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Forecasting Unemployment Rates in Greece

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Abstract

This paper aims to model and forecast the evolution of unemployment rate in Greece, using the Box- Jenkins methodology during the period 1980-2013. The empirical study relieves that the most adequate model for the unemployment rate for this period is ARIMA (1,2,1). Using this model, we forecast the values of unemployment rate for 2014, 2015 and 2016. We found that the unemployment rate for 2014, 2015 and 2016 are 26.39% , 25.33% and 25.27% respectively.

Keywords: ARIMA models; Box-Jenkins; unemployment rates; forecasting; Greece.

1. Introduction

Unemployment is one of the most acute problems faced by the governments of all countries. An unemployed person is twice more likely to suffer poverty than a person in employment. Therefore unemployment is a crucial factor for the risk of poverty but neither is it the only one nor the most significant factor.The unemployment rates as the growth rate are the most important measures of the economy.

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The unemployment rate is an indicator used by the investors to determine the health of the economy. In addition, from the unemployment rate they can see which sectors are losing jobs faster. Therefore, it is very important to estimate and forecast the unemployment rate in a country.

In Greece, the level of unemployment is very high especially in recent years and as a result the level of poverty has been increased greatly. Officially, Greece is the country with the highest unemployment rate in the E.U. Statistics unfortunately cannot be taken because of many Greeks and immigrant workers are off-the-books. In addition, the immigrants make up nearly one-fifth of the work force, mainly in menial jobs.

Greece is a low-productivity economy with an ineffective welfare state, relying almost exclusively on low wages and social transfers. The Centre for Planning and Economic Research (KEPE) reports that the areas where the most jobs can be found today in Greece are trade, construction, industry and tourism. The failure of governments is not to be compromised with this reality. They should be engaged seriously with the problem of unemployment.

The rest of the paper is organized as follows: Section 2 describes literature review while in Section 3 data and econometric methodology are given. In Section 4 the empirical results are presented. The 5 section is the forecasting and finally, discussion and conclusions are provided in Section 6.

2. Literature Review

Literature on macroeconomic modeling, and forecasting, with the use of historical data from time series is vast. Modeling unemployment rates like any other macroeconomic variables has been analyzed by building econometric models, often related to stationary time series, and technique including autoregressive integrated moving average models (ARIMA).

Box and Jenkins [1] methodology has been used extensively by many researchers in order to highlight the future rates of unemployment. Specifically the authors in [4] are checking the evolution of unemployment in Romania using Box and Jenkins methodology during the period 1998 – 2007. The empirical results showed that the model ARIMA (2,1,2) is suitable to forecast the unemployment rate for January and February 2008.

Moreover, the research of author [6] is trying to forecast the unemployment rate in the Czech Republic and its regions. She estimates a SARIMA model for the period of January 2000 to March 2008 and the results of the forecasts showed that the unemployment rate in the Czech Republic at the end of the year 2009 will be about 10%.

In research [5] the authors are using monthly data of unemployment rates for Nigeria from January 1999 until December 2008. The forecasts of unemployment rates that were find by the model ARIMA (1,2,1) for Nigeria were: for January, February and March of 2009, 7.9%, 9.2% and 11.3% respectively.

The authors in their research in [7] have tried to forecast the unemployment rate in Thailand involving two approaches: the Box-Jenkins methodology and the artificial neuron network. The findings of their work have shown that Box-Jenkins methodology is more effective in forecasting the unemployment rate with smaller MAPE in comparison with the second approach.

The authors in [13] examined the possibility to forecast the time series of the unemployment rates in Slovakia using techniques that didn't require the assumption of constant variance over time. The analyzed data represent the monthly rates of unemployment during the period January 1999 - May 2013. Thereafter they examined whether the observed changing variability of the time series was statistically significant and could be described by appropriate ARIMA–ARCH model. Their findings proposed a combination of the ARIMA (0,1,2)(0,1,1)12 + GARCH(1,1) models, that proved to provide good predictors for both the conditional mean and the conditional variance.According to a new research [1] the author is trying to compare forecasts of unemployment rates in the Baltic States using time-varying parameter models. The time span of the data was from 2001 to 2014 and it included the global financial crisis. She founds that the forecasting ability of the models depends on both the forecasting horizon and the moment in time when the forecasts are done. The empirical evidence suggests that no single model is the best one, but models that include a cyclical component tend to perform better than others. The findings show that the preferred models differ in the time of increase or decrease in unemployment rates.Finally, the author in [11] is using Phillips curve to examine unemployment rates and inflation for USA from January 1980 to April 2015. Examining these variables with ARIMA and VAR models, she concluded that VAR models give better forecast than ARIMA.

3. Methodology and Data

The variable used in the analysis is the unemployment rate from 1960 to 2013 extracted from the official website of National Bank of Greece. We define linear time series model. Suppose that there are Y_1, Y_2, …, Y_t observations. The variable y_t is explained by relating it to its own past values and to a weighted sum of current and lagged random disturbances. The Autoregressive Moving Average (ARMA) (p,q) is represented by the following model

$$y_t = \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \delta + \varepsilon_t - \alpha_1 \varepsilon_{t-1} - \ldots - \alpha_q \varepsilon_{t-q} \tag{1}$$

If the time series is homogenous stationary, then after differenced the series y_t to produce stationary series w_t, we can model w_t as an ARMA process. If $w_t = \Delta^d y_t$ and w_t is an ARMA (p,q) process, then we say that y_t is an integrated autoregressive moving average process of order (p,d,q), or simple ARIMA(p,d,q). Box and Jenkins (1976) were the first researchers who systematically tried to answer whether the various time series can be captured within an ARIMA model (p,d,q) or:

$$\beta(L)\Delta^d y_t = \delta + \alpha(L)\varepsilon_t . \tag{2}$$

Where:

$\beta(L)=1-\beta_1 L-\beta_2 L-...-\beta_p L^p$ is the autoregressive operator and

$\alpha(L)=1-\alpha_1 L-\alpha_2 L-...-\alpha_p L^p$ is the moving average operator.

and thereafter to forecast their future development.

Theoretically Box-Jenkins model identification is relatively easy if one has a pure AR or a pure MA process. However, in the case of mixed ARMA models (especially those of high order) it can be difficult to interpret sample autocorrelation ACF and partial autocorrelation PACF, so Box-Jenkins identification becomes a subjective exercise depending on the skill of the forecaster. Random noise in time series, especially price data, makes Box-Jenkins model identification even more problematic [10].

The Box-Jenkins methodology consists of the following steps:

- Detection of the stationarity of the time series. If time series is not stationary in levels, we obtain successively the first or the second differences to in order to attain stationarity. The autocorrelation function (ACF), partial autocorrelation (PACF) as well as the Augmented Dickey-Fuller test [3] and the Phillips - Perron test [12] are used for testing stationarity of the time series.
- When the time series is stationary, then the order of the model ARMA (p,q) can be determined. To determine the order of ARMA(p,q), we use the sample of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the stationary series. These two plots are suggesting the model we should build. The parameter p of autoregressive operator β(L) is determined by the rate of partial autocorrelation for which $\varphi_{kk}=0$ for k > p, and by decreasing rapidly to zero procedure of the partial autocorrelation coefficients. One other simple way to determine the significance of the partial autocorrelation coefficient $\hat{\varphi}_{kk}$ is to compare its value with the critical value $\pm\frac{2}{\sqrt{n}}$. The parameter q of the moving average operator $\alpha(L)$ is specified by the autocorrelation coefficient ρ_k for which $\rho_k=0$ for k > p, and by decreasing rapidly to zero procedure of the autocorrelation coefficients. One other simple way to determine the significance of the autocorrelation coefficient $\hat{\rho}_k$ is to compare its value with the critical value $\pm\frac{2}{\sqrt{n}}$. According to all the above an autoregressive model AR(p) is resulting from the partial autocorrelation function which is trimmed to the lag p and a model of moving average MA (q) is resulting from the autocorrelation function which is trimmed to the lag q. In fact we use the limits $\pm\frac{2}{\sqrt{n}}$ for the non-significance of the two functions, so we will have a number ARMA models (a, b), where 0 ≤ α ≤ p, 0≤ b ≤ q.. For the optimum model we are using the criteria of Akaike (AIC) Schwartz (SIC) and Hannan-Quinn (HQ).
- Estimation of the model. The involvement of the white noise terms in an ARIMA model entails a nonlinear iterative process in the estimation of the parameters, β_i and α_j. To overcome this situation an optimized criterion

like least error of sum of squares, maximum likelihood or maximum entropy is used. An initial estimate is usually used, and then each iteration is expected to be an improvement of the prior estimate until the estimate converges to an optimal one [5]. However, many researchers are trying to adopt linear methods in order to estimate ARIMA models [2, 8].

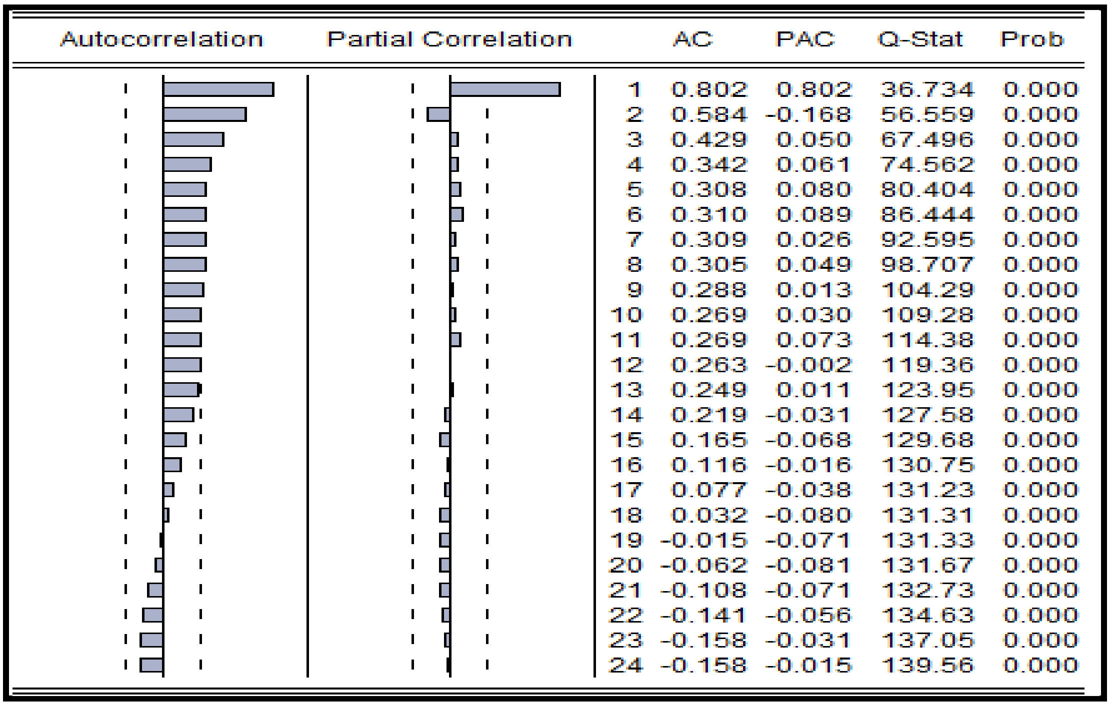
- Diagnostic checking of the model. With diagnostic checking we investigate whether the estimated model is acceptable and statistically significant, i.e. if it fits well to the data. Box and Jenkins for the adequacy of estimated ARIMA model suggested checking the randomness of the residuals, i.e. whether the residuals from the estimated ARIMA model is white noise, and are not serially correlated.
- Forecasting: One of the main reasons of the analysis of time series models is forecasting. The forecasts are very useful either for policy making or for decision making. The accuracy of the forecasts depends on the forecasting error, i.e. the deviation of the forecast and the real one. The smaller the difference is, the better will be the forecast.

4. Empirical Results

The ARIMA approach is an iterative three-stage process of identification, estimation and testing.

4.1. Testing for non-stationarity

Autocorrelation function (Box-Jenkins approach) if autocorrelations start high and decline slowly, then series is non-stationary, and should be differenced. Figures 1 and 2, represents the correlogram of the unemployment rate series with a pattern of up to the 24 lags in level and for first differences.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.802	0.802	36.734	0.000
		2	0.584	-0.168	56.559	0.000
		3	0.429	0.050	67.496	0.000
		4	0.342	0.061	74.562	0.000
		5	0.308	0.080	80.404	0.000
		6	0.310	0.089	86.444	0.000
		7	0.309	0.026	92.595	0.000
		8	0.305	0.049	98.707	0.000
		9	0.288	0.013	104.29	0.000
		10	0.269	0.030	109.28	0.000
		11	0.269	0.073	114.38	0.000
		12	0.263	-0.002	119.36	0.000
		13	0.249	0.011	123.95	0.000
		14	0.219	-0.031	127.58	0.000
		15	0.165	-0.068	129.68	0.000
		16	0.116	-0.016	130.75	0.000
		17	0.077	-0.038	131.23	0.000
		18	0.032	-0.080	131.31	0.000
		19	-0.015	-0.071	131.33	0.000
		20	-0.062	-0.081	131.67	0.000
		21	-0.108	-0.071	132.73	0.000
		22	-0.141	-0.056	134.63	0.000
		23	-0.158	-0.031	137.05	0.000
		24	-0.158	-0.015	139.56	0.000

Figure 1: Correlogram of Unemployment Rate Series (Level)

Lag	AC	PAC	Q-Stat	Prob
1	0.759	0.759	32.310	0.000
2	0.402	-0.411	41.562	0.000
3	0.111	-0.021	42.287	0.000
4	-0.102	-0.137	42.909	0.000
5	-0.121	0.262	43.798	0.000
6	-0.104	-0.246	44.474	0.000
7	-0.085	0.096	44.934	0.000
8	-0.065	-0.129	45.206	0.000
9	-0.130	-0.103	46.324	0.000
10	-0.141	0.114	47.668	0.000
11	-0.105	-0.047	48.429	0.000
12	-0.056	0.069	48.652	0.000
13	0.048	0.023	48.822	0.000
14	0.085	-0.054	49.367	0.000
15	0.057	-0.048	49.615	0.000
16	0.055	0.135	49.856	0.000
17	0.050	0.012	50.055	0.000
18	0.035	-0.116	50.158	0.000
19	0.017	0.020	50.183	0.000
20	-0.007	0.027	50.187	0.000
21	-0.037	-0.094	50.312	0.000
22	-0.072	0.023	50.802	0.000
23	-0.082	0.026	51.450	0.001
24	-0.072	-0.069	51.978	0.001

Figure 2: Correlogram of Unemployment Rate Series (First Differences)

From the above diagrams we can conclude that the coefficients of autocorrelation (ACF) starts with a high value and declines slowly, indicating that the series is non-stationary. Also the Q-statistic of Ljung-Box [9] at the 24th lag has a probability value of 0.000 which is smaller than 0.05, so we cannot reject the null hypothesis that the unemployment rate series is non-stationary. Thus the series must be configured in second differences.

The third diagram represents the coefficients of the autocorrelation for the time series of unemployment rates, with up to 24 lags again but in second differences.

Lag	AC	PAC	Q-Stat	Prob
1	0.046	0.046	0.1158	0.734
2	-0.069	-0.071	0.3815	0.826
3	-0.072	-0.066	0.6825	0.877
4	-0.391	-0.394	9.6429	0.047
5	0.061	0.091	9.8652	0.079
6	-0.003	-0.091	9.8657	0.130
7	0.020	-0.009	9.8911	0.195
8	0.176	0.024	11.857	0.158
9	-0.227	-0.222	15.236	0.085
10	-0.031	-0.029	15.301	0.121
11	-0.044	-0.090	15.432	0.164
12	-0.118	-0.088	16.408	0.173
13	0.183	0.001	18.830	0.128
14	0.055	0.028	19.054	0.163
15	-0.101	-0.205	19.830	0.179
16	0.078	0.041	20.307	0.207
17	0.010	0.112	20.315	0.258
18	0.014	-0.051	20.332	0.314
19	0.021	-0.054	20.371	0.373
20	-0.006	0.069	20.374	0.435
21	0.013	-0.032	20.390	0.497
22	-0.063	-0.052	20.766	0.535
23	-0.000	0.076	20.766	0.595
24	0.058	-0.001	21.099	0.633

Figure 3: Correlogram of Unemployment Rate Series (Second Differences)

The results are indicating that the series of unemployment rates is stationary in the second differences. The results of Augmented Dickey–Fuller (ADF) test and Phillips-Perrons (PP) test on unemployment rate series are representing in Table 1.

Table 1: ADF and Phillip-Perron's Test on Unemployment Series

	Level		**First Differences**		**Second Differences**	
	C	**C,T**	**C**	**C,T**	**C**	**C,T**
ADF	0.525 (0.985)	-3.098 (0.117)	-2.566 (0.107)	-2.962 (0.153)	-6.371 (0.000)	-6.412 (0.000)
PP	1.468 (0.999)	-0.340 (0.987)	-2.276 (0.183)	-2.713 (0.235)	-5.275 (0.000)	-4.689 (0.002)

The results in Table 1 indicate that unemployment rate is stationary in second differences. Therefore for our model ARIMA (p,d,q) we will have the value d=2

4.2. Identification of the model

After the identification of the stationarity of the time series we can use the correlogram of Figure 3 to determine the model ARMA (p,q), i.e. the values of parameters p and q.

One other simple way in order to determine the parameters p and q is to compare the coefficients of partial autocorrelation and autocorrelation respectively with the critical values $\pm\frac{2}{\sqrt{n}}$.

The limits for both functions (ACF, PACF) are $\pm\frac{2}{\sqrt{54}} = \pm 0.272$. From the column of autocorrelation in Figure 3 we can notice that only the value of the coefficient ρ_4 is greater from the value ± 0.272, while from the column of the coefficients of partial autocorrelation the values $\hat{\varphi}_4$ is greater than the value ± 0.272. Therefore, the value of p will be between $0 \leq p \leq 4$ (since the parameters are determined by the rate of partial autocorrelation). Respectively, the value of q will be between to $0 \leq q \leq 4$ (since parameter q are determined by the rate of autocorrelation).

From figure 3, the ACF cuts off at lag 4 (q=4) and the PACF at lag 4 (p=4). Exploring the range of models {ARMA(p,q): $0 \leq p \leq 4$ 0, $0 \leq q \leq 4$ } for the optimal on the basis of AIC, SIC and HQ. Thereafter we create Table 2 with the values of p and q as follows:

Table 2: Comparison of models within the range of exploration using AIC, SIC and HQ

p	q	AIC	SIC	HQ
0	1	2.708	2.783	2.736
0	2	2.636	2.748	2.679
0	3	2.624	2.774	2.682
0	4	2.367	2.555	2.439
1	1	2.645	2.758	2.688
1	2	2.679	2.831	2.737
1	3	2.618	2.807	2.690
1	4	2.104	2.331	2.191
2	1	2.699	2.852	2.757
2	2	2.584	2.775	2.657
2	3	**1.822**	**2.051**	**1.909**
2	4	2.005	2.272	2.107
3	1	2.754	2.947	2.828
3	2	2.582	2.814	2.670
3	3	2.369	2.639	2.472
3	4	2.065	2.374	2.182
4	1	2.508	2.742	2.596
4	2	2.426	2.699	2.529
4	3	2.171	2.483	2.289
4	4	2.484	2.835	2.616

The results from Table 2 indicate that according to the criteria of Akaike (AIC), Schwartz (SIC) and Hannan-Quinn (HQ) the model ARMA is formulated to ARMA (2,3). As the model is stationary on second differences, i.e. (d=2) our ARIMA model will be ARIMA (2,2,3).

4.3. Estimation of the model

Thereafter we can proceed to the second stage estimating the above model. Because the model ARIMA (2,2,3) has not statistically significant coefficients, we create the model ARIMA (1,2,1) which it has statistically significant coefficients.

The following Table 3 presents the results of this model.

Dependent Variable: DDUNE
Method: Least Squares
Date: 11/20/14 Time: 09:47
Sample (adjusted): 1983 2013
Included observations: 31 after adjustments
Convergence achieved after 17 iterations
MA Backcast: 1982

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.648121	0.170713	3.796541	0.0007
MA(1)	-0.921870	0.101163	-9.112736	0.0000

R-squared	0.113993	Mean dependent var	0.034516
Adjusted R-squared	0.083441	S.D. dependent var	1.178598
S.E. of regression	1.128355	Akaike info criterion	3.141740
Sum squared resid	36.92238	Schwarz criterion	3.234255
Log likelihood	-46.69697	Hannan-Quinn criter.	3.171898
Durbin-Watson stat	1.563646		

Inverted AR Roots	.65
Inverted MA Roots	.92

Figure 4: Estimation Model ARIMA(1,2,1)

The results in Table 3 indicate that both coefficients are statistically significant at 1% level of significance.

The non-linear techniques used by Eviews 8.0 involved an iterative process that is converged after 17 iterations. The roots of $\beta(L)=0$ and $\alpha(L)=0$ are 0.65 and 0.92, both inside the unit circle indicating stationarity and invertibility respectively.

The chosen model as summarized in Table 3 is ARIMA(1,2,1) and is given by:

$DDUNEt = 0.648121 DDUNE_{t-1} - 0.921870 \varepsilon_{t-1} + \varepsilon_t$

t-stat.	(3.796)	(-9.112)
prob.	[0.000]	[0.000]
s.e	{0.170}	{0.101}

On the following diagram the inverse roots of AR and MA characteristic polynomials for the stability of ARIMA model are presented.

From diagram 4 we can see that the ARIMA model is stable since the corresponding inverse roots of the characteristic polynomials are in the unit circle.

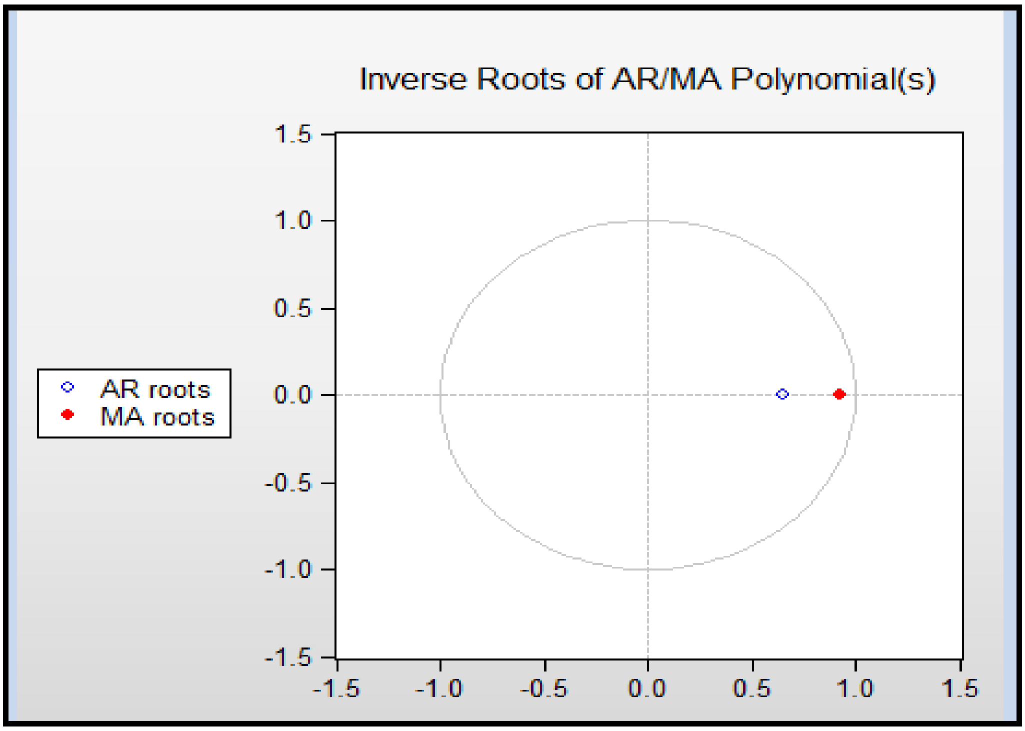
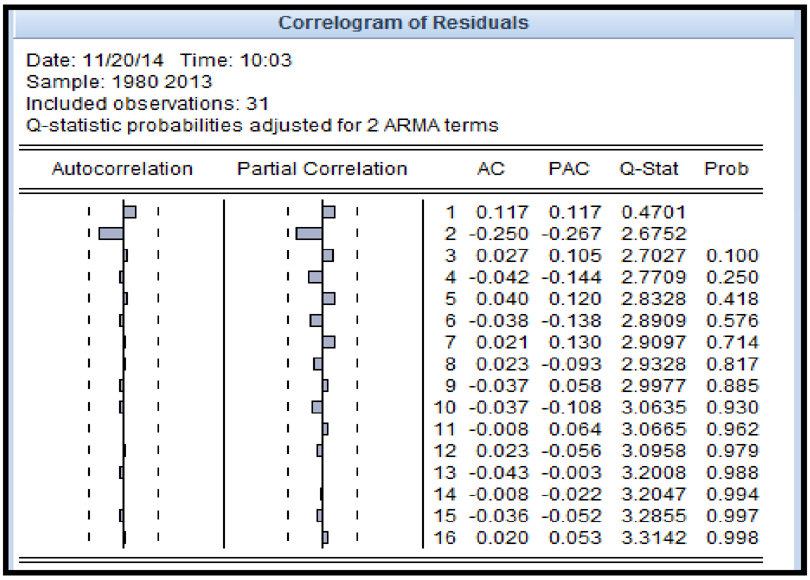


Figure 5: Inverse Roots of AR and MA

4.4. Diagnostic checking of the model

Diagnostic checking of the model, help us to check if the estimated model is acceptable and statistical significant that means that the residuals do not autocorrelated. For the check of autocorrelation we use Q statistic of Ljung-Box [9]. The diagram below represents the test of the autocorrelation of the residuals of the model ARIMA (1,2,1).


Correlogram of Residuals

Date: 11/20/14 Time: 10:03
Sample: 1980 2013
Included observations: 31
Q-statistic probabilities adjusted for 2 ARMA terms

	AC	PAC	Q-Stat	Prob
1	0.117	0.117	0.4701	
2	-0.250	-0.267	2.6752	
3	0.027	0.105	2.7027	0.100
4	-0.042	-0.144	2.7709	0.250
5	0.040	0.120	2.8328	0.418
6	-0.038	-0.138	2.8909	0.576
7	0.021	0.130	2.9097	0.714
8	0.023	-0.093	2.9328	0.817
9	-0.037	0.058	2.9977	0.885
10	-0.037	-0.108	3.0635	0.930
11	-0.008	0.064	3.0665	0.962
12	0.023	-0.056	3.0958	0.979
13	-0.043	-0.003	3.2008	0.988
14	-0.008	-0.022	3.2047	0.994
15	-0.036	-0.052	3.2855	0.997
16	0.020	0.053	3.3142	0.998

Figure 6: Correlogram residuals of model ARIMA (1,2,1)

The results indicate that the Q statistic of Ljung – Box for all the 16 lags has values greater than 0.05 thus the null hypothesis cannot be rejected i.e. there is no autocorrelation for the examined residuals of the series.

5. Forecasting

Forecasting plays an important role in decision making process.

From previous studies, many researchers have found that the selected model is not necessary the model that provides best forecasting.

In this sense further forecasting accuracy test such as mean squared error, root mean squared error, mean absolute error, mean absolute percentage error and the inequality coefficient of Theil.

An ARIMA(1, 2, 1) model may be written as $\nabla^2 y_t = \beta_1 \nabla^2 y_{t-1} + \alpha_1 \varepsilon_{t-1} + \varepsilon_t$

This translates into

$$y_t - 2y_{t-1} + y_{t-2} = \beta_1 \left(y_{t-1} - 2y_{t-2} + y_{t-3} \right) + \alpha_1 \varepsilon_{t-1} + \varepsilon_t$$

$$y_t = 2y_{t-1} - y_{t-2} + \beta_1 y_{t-1} - 2\beta_1 y_{t-2} + \beta_1 y_{t-3} + \alpha_1 \varepsilon_{t-1} + \varepsilon_t$$

$$y_t = (\beta_1 + 2) y_{t-1} - (1 + 2\beta_1) y_{t-2} + \beta_1 y_{t-3} + \alpha_1 \varepsilon_{t-1} + \varepsilon_t$$

At time t+k, the model may be written as:

$$y_{t+k} = (\beta_1 + 2) y_{t+k-1} - (1 + 2\beta_1) y_{t+k-2} + \beta_1 y_{t+k-3} + \alpha_1 \varepsilon_{t+k-1} + \varepsilon_t$$

Taking conditional expectations at time t, we have

$$\hat{y}_t(1) = (\beta_1 + 2) y_t - (1 + 2\beta_1) y_{t-1} + \beta_1 y_{t-2} + \alpha_1 \varepsilon_t$$

$$\hat{y}_t(2) = (\beta_1 + 2) \hat{y}_t(1) - (1 + 2\beta_1) y_t + \beta_1 y_{t-1}$$

$$\hat{y}_t(3) = (\beta_1 + 2) \hat{y}_t(2) - (1 + 2\beta_1) \hat{y}_t(1) + \beta_1 y_t$$

$$\hat{y}_t(k) = (\beta_1 + 2) \hat{y}_t(k-1) - (1 + 2\beta_1) \hat{y}_t(k-2) + \beta_1 \hat{y}_t(k-3)$$

In Figure 6 we represent the criteria for the evaluation of the forecasts of the model ARIMA (1,2,1)

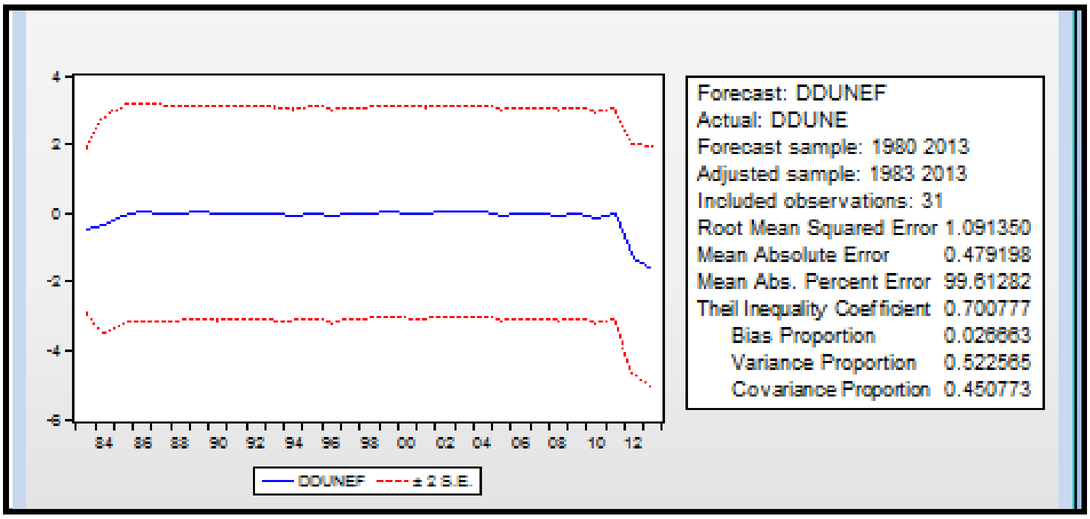


Figure 7: Forecast Accuracy Test on the model ARIMA (1,2,1)

The results in Figure 6 indicate that the inequality coefficient of Theil has a high value U = 0.70 which means that our model do not have a good forecasting ability. Table 6 below summarizes the forecasting results of the unemployment rates over the period 2014 to 2016.

Table 4: The unemployment rate forecasts

Years	Residuals	DDUNE	DUNE	UNE
2011	4.764	4.716	5.122	17.653
2012	2.798	1.463	6.585	24.238
2013	-2.205	-3.837	2.748	26.986
2014	---	-3.342	-0.594	26.39
2015	---	-1.564	-1.06	25.33
2016	---	-1.124	-0.064	25.266

6. Conclusion - Recommendations

Unemployment plagues many countries so it is important to capture the trend of this series. The use of ARIMA models is a highly flexible tool in order to forecast unemployment rate if there is no government's intervention which will change this trend. In this paper using Box – Jenkins technique we are trying to forecast the unemployment rates in Greece for the next three years with an ARIMA model. In ARIMA models many researchers find drawbacks, since they are neglecting the inclusion of explanatory variables and the conducts the forecasts only on past values of dependent variable in combination with present and past moving average terms. However, many empirical studies have been done regarding the effectiveness of ARIMA model in economic forecasting and as a result it is an essential component of all forecasting techniques. The proper evaluation of the ARIMA model is necessary to study and carry out the forecast process. The properly selected models enhance the predictability of the models and assist the players in making sound government policy. After checking for the stationarity of the data series, we find the appropriate ARIMA (p, d, q) process. The corresponding correlogram helped in choosing the appropriate p and q for the data series. Forecasting plays an important role in decision making process so an ARIMA (1.2.1) model was created through the data used and estimating this model we found that the unemployment rate for the years 2014, 2015 and 2016 is forecast to be 26.39%, 25.33% and 25.27% respectively.

It is more than obvious that Greece during the last years is trying to decrease the unemployment rates and to increase the growth rates. That achievement will lead the country to the exit from the most severe recession and crisis of its modern history. Our results suggest that Greece is in the right way and the goal to decrease the unemployment rates will be achieved in the near future time.

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