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Forecasting Unemployment Rate in Selected European Countries Using Smoothing Methods

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Abstract**—**The aim of this paper is to select the most accurate forecasting method for predicting the future values of the unemployment rate in selected European countries. In order to do so, several forecasting techniques adequate for forecasting time series with trend component, were selected, namely: double exponential smoothing (also known as Holt`s method) and Holt-Winters` method which accounts for trend and seasonality. The results of the empirical analysis showed that the optimal model for forecasting unemployment rate in Greece was Holt-Winters` additive method. In the case of Spain, according to MAPE, the optimal model was double exponential smoothing model. Furthermore, for Croatia and Italy the best forecasting model for unemployment rate was Holt-Winters` multiplicative model, whereas in the case of Portugal the best model to forecast unemployment rate was Double exponential smoothing model. Our findings are in line with European Commission unemployment rate estimates.

Keywords**—**European Union countries, exponential smoothing methods, forecast accuracy unemployment rate.

I. Introduction

PRIMARY application of many econometrics models is forecasting, thus this paper aims to select the most accurate forecasting model among smoothing methods for the short-term forecast of the unemployment rate in selected European countries. The authors found challenging enough to explore potential forecasting models suitable for predicting the future values of unemployment rate, since recent analysis conducted by Eurostat revealed some interesting trends. Namely, the euro area seasonally-adjusted unemployment rate in August 2014 reached 11.5%, which was stable when compared to July 2014, but also smaller then in August 2013 when it was 12.0%. The EU-28 unemployment rate was 10.1% in August 2014, which is the lowest recorded value since February 2012. Furthermore, unemployment rate was lower in July 2014 and August 2013 when it reached 10.2% and 10.8%, respectively. Among the Member States, the lowest unemployment rates were recorded in Austria (4.7%) and Germany (4.9%), while the highest recorded unemployment rates were in Greece (27.0%) and Spain (24.4%). Following for mentioned unemployment rate trends, in this paper quarterly data on unemployment rate from first quarter 2001 to fourth quarter 2013 will be analyzed and also, the most suitable forecasting method will be selected. Since Eurostat already delivered data on unemployment rate for first two quarters of 2014, the accuracy of estimated forecasting models could be directly checked. For the purpose of the empirical analysis, we selected five European countries, namely: Croatia, Greece, Italy, Portugal and Spain. Even though, substantial differences exist among them in the analyzed period; they all record substantially high unemployment rates.

As already mentioned, the aim of this paper is to select the most accurate forecasting method for predicting the future values of the unemployment rate. In order to do so, several forecasting techniques adequate for forecasting time series with trend component, were selected, namely: double exponential smoothing (also known as Holt`s method) and Holt-Winters` method which accounts for trend and seasonality.

The remainder of this paper is as follows. After the introduction in Section II a brief relevant literature review is given. Section III presents data and methods used in the empirical analysis. Section IV gives the results of the estimated forecasting models. Finally, Section V concludes.

II. Literature Review

In their research [7] analyzed accuracy, bias and forecasts efficiency for the following macroeconomic variables: gross domestic product, inflation, industrial production and private consumption in G7 countries. Since most international institutions provide their own macroeconomic forecasts, large discrepancies in the results are not present only between countries, but also within individual country [9]. The accuracy of forecasts is especially relevant in the case of economic crisis.

Unemployment rate forecasts are compared in the USA conducted by different institutions, according to [11]. In the process of forecast accuracy evaluating, multi-criteria ranking were used and the following indicators, namely: root mean squared error (RMSE), mean error (ME), mean absolute error (MAE) and U Theil's statistics were taken into account. In order to evaluate forecast accuracy of unemployment rate in Romania according to [8] in multi-criteria ranking, the following measures of accuracy were used: RMSE, ME, MAE, U1 and U2 Theil's statistics. Except the multi-criteria ranking the method of relative distance was used, leading to the same conclusions.

Furthermore, [13] emphasized significant increase of the

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need for high-quality statistics in labor policy. In order to forecast monthly unemployment rate in Romania, they used double exponential smoothing or Holt's linear exponential smoothing model. Accordingly, the exponential smoothing models react more quickly to changes in data patterns than the moving average models. On the other hand, the main problem, when using exponential smoothing models, is determining the size of smoothing coefficients [13].

In the case of the inflation rate, the unemployment rate and the interest rate in the Czech Republic, [10] has shown that exponential smoothing techniques generate better short run predictions than simple econometric models. The research of [4] led to similar conclusion. They used ARIMA and exponential smoothing modelling to forecast tourist arrivals in Greece. In their analysis, they included unemployment, tourists' cost of living and the consumer confidence indicator. The analysis has shown that the ARIMA (1,1,1) model has better statistical properties than other exponential smoothing models known as direct forecasting tools. Furthermore, it was shown that exponential smoothing models were more accurate when compared to ARIMA models.

In order to forecast main macroeconomic variables in Turkey, which is an EU candidate, [5] used variety of different forecasting methods. According to their research the Holt's linear exponential smoothing method was the most appropriate for unemployment rate forecasting.

After the period of increasing unemployment rate, [6] forecasted decline of the unemployment rate for the EU and euro area in forthcoming years. However, the unemployment rate forecast for Croatia is set at 18% in 2014 and 2015. Consequently, Croatia after Greece (forecast for 2014 and 2015 is 26% and 24%, respectively), Spain (forecast for 2014 and 2015 is 25.5% and 24%, respectively) and Cyprus (forecast for 2014 and 2015 is 19.2% and 18.4%, respectively), has the highest forecasted unemployment rate in European Union. Accordingly, there is a need for a closer analysis of an unemployment rate in European countries.

Our paper contributes to the existing literature by giving insights on the most appropriate forecasting methods among smoothing methods for predicting unemployment rate. Our findings are in line with European Commission unemployment rate estimates.

III. Data and Methods

In the empirical analysis of this paper, the quarterly data on unemployment rate in the period from first quarter of 2001 to fourth quarter of 2013 is used. Since the global financial crisis started in the third quarter of 2008, in our analysis, we will be able to capture the impact of that crisis on the unemployment rate. The data was taken from Eurostat database (European Union labour force survey, EU-LFS) for the following 5 European countries: Croatia, Greece, Italy, Portugal and Spain.

Based on International Labour Office (ILO) definition, the unemployment rate represents unemployed persons as a percentage of the labour force. The labour force is the total number of people employed and unemployed. Unemployed persons comprise persons aged 15 to 74 who: are without work during the reference week; are available to start work within the next two weeks; and have been actively seeking work in the past four weeks or had already found a job to start within the next three months. In this paper, according to Eurostat definition, the variable of interest is total unemployment rate by sex and age groups given as quarterly average, expressed in percentages (Eurostat variable code: une_rt_q).

Variety of forecasting methods exists, but a pragmatic question still remains: how can a forecaster choose a right model for a data set? A main objective is to decide on the nature of trend and seasonality and a usual way to do so is to construct a time plot of the raw data. Accordingly, in Fig. 1, a time plot of unemployment rate in selected European countries for the analyzed period is given.

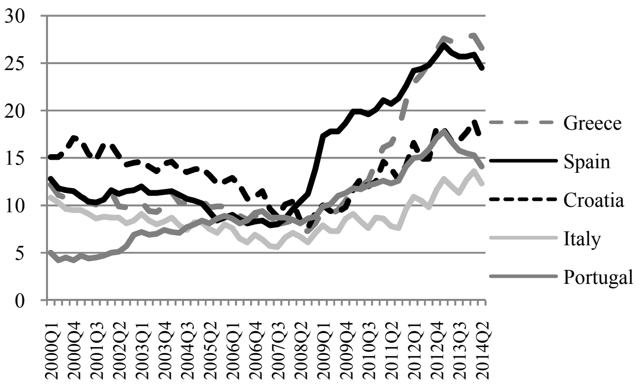

Fig. 1 Quarterly unemployment rate in selected European countries

As it can be seen from the graph, two different trends in unemployment rate in all analyzed countries may be observed. Namely, in all countries but Portugal, there is a downward trend in unemployment rate from first quarter of 2001 to third quarter of 2008 when the global financial crisis began. From then on, in all analyzed countries, a growth in unemployment rate can be observed. Interestingly, in Portugal, for the whole analyzed period, a growth in unemployment rate is evident.

Extremely unfavorable period for the unemployment rate in Croatia began in 2008. The development of such situation is due to fore mentioned global economic crisis, which reached its peak in the third quarter of 2008. The impact of that crisis on the labour market can easily be explained on the example of Greece, where it all began by a credit crisis development. Consequently, it led to the economic crisis that adversely affected the financial condition of Greece. The reported decline in GDPs also led to a drop in budget revenues. At the same time, a decline in budget revenues has led to the growth of corruption and the gray economy. The labor market was not left behind. Rising unemployment caused an increase in public expenditure due to rising costs of unemployment benefits. Furthermore, expenses exceeded revenues which led to a budget deficit. For its coverage, Greece used foreign loans that resulted in over-indebtedness and deepening credit crisis. However, the crisis did not skip Spain, Italy and Portugal, but it had less impact on those countries when compared to Greece. Still, these countries recorded a negative tendency of the unemployment rate.

As far as the methods for the empirical analysis in this paper are concerned, as mentioned before, exponential smoothing methods will be used, since they react more quickly to the changes in data pattern. Moreover, exponential smoothing was first suggested by [2] in the 1957 and was intended to be used for time series without trend. But in 1958, Holt offered a method that also handles trend in data, which is now known as Holt`s linear method. Furthermore, in 1965 Winters generalized that method to include seasonality, which is called Holt-Winters Method.

According to Fig. 1, there is pronounced trend and seasonal component in unemployment rate, with the seasonal component being most pronounced in the case of Croatia and Italy. Thus, in the empirical analysis Holt double exponential smoothing and Holt Winters method will be used in forecasting future unemployment rate. The Holt's forecasting model consists of both an exponentially smoothed permanent component denoted by L_t and a smoothed trend component b_t. Consequently, the technique is sometimes called two-parameter double exponential smoothing [1]. The trend component is used in the calculation of the exponentially smoothed value. The following equations show that both L_t and b_t are weighted averages [12]:

$$\begin{aligned} L_t &= \alpha Y_t + (1-\alpha)(L_{t-1} + b_{t-1}) \\ b_t &= \gamma(L_t - L_{t-1}) + (1-\gamma)b_{t-1} \end{aligned} \tag{1}$$

It should be noted that the equations require two subjectively chosen smoothing constants, α and γ, each of which is between zero and one. If two constants are equal the model is called Brown's double exponential smoothing. The constant α controls the smoothness of L_t. The closer the constant α is to zero, the more emphasis is given to the past values of the time series, while a value of α near one gives more weight to the current values of the series, minimizing the influence of historical values. The trend component of the series is estimated adaptively, using a weighted average of the most recent change in the level ($L_t - L_{t-1}$), and the trend estimate (b_{t-1}) from the previous period. Furthermore, a choice of the weight γ near zero places more emphasis on the past estimates of trend, while a choice of γ near one gives more weight to the current value of a change in level.

In the empirical applications of models to macroeconomics time series, in our case unemployment rate, Holt-Winters` multiplicative method is often used, whereas the basic equations are given by:

$$\begin{aligned} L_t &= \alpha \frac{y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1}) \\ b_t &= \gamma(L_t - L_{t-1}) + (1-\beta)b_{t-1} \\ S_t &= \delta \frac{y_t}{L_t} + (1-\delta)S_{t-s} \end{aligned} \tag{2}$$

Namely, s is the length of seasonality (in our case number of quarters in a year), L_t represents the level of the series, b_t denotes the trend and S_t seasonal component [12]. Constants that need to be chosen for this model are: α (level smoothing constant), γ (trend smoothing constant) and δ (seasonal smoothing constant). As in Holt double exponential model smoothing constant take on the values between 0 and 1.

When the seasonal component of the analyzed time series has statistically constant amplitude, additive Holt-Winters` method is usually used, with the following basic equations:

$$\begin{aligned} L_t &= \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \\ b_t &= \gamma(L_t - L_{t-1}) + (1-\gamma)b_{t-1} \\ S_t &= \delta(y_t - L_t) + (1-\delta)S_{t-s} \end{aligned} \tag{3}$$

Initial values for L_S and b_S are identical as in the case of the multiplicative Holt-Winter`s method. Usually, for the seasonal indices initial values, the following expressions are used:

$$S_1 = y_1 - L_S, S_2 = y_2 - L_S, ..., S_S = y_S - L_S \tag{4}$$

There is no universally accepted way of choosing the most appropriate smoothing constants. Some practitioners recommend always using a value around 0.1 or 0.2. Others recommend experimenting with different values of smoothing constants until a measure such as the mean absolute percentage error (MAPE) is minimized. Finally, [14] suggested using an optimization option to select "the best" smoothing constants. In the empirical analysis of this paper an optimization option of selecting smoothing constants in the case of Holts double exponential smoothing models are used, whereas in the case of additive and multiplicative Holt-Winters` models, smoothing constants are chosen by experimenting with different values of smoothing constants until Mean absolute percentage error (MAPE) is minimized. In the next section, only models with optimal smoothing constants are shown and interpreted.

In order to check the accuracy of the estimated prognostic models, the following accuracy measures were employed:

MSD (Mean Square Deviation), also called MSE (Mean Square Error), which is a measure of the variability in the forecast error, calculated using the expression:

$$MSD = \sum_{t=1}^{n} (Y_t - F_t)^2 \Big/ n \tag{5}$$

MAD (Mean Absolute Deviation), which measures the average magnitude of the forecast error, given by:

$$MAD = \sum_{t=1}^{n} |Y_t - F_t| \Big/ n \tag{6}$$

and MAPE (Mean Absolute Percentage Error), which indicates that on average, the chosen exponential smoothing model produced a forecast that differs from the actual value by calculated percentage. MAPE is given by:

$$MAPE = \sum_{t=1}^{n}\left[\left(Y_t - F_t\right)/Y_t\right] \Big/ n \cdot 100 \tag{7}$$

In the next section, only models with optimal smoothing constants, selected by the optimization algorithm or with the smallest values of MAPE are shown and interpreted.

IV. Results of the Empirical Analysis

Forecasting future trends of unemployment rate based on its historical behaviour, without considering causal relationship with other variables, is a simple but direct way of forecasting. Empirical studies have shown that the forecasts obtained by univariate methods of modeling time series are sensitive, but also time-and cost-effective, since they use historical data of the variable of interest, whose behavior with the respect to other associated variables is unknown and/ or difficult to explain.

In this section, the series of total unemployment rate by sex and age groups given as quarterly average, expressed in percentages, for five selected European countries from third quarter of 2008 to fourth quarter of 2013 is forecasted using statistical software MINITAB 14. It is important to stress, that the period from 2001Q1 to 2008Q2 is not included in the analysis, since this was the period before the global financial crisis when all countries of interest recorded downward unemployment rate trend. The break in that trend was the beginning of global financial crisis which started in third quarter of 2008. Namely, from then on, in all analyzed countries, an upward trend in total unemployment rate is noticed and analyzed here in more detail. In this section, the aim is to define an adequate model within the group of exponential smoothing models, described in Section III, that will provide most accurate short-term forecasts. Furthermore, based on the chosen model, the future value of total unemployment rate will be the estimated for 2014. Fore mentioned forecast are short-term forecasts and taking into account that a large number of factors are affecting unemployment rate, it is fairly realistic, that forecast are possible only in a very short period of time. Since we use quarterly data on total unemployment rate, forecasting horizon τ = 4 is still considered reliable because of "seasonal" terms, namely according to [3], it is actually a forecast for only one period ahead (one-step-ahead forecast).

According to selected criteria described in Section III, namely: MSD, MAD and MAPE, the most accurate forecasting model for the variable of interest in analyzed five European countries will be selected. The accuracy measures for analyzed forecasting methods and countries are given in Table I.

TABLE I
FORECASTING MODELS AND ACCURACY MEASURES

Method/ Country	Greece			Spain			Croatia			Italy			Portugal		
	MAPE	MAD	MSD	MAPE	MAD	MSD	MAPE	MAD	MSD	MAPE	MAD	MSD	MAPE	MAD	MSD
Model 1: Double exponential smoothing															
	4.992	0.649	0.771	*3.933*	0.733	1.079	7.879	1.017	1.605	8.647	0.779	0.946	*4.202*	0.522	0.409
Selected smoothing constants(algorithm: optimal ARIMA)															
α(level)=		1.479			1.472			1.774			1.552			1.323	
γ(trend)=		0.081			0.096			0.063			0.067			0.099	
Model 2: Holt-Winters` multiplicative method															
	4.721	0.839	1.084	7.759	1.618	3.796	*4.695*	0.643	0.613	*4.679*	0.420	0.274	5.116	0.696	0.759
Selected smoothing constants:															
α(level)=		0.50			0.47			0.80			0.55			0.32	
γ(trend)=		0.08			0.10			0.06			0.07			0.10	
δ(seasonal)=		0.20			0.20			0.20			0.30			0.20	
Model 3: Holt-Winters` additive method															
	3.684	0.715	0.925	7.678	1.595	3.683	4.794	0.647	0.698	4.966	0.443	0.271	5.125	0.699	0.768
Selected smoothing constants:															
α(level)=		0.50			0.47			0.80			0.55			0.32	
γ(trend)=		0.08			0.10			0.06			0.07			0.10	
δ(seasonal)=		0.20			0.20			0.20			0.30			0.20	

According to the results given in Table I and measure of forecast accuracy Mean Absolute Percentage Error (MAPE), the optimal model for forecasting unemployment rate in Greece is Model 3, namely Holt-Winters` additive method. In the case of Spain, according to MAPE, the optimal model is Model 1 (double exponential smoothing). Furthermore, for Croatia and Italy the best forecasting model for unemployment rate is Model 2 (Holt-Winters` multiplicative method). This is an interesting and logical founding, since the unemployment rate for the analyzed period in these two countries had pronounced seasonal component, as shown in Figs. 2 (a) and (b), respectively.

Finally, the best model to forecast unemployment rate in Portugal is Model 1 or Double exponential smoothing model.

Furthermore, if we look at the actual data published by Eurostat for the unemployment rate for first quarter of 2014, we come to a bit different conclusions. Namely, in Table II, the actual and forecasted unemployment rate data for first quarter of 2014 using analyzed forecasting methods are given.

Accordingly, we can conclude that in all analyzed countries, but Italy, Model 1, or double exponential smoothing method, shown to be the most accurate. In the case of Italy, Model 3 or

Holt-Winters` additive method, gave the most accurate forecasts.

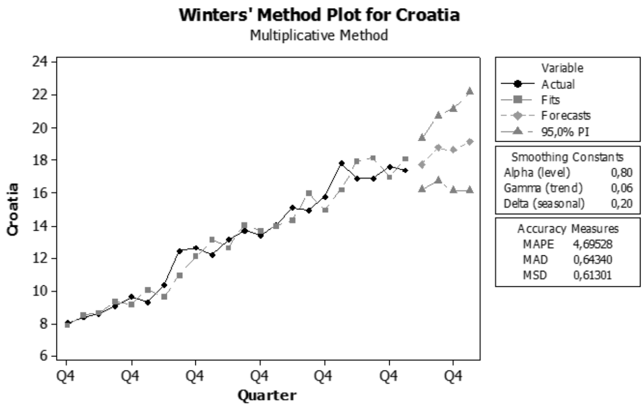

Fig. 2 (a) Quarterly unemployment rate from 2008Q4-2014Q4 for Croatia

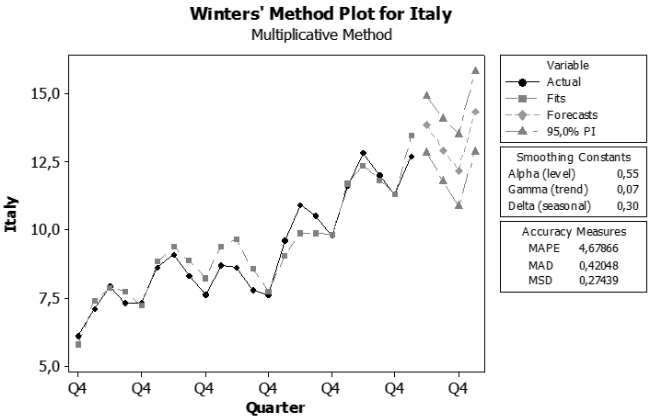

Fig. 2 (b) Quarterly unemployment rate from 2008Q4-2014Q4 for Italy

TABLE II
ACTUAL AND FORECASTED UNEMPLOYMENT RATE FOR SELECTED EUROPEAN COUNTRIES

Country	Actual data	Model 1	Model 2	Model 3
Greece	27.9	*28.614*	30.237	30.047
Spain	25.9	*25.951*	28.622	28.470
Croatia	18.9	*18.510*	17.741	19.297
Italy	13.6	13.808	13.855	*13.619*
Portugal	15.3	*15.585*	17.788	17.763

V. CONCLUSION

The authors found challenging enough to explore potential forecasting models suitable for predicting the future values of unemployment rate, since recent analysis conducted by Eurostat revealed some interesting trends.

For the purpose of the empirical analysis, five European countries, namely: Croatia, Greece, Italy, Portugal and Spain were selected, even though, substantial differences exist among them, in the analyzed period; they all recorded substantially high unemployment rates. The aim of this paper was to select the most accurate forecasting method for predicting the future values of the unemployment rate and several forecasting techniques adequate for forecasting time series with trend component, were explored. The results of the empirical analysis showed that the optimal model for forecasting unemployment rate in Greece was Holt-Winters` additive method. In the case of Spain, according to MAPE, the optimal model is double exponential smoothing model. Furthermore, for Croatia and Italy the best forecasting model for unemployment rate is Holt-Winters` multiplicative model. Finally, the best model to forecast unemployment rate in Portugal is Double exponential smoothing model.

Furthermore, when we explored the actual data published by Eurostat for the unemployment rate for first quarter of 2014 and the forecasted data, we came to different conclusions. Accordingly, we concluded that in all analyzed countries, but Italy, Model 1, or double exponential smoothing method, shown to be the most accurate, whereas, in the case of Italy, Model 3 or Holt-Winters` additive method, gave the most accurate forecasts.

This paper contributes to the existing literature by giving insights on the most appropriate forecasting methods among smoothing methods for predicting unemployment rate. The findings are in line with European Commission unemployment rate estimates.

REFERENCES

[1] B. L. Bowerman, and R. T. O'Connell, *Forecasting and Time Series*. 3rd ed., Belmont, CA: Duxbury Press, 1993.
[2] C. C. Holt, *Forecasting seasonal and trends by exponentially weighted moving averages*. Office of Naval Research, Research Memorandum no. 52, 1957.
[3] D. C. Montgomery, C. L. Jennings, and M. Kulahci, *Introduction to Time Series Analysis and Forecasting*. New Jersey: John Wiley & Sons, 2008.
[4] D. Gounopoulos, D. Petmezas, and D. Santamaria, "Forecasting Tourist Arrivals in Greece and the Impact of Macroeconomic Shocks from the Countries of Tourists' Origin," *Annals of Tourism Research*, vol. 39, no. 2, pp. 641–666, 2012.
[5] E. Önder, F. Bayır, and A. Hepsen, "Forecasting Macroeconomic Variables Using Artificial Neural Network and Traditional Smoothing Techniques," *Journal of Applied Finance and Banking*, vol. 3, no. 4, pp. 73–104, 2013.
[6] European Commision, (2014), European Economic Forecast: Spring 2014, available at: http://ec.europa.eu/economy_finance/publications/european_economy/2014/pdf/ee3_en.pdf (15 October 2014).
[7] J. Dovern, and J. Weisser, "Accuracy, unbiasedness and efficiency of professional macroeconomic forecasts: An empirical comparison for the G7," *International Journal of Forecasting*, vol. 27, no. 2, pp. 452–465, 2011.
[8] M. Simionescu, "The Performance of Unemployment Rate Predictions in Romania: Strategies to Improve the Forecasts Accuracy," *Review of Economics Perspectives*, vol. 13, no. 4, pp. 161–175, 2013.
[9] S. M. Bratu, "Forecasts for Inflation and Unemployment Rate Based on Models Using Resample Techniques," *International Journal of Economic Practices and Theories*, vol. 3, no. 2, pp. 103–107, 2013.
[10] S. M. Bratu, "Predicting Macroeconomic Indicators in the Czech Republic Using Econometric Models and Exponential Smoothing Techniques," *South East European Journal of Economics and Business*, vol. 7, no. 2, pp. 89–99, 2012a.
[11] S. M. Bratu, "The Accuracy and Bias Evaluation of the Unemployment Rate Forecasts: Methods to Improve the Forecasts Accuracy," *Annals of the University of Petrosani – Economics*, vol. 12, no. 4, pp. 17–32, 2012b.
[12] S. Makridakis, S. C. Wheelwright, and R. J. Hyndman, *Forecasting, Methods and Applications*. 3rd ed., New York: Wiley, 1998.
[13] V. Voineagu, S. Pisica, and N. Caragea, "Forecasting Monthly Unemployment by Econometric Smoothing Techniques," *Journal of*

Economic Computation and Economic Cybernetics Studies and Research, vol. 46, no. 3, pp. 255–267, 2012.
[14] W. L. Winston, S. C. Albright, and M. Broadie, *Practical Management Science*. 2nd ed., Duxbury, Pacific Grove: Thomson Learning 2001.