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Forecasting Real GDP Rate through Econometric Models: An Empirical Study from Greece

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Abstract

Gross Domestic Product (GDP) is an important indicator of economic activity, and is often used by decision makers to plan economic policy. This paper aims at modeling and forecasting real GDP rate in Greece. For this purpose using the Box- Jenkins methodology during the period 1980-2013 with one ARIMA (1,1,1) model. Using this model, we forecast the values of real GDP rate for 2015, 2016 and 2017. Statistical results show that Greece's real GDP rate is steadily improving.

Keywords: real GDP rate**,** ARIMA Modelling, Box-Jenkins methodology, forecasting, Greece.

JEL Classification: C53, E27

1. Introduction

Gross Domestic Product (GDP) of a country is the money value of all final goods and services produced by all the enterprises within the borders of a country in a year. It represents the aggregate statistic of all economic activity. The performance of economy can be measured with the help of GDP. According to Eurostat, there are three ways in which the GDP of a country can be measured.

a) GDP is the sum of gross value added of the various institutional sectors or the various industries plus taxes and less subsidies on products (which are not allocated to sectors and industries) - production approach,
b) GDP is the sum of final uses of goods and services by resident institutional units (actual final consumption and gross capital formation), plus exports and minus imports of goods and services - expenditure approach,
c) GDP is the sum of uses in the total economy generation of income account (compensation of employees, taxes on production and imports less subsidies, gross operating surplus and mixed income of the total economy) - income approach.(see The European System of Accounts ESA 1995, Eurostat, 1996).

Forecasting future economic outcomes is a vital component of the decision-making process in central banks for all countries. Monetary policy decisions affect the economy with a delay, so, monetary policy authorities must be forward looking, i.e. must know what is likely to happen in the future. Gross domestic product (GDP) is one of the most important indicators of national economic activities for countries. Scientific prediction of the indicator has important theoretical and practical significance on the development of economic development goals. For the forecasting of time series we use models that are based on a methodology that was first developed in Box and Jenkins (1976), known as ARIMA (Auto-Regressive-Integrated-Moving-Average) methodology. This approach was based on the World representation theorem, which states that every stationary time series has an infinite moving average (MA) representation, which actually means that its evolution can be expressed as a function of its past developments (Jovanovic and Petrovska 2010). The rest of the paper is organized as follows: Section 2 describes literature review while in Section 3 theoretical background is given. In Section 4 the empirical results are presented. Section 5 is the forecasting and finally, conclusions are provided in Section 6.

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2. Literature Review

Box and Jenkins (1976) methodology has been used extensively by many researchers in order to highlight the future rates of GDP. Wei and al. (2010) use data from Shaanxi GDP for 1952-2007 to forecast country's GDP for the following 6 years. Applying the ARIMA (1,2,1) model they find that GDP of Shaanxi present an impressive increasing trend. Maity and Chatterjee (2012) examine the forecasting of GDP growth rate for India using ARIMA(1,2,2) model and a time period of 60 years. The results of their study showed that predicted values follow an increasing trend for the following years. Zhang Haonan (2013) using three models ARIMA, VAR, AR(1) examines the forecasting of per capita GDP for five regions of Sweden for the years 1993 – 2009. The results of the study showed all three models can be used for forecasting in the short run. However, the autoregressive first order model is the best for forecasting the per capita GDP of five regions of Sweden. Shahini and Haderi (2013) test GDP forecasting for Albania using quarterly data from the first quarter of2003 until the second quarter of 2013. For the forecasting they used two model groups ARIMA and VAR. Their results showed that the group of VAR model gives better results on GDP's forecasting rather than ARIMA model. Zakai (2014) investigates forecasting of Gross Domestic Product (GDP) for Pakistan using quarterly data from 1953 until 2012. Choosing a ARIMA (1,1,0) model he finds out the size of the increase for Pakistan's GDP for the years 2013- 2025.

3. Theoretical Background

The Box-Jenkins ARMA model is a combination of the AR (Autoregressive) and MA(Moving Average) models as follows:

$$y_t = \beta_0 + \beta_1 y_{t-1} + ... + \beta_p y_{t-p} - \alpha_1 u_{t-1} - \alpha_2 u_{t-2} - ... - \alpha_q u_{t-q} + u_t \qquad (1)$$

The Box-Jenkins methodology consists of the following phases:

- Establishment of the stationarity of time series. The autocorrelation function (ACF) as well as Augmented Dickey-Fuller test (ADF) (1979) and Phillips-Perron (1988) test (PP) are used for stationarity testing of time-series.
- Model Identification of the model ARMA(p,q). 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 operatoris determined by the partial autocorrelation coefficient and the parameter q of the moving average operator is specified by the autocorrelation coefficient. 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 $0 \le a \le p$, $0 \le b \le q$. For the optimum model we are using the criteria of Akaike (AIC) Schwartz (SIC).
- Model Estimation. The involvement of the white noise terms in an ARIMA model entails a nonlinear iterative process in the estimation of the parameters. maximum likelihood estimation is generally the preferred technique.
- 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 accuracy of the forecasts depends on the forecasting error. Moreover, a number of statistical measures are employed for this aim, such as root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and the inequality coefficient of Theil (U).

Then the forecast value one period ahead conditional on all information up to time, t, given at time t+k, as:

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

4. Empirical Results

The variable used in the analysis is the GDP growth (annual %) that span from 1980 to 2014. The source of data is the World Bank. The ARIMA approach is an iterative four-stage process of stationary, identification, estimation and testing.

4.1 Testing for Stationarity

Figures 1 and 2 represent the correlogram of the real GDP rate series with a pattern of up to the 16 lags in level and for first differences.

Figure 1: Correlogram of Real GDP Rate Series (Level)

Lag	AC	PAC	Q-Stat	Prob
1	0.700	0.700	18.682	0.000
2	0.451	-0.078	26.655	0.000
3	0.336	0.099	31.222	0.000
4	0.091	-0.330	31.570	0.000
5	-0.077	-0.019	31.828	0.000
6	-0.063	0.123	32.005	0.000
7	-0.160	-0.195	33.183	0.000
8	-0.206	0.033	35.221	0.000
9	-0.170	-0.085	36.660	0.000
10	-0.194	-0.037	38.611	0.000
11	-0.191	0.009	40.581	0.000
12	-0.140	-0.068	41.692	0.000
13	-0.222	-0.216	44.599	0.000
14	-0.218	0.068	47.523	0.000
15	-0.116	0.054	48.391	0.000
16	-0.121	-0.076	49.394	0.000

From the above figure 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 (1978) at the 16th lag has a probability value of 0.000 which is smaller than 0.05, so we cannot reject the null hypothesis that the real GDP rate series is non-stationary. Thus, the series must be configured in first differences.

Figure 2: Correlogram of Real GDP Rate Series (First Differences)

Lag	AC	PAC	Q-Stat	Prob
1	-0.088	-0.088	0.2873	0.592
2	-0.226	-0.236	2.2458	0.325
3	0.216	0.182	4.0798	0.253
4	-0.122	-0.155	4.6880	0.321
5	-0.304	-0.260	8.5915	0.127
6	0.186	0.065	10.096	0.121
7	-0.084	-0.169	10.417	0.166
8	-0.131	-0.032	11.219	0.190
9	0.097	-0.088	11.684	0.232
10	-0.047	-0.122	11.795	0.299
11	-0.076	-0.038	12.100	0.356
12	0.217	0.087	14.716	0.257
13	-0.146	-0.192	15.959	0.251
14	-0.159	-0.157	17.508	0.230
15	0.179	-0.017	19.570	0.189
16	-0.091	-0.138	20.131	0.214

From the figure 2 we can conclude that the Q-statistic of Ljung-Box at the 16th lag has a probability value larger than 0.05, so we cannot reject the null hypothesis that the real GDP rate series is stationary. The results of Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test on real GDP rate series are representing on Table 1.

Table 1: ADF and Phillip-Perron's Test

	Level		First Differences	
	C	C,T	C	C,T
ADF	-2.773(3)	-2.757(3)	-5.968(0)***	-5.889(0)***
PP	-2.452[3]	-2.394[2]	-5.970[1]***	-5.889[1]***

Note:
1.Lag length in ( ) and Newey-West value using Bartlett kernel in [ ]
2.Asterisks (***) denote statistically significant at 1% significance levels.
The results in table 1 indicate that real GDP rate is stationary in first differences.Therefore for our model ARIMA (p,d,q) we will have the value d=1.

4.2 Identification of the Model

We can use the correlogram of figure 1 to determine the model ARMA (p,q), i.e. the values of parameters p and q.As already mentioned above, an AR(p) model has a PACF that truncates at lag p and an MA(q)) has an ACF that truncates at lag q. In practice $\pm\frac{2}{\sqrt{n}}$ are the nonsignificance limits for both functions. We shall explore the range of models ARMA(α,b), $0 \le a \le p$, $0 \le b \le q$ for an optimum one. To do this we shall use the automatic model determination criteria AIC and SIC.The limits for both functions (ACF, PACF) are $\pm\frac{2}{\sqrt{35}} = \pm 0.338$.From figure 1, the ACF cuts off at lag 2 (q=2) and the PACF at lag 1 (p=1). Exploring the range of models {ARMA(p,q): $0 \le p \le 1$ 0, $0 \le q \le 2$}for the optimal on the basis of AIC and SIC. 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 and SIC

p	q	AIC	SIC
0	1	4.92	4.96
0	2	4.90	4.99
1	0	4.94	4.98
1	**1**	**4.88**	**4.95**
1	2	4.97	5.11

The results from table 2 indicate that according to the criteria of Akaike (AIC), and Schwartz (SIC) the model ARMA is formulated to ARMA(1,1). As the model is stationary on first differences, i.e. (d=1) our ARIMA model will be ARIMA (1,1,1).

4.3 Estimation of the Model

Thereafter we can proceed to estimating the above model. The following table 3 presents the results of this model.

Table 3: Estimation Model ARIMA (1,1,1)

Dependent Variable: DGDP
Method: Least Squares
Date: 03/30/15 Time: 10:38
Sample (adjusted): 1982 2014
Included observations: 33 after adjustments
Convergence achieved after 43 iterations
MA Backcast: 1981

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.683122	0.131445	5.197015	0.0000
MA(1)	-0.951456	0.038664	-24.60813	0.0000

R-squared	0.119603	Mean dependent var	0.072727
Adjusted R-squared	0.091203	S.D. dependent var	2.832322
S.E. of regression	2.700076	Akaike info criterion	4.883128
Sum squared resid	226.0026	Schwarz criterion	4.973826
Log likelihood	-78.57162	Hannan-Quinn criter.	4.913645
Durbin-Watson stat	1.849581		

Inverted AR Roots	.68
Inverted MA Roots	.95

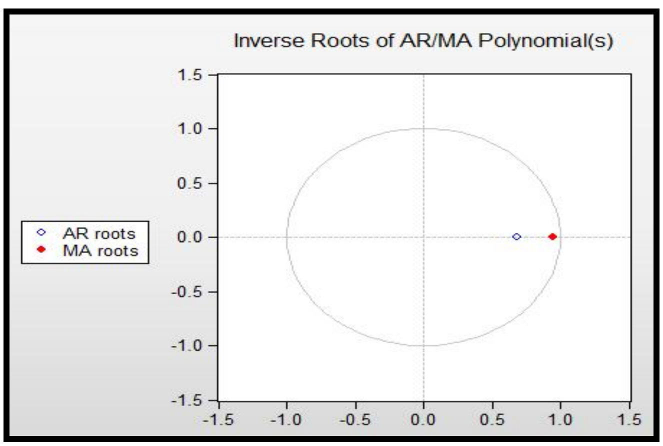
The results in table 3 indicate that both coefficients are statistically significant at 1% level of significance. The non-linear techniques used by Eviews 8.1 involved an iterative process that is converged after 43 iterations. The roots are 0.68 and 0.95, both inside the unit circle indicating stationarity and invertibility respectively. The chosen model as summarized in Table 3 is ARIMA(1,1,1) and is given by

$$DGDP_t = 0.683122 DGDP_{t-1} - 0.951456 \varepsilon_{t-1} + \varepsilon_t$$

t-stat.	(5.197)	(-24.608)
prob.	[0.000]	[0.000]
s.e	{0.131}	{0.038}

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

Figure 3: **Inverse Roots of AR and MA**



From diagram 3 we can see that the ARIMA model is stable since the corresponding inverse roots of the characteristic polynomials are in the unit circle.

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 are not auto correlated and follow normal distribution. For checking autocorrelation we use Q statistic of Ljung-Box (1978)and normality test using Jarque-Bera (JB) test (1980). The figures below represents the tests of the autocorrelation and normality of the residuals of the model ARIMA(1,1,1).

Figure 4: Histogram of the residuals of model ARIMA (1,1,1)

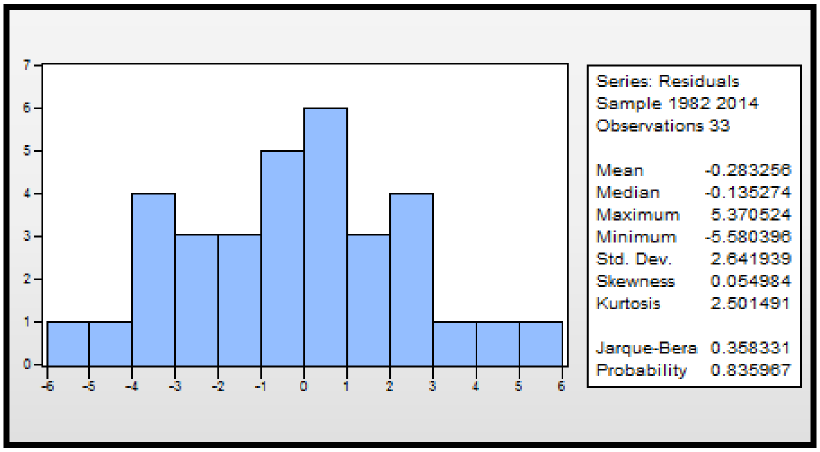
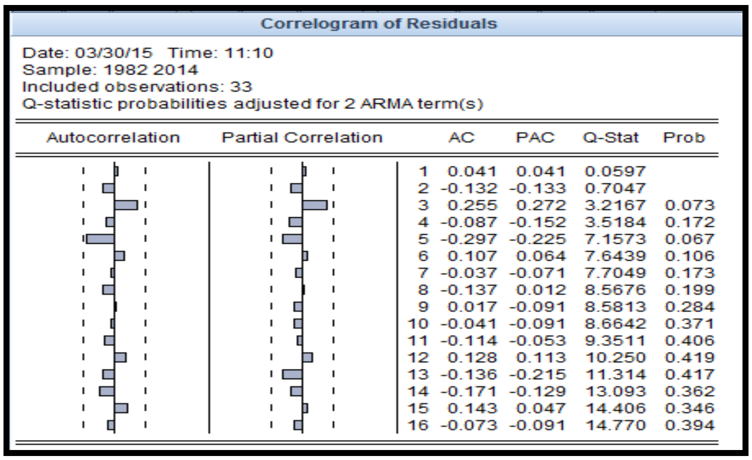


Figure 5: Correlogram Residuals of Model ARIMA (1,1,1)



Correlogram of Residuals

Date: 03/30/15 Time: 11:10
Sample: 1982 2014
Included observations: 33
Q-statistic probabilities adjusted for 2 ARMA term(s)

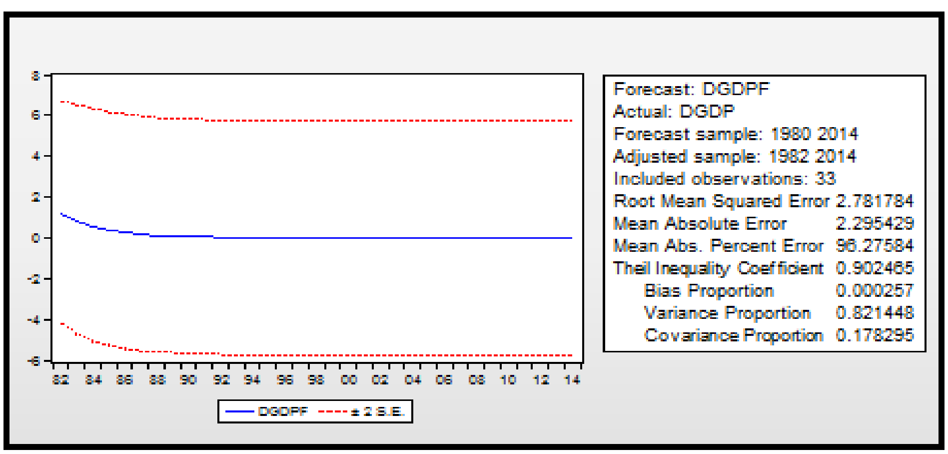
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.041	0.041	0.0597	
		2	-0.132	-0.133	0.7047	
		3	0.255	0.272	3.2167	0.073
		4	-0.087	-0.152	3.5184	0.172
		5	-0.297	-0.225	7.1573	0.067
		6	0.107	0.064	7.6439	0.106
		7	-0.037	-0.071	7.7049	0.173
		8	-0.137	0.012	8.5676	0.199
		9	0.017	-0.091	8.5813	0.284
		10	-0.041	-0.091	8.6642	0.371
		11	-0.114	-0.053	9.3511	0.406
		12	0.128	0.113	10.250	0.419
		13	-0.136	-0.215	11.314	0.417
		14	-0.171	-0.129	13.093	0.362
		15	0.143	0.047	14.406	0.346
		16	-0.073	-0.091	14.770	0.394

The results of figure 4 indicate that the residuals of ARIMA(1,1,1) model follow normal distribution. Moreover, the results of figure 5 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

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

Figure 6: **Forecast Accuracy Test on the Model ARIMA (1,1,1)**



The results in figure 6 indicate that the inequality coefficient of Theil has a high value U = 0.902 which means that our model does not have a good forecasting ability. Table 6 below summarizes the forecasting results of the real GDP rate over the period 2015 to 2017.

Table 6: The Real GDP Rate Forecasts

Years	Residuals	DGDP	GDP
2012	-0.618	2.30	-6.60
2013	1.140	3.30	-3.30
2014	2.930	4.10	0.80
2015	-----	0.76	1.56
2016	-----	5.41	2.85
2017	-----	6.65	3.12

6. Conclusion

In this paper, using Box – Jenkins technique, we are trying to forecast the real GDP rate in Greece for the next three years with an ARIMA model. 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. An ARIMA(1,1,1) model was created through the data used and estimating this model we found that the real GDP rate for the years 2015, 2016 and 2017 is forecast to be 1.56%, 2.85% and 3.12% respectively. Results of the study will be helpful for the policy makers to formulate effective policies for attracting foreign direct investment. Furthermore, the findings of the study will also help the managerial business executives for implementing the new project ideas or taking decisions concerned with the expansion of the existing business.

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