012/5-2/4,

[6] Nkwatoh, L.S.: *Forecasting Unemployment Rates in Nigeria Using Univariate Time Series Models.* International Journal of Business and Commerce **1**(12), 33-46, 2012,

[7] Voineagu, V.; Pisica, S. and Caragea, N.: *Forecasting monthly unemployment by econometric smoothing techniques.* Economic computation and economic cybernetics studies and research / Academy of Economic Studies **3**(3), 255-267, 2012,

[8] Dumičić, K.: *Developing Forecasting Models for Unemployment Rate by Gender: Cross Countries Comparison.*
Proceedings of the World Statistics Congress – WSC ISI'2015, Rio de Janeiro, 2015, http://www.isi2015.org/components/com_users/views/registration/tmpl/media/uploadedFiles/paper/2840/10592/PP-A10-P12-S.pdf,
[9] The World Bank: *World Development Indicators.*
http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators,
[10] The World Bank: *GDP per capita growth (annual %).*
http://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG?end=2015&name_desc=false&start=1961&view=chart.