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GDP Modeling Using Autoregressive Integrated Moving Average (ARIMA): A Case for Greek GDP

Georgios Rigopoulos[1]
[1] *Department of Economics / University of Athens, Greece*

Abstract: *Gross Domestic Product (GDP) has become the single best indicator of economic growth and represents the total worth of all goods and services produced within a country's boundaries in a specific year. On the other hand, GDP per capita, is mostly related to the living standard through time. In this work, we focus on the Greek GDP for the period 1971-2020, and we using the Box-Jenkins approach (BJ) to build an Autoregressive-Integrated Moving-Average (ARIMA) model. GDP data was collected in annual form from the World Bank with values in constant USD2015. The results indicate that the ARIMA(1,2,1) is the most appropriate model, given model selection criteria. The work aims to contribute at the limited literature related to the Greek GDP and ARIMA, and show some direction for future research.*

Keywords - *Gross domestic product; Autoregressive-Integrated Moving-Average model; Box-Jenkins approach; Greek economy*

I. INTRODUCTION

Modern economic environment is characterized by increasing competition, constant change and continuous volatility at local and global scale, with technology developments playing a key role in this [1]. All modern societies set at the forefront of their interest the macroeconomic indicators, which affect lives and welfare of all economic units, including economic recession, inflation, unemployment, budget deficits, changes in interest rates and exchange rates among others. The evolution of macroeconomic variables is an important indicator of countries' economic well-being. So, their study is considered a necessity, for countries to anticipate economic changes and take appropriate measures critical moments. Forecasting thus has gained significant importance, as it allows for estimation of future trends in the short or medium term [2].

Among other macroeconomic indicators, the most widely used measure for an economy's size is GPD (Gross Domestic Product). Some economists consider it as a major invention of the 20th century [3]. Samuelson & Nordhaus [3], support that GDP can provide the overall picture of economy, similar to a satellite in the outer space, which can study the weather across a whole continent. So, as an indicator, it enables policymakers to examine the growth level of an economy (whether it is contracting or expanding), undertake appropriate measures, if required, and foresee any recession or inflation periods. GDP forecasting is thus of significant importance for policy makers and central banks.

Forecasting methods for macroeconomic indicators, like GDP, rely mainly on statistical methods and have been developed extensively during the past years, with the assistance of computing developments. Lately, machine learning is also considered as a promising approach which provides a data driven option, contrasted to the theory driven approach of the statistics and econometrics. In this context, this work focuses on GDP forecasting and mainly in ARIMA modelling. The aim of this work is to obtain an appropriate ARIMA model for the Greek GDP following the Box-Jenkins methodology for the period 1971-2020, and contribute to the limited literature in the domain.

The structure of the paper is as follows: Initially, a literature review in forecasting and GDP is presented and next a background in theoretical notions and terms. Next, the methodology is presented, along with the results and finally, the conclusion with some discussion.

II. LITERATURE REVIEW

The forecasting research domain is very active and rich in methods and theories in an effort to capture the complexity and reduce uncertainty [4]. In general, we can distinguish forecasting methods in literature, in two major approaches [5]. The ones based on parametric modeling, and the ones based on non-parametric methods. Some well-known parametric methods comprise the linear Autoregressive models [6] and the non-linear and Markov switching models [7]. In the non-parametric ones, we can find kernel methods, neural network methods, nearest neighbor method, wavelet methods among others [8]. The parametric models received substantial attention in economic forecasting, as they include substantial theoretical development in parameter modelling robustness and consistency, as well as their asymptotic properties. The non-parametric models, do not specify the model and residuals distribution beforehand, and they use the data to direct model specification. As such, they overcome problems that we find in the parametric models, like the strong hypotheses of model specification, or the estimation of parameters and their asymptotic properties. So, non-parametric modelling can be considered as more objective approach, as researcher lets data drive the model specification. One disadvantage, however, of non- parametric methods is increased mathematical complexity, something that can be adequately handled, however, by novel algorithms and increasing computing capacity [9]. However, both approaches are followed in research and the domain is very active, due to the significance of forecasting in economic decision making. Lately, machine learning methods are gaining importance and are also highly considered for forecasting, on top of the traditional ones.

For time series forecasting, a well known methodology, which is applied by researchers, is the Auto Regressive Integrated Moving Average, or ARIMA, that was introduced by Box and Jenkins [6]. It is based on the Wold representation theorem, which states that any stationary process can be expressed as a sum of two components: a stochastic component: a linear combination of lags of a white noise process and a deterministic component, uncorrelated with the latter stochastic component. This theorem implies that any stationary process can be written as a linear combination of a lagged values of a white noise process (MA(∞) representation) or has an infinite moving average (MA) representation, so its evolution can be expressed as a function of its past developments [10].

Among other macroeconomic indicators, GDP plays an important role in economic analysis, as it reflects and summarizes economic growth. Works that focus on GDP forecasting employ a variety of methods either parametric and non-parametric ones. A review of the works in literature, reveals that the approaches are mixed, but the linear autoregressive models play a substantial role. GDP forecasting has been studied from the early developments of linear autoregressive models [6]. Some early works, include the works of Sims and Litterman [11], [12]. Sims, proposes a linear VAR model for American GDP forecasting, while Litterman extends into Bayesian VAR model. Work originating from Engle and Granger with cointegration between GDP and M2 [13], is also applied in newer study from Gupta for GDP forecast in South Africa [14]. Some non-linear models are also introduced and approaches which combine linearity [15]; [16] and aggregation [17]. Subsequent works include factor models with a great number of indicators [18] and dynamic extensions [19], [20], [21]. There exist also some alternative models based on microeconomic foundation and stochastic equilibrium, from [22]. However, the ARIMA and VAR linear univariate models, still remain the benchmark models in the domain. Compared to parametric models, the application of non-parametric models was limited to economic forecasting in literature [23]. Some works include use of neural networks to forecast Canadian GDP [24], or nearest neighbors, and radial basis function methods for euro area GDP forecast [25], [26]. However, we see some expansion in recent literature on those methods mainly to theoretical developments, which reduce the restrictions that techniques, line kernel method, have for confidence intervals estimation and robustness.

Some indicative recent works which focus on specific countries' GDP forecasting are the following: Stundziene uses a regression model for Lithuanian GDP forecast and compares time series to regression approaches [27], [28]. Hassana, and Mirzab aply an ARIMA model for Indian GDP [29]. Likewise, Hang and Dun forecast Vietnam's GDP using ARIMA model [30] and Nwokike and Okereke for Nigerian GDP [31]. ARIMA is also used by Dritsaki and Dritsaki for Greek GDP [32], while Gawthorpe applies a random forest model for Posilh GDP [33].

From this limited review, it is evident that the domain is very rich in methods and applications and developments along with computing capacity have lead to more complex models. However, a further systematic review of the domain is required in order to evaluate the approaches in terms of validity and forecasting efficiency. Also, there is limited work on countries that exhibit the characteristics of economies like Greek one, in terms of GDP volume, and on the other hand with recession periods originating from the global 2007 subprime crisis.

III. METHODOLOGY AND EMPIRICAL RESULTS

Following the research in the domain, we apply time series analysis in this work for Greek GDP. The methodology we use is the ARIMA (Auto-Regressive-Integrated-Moving-Average) approach, developed by Box and Jenkins [6]. The purpose of the work is to explore which ARIMA model fits best in the Greek GDP for the period 1971-2020, on annual basis, validate the fit, and examine its predictive power. In addition, to offer insights for modeling GDP of countries which share common characteristics with Greek economy. The methodology we followed is based on the Box-Jenkins methodology and is presented in the next.

3.1 Data collection

In this phase we collected data for Greek GDP and adapted the dataset. We used GDP data from the WorldBank database in constant USD2015 values for the period 1971-2020. The line plot below (Fig. 1) depicts the evolution of GDP through this period (in USD millions). It is obvious that there is an increasing trend until 2005, and a decreasing trend after, showing that GDP series is a non-stationary process.

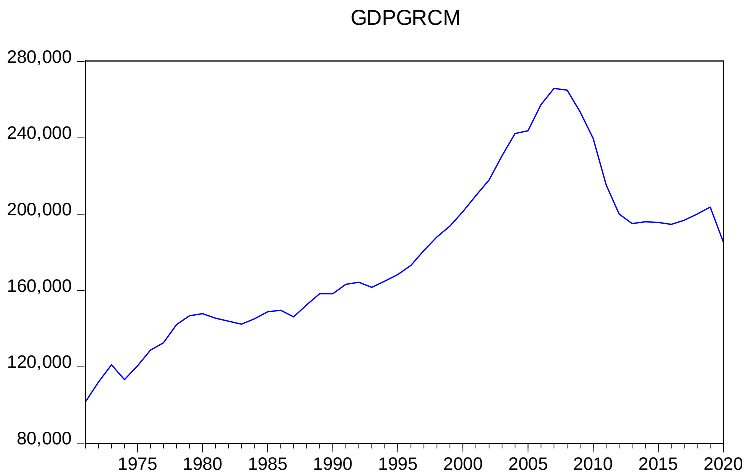


Figure 1: Greek GDP in constant millions USD2015 (1971-2020)

3.2 Identification of stationarity of time series

The stationarity of time series is pre-requisite in order to apply the method. We examine the stationarity using the autocorrelation function (ACF), partial autocorrelation function (PACF) as well as the ADF (Augmented Dickey-Fuller) test.

The correlogram of the Greek GDP series with a pattern up to 24 lags in level (Fig. 2), shows that the coefficients of autocorrelation (ACF) begin with a high value and decline slowly indicating a non-stationary series. Also, the Ljung-Box Q-statistic has a probability less than 0.5, so we cannot reject the null hypothesis that the GDP series is non-stationary. So, we take the first difference and examine for stationarity.

Sample: 1971 2021
Included observations: 50

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.949	0.949	47.767	0.000
		2	0.885	-0.154	90.181	0.000
		3	0.816	-0.068	127.03	0.000
		4	0.731	-0.201	157.22	0.000
		5	0.648	0.015	181.49	0.000
		6	0.573	0.028	200.88	0.000
		7	0.501	-0.001	216.08	0.000
		8	0.440	0.039	228.09	0.000
		9	0.386	-0.025	237.52	0.000
		10	0.330	-0.073	244.58	0.000
		11	0.270	-0.104	249.45	0.000
		12	0.208	-0.067	252.42	0.000
		13	0.144	-0.046	253.88	0.000
		14	0.085	0.022	254.40	0.000
		15	0.035	0.053	254.49	0.000
		16	-0.013	-0.045	254.50	0.000
		17	-0.063	-0.116	254.81	0.000
		18	-0.105	-0.012	255.72	0.000
		19	-0.143	-0.022	257.43	0.000
		20	-0.182	-0.042	260.30	0.000
		21	-0.214	0.016	264.41	0.000
		22	-0.244	-0.024	269.94	0.000
		23	-0.276	-0.065	277.25	0.000
		24	-0.303	-0.045	286.44	0.000

Figure 2: Correlogram of Greek GDP series (Level)

The correlogram of the first difference (Fig. 3), shows that the coefficients of autocorrelation (ACF) begin with a high value and decline after the second lag. Also, the Ljung-Box Q-statistic has a probability less than 0.5, so we cannot reject the null hypothesis that the GDP series is non-stationary. So, we take the second difference and examine for stationarity again.

Sample: 1971 2021
Included observations: 49

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.548	0.548	15.615	0.000
		2	0.336	0.051	21.609	0.000
		3	0.252	0.071	25.061	0.000
		4	0.065	-0.157	25.295	0.000
		5	-0.058	-0.090	25.483	0.000
		6	-0.054	0.032	25.651	0.000
		7	-0.103	-0.054	26.276	0.000
		8	-0.109	-0.005	27.000	0.001
		9	-0.025	0.071	27.039	0.001
		10	-0.073	-0.102	27.385	0.002
		11	-0.075	-0.011	27.755	0.004
		12	-0.084	-0.078	28.237	0.005
		13	-0.141	-0.080	29.614	0.005
		14	-0.248	-0.176	33.996	0.002
		15	-0.088	0.197	34.563	0.003
		16	-0.082	-0.055	35.076	0.004
		17	-0.107	-0.043	35.971	0.005
		18	-0.001	0.033	35.971	0.007
		19	-0.004	-0.059	35.972	0.011
		20	-0.091	-0.126	36.690	0.013

Figure 3: Correlogram of Greek GDP series (first difference)

In the correlogram of the second difference (Fig. 4), we see that Ljung-Box Q-statistic has a probability larger than 0.5, so we reject the null hypothesis that the GDP series is non-stationary.

Sample: 1971 2021
Included observations: 48

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.122	-0.122	0.7633	0.382
		2	-0.108	-0.125	1.3709	0.504
		3	0.069	0.040	1.6250	0.654
		4	-0.123	-0.126	2.4470	0.654
		5	-0.150	-0.178	3.7044	0.593
		6	0.057	-0.021	3.8903	0.692
		7	-0.096	-0.129	4.4287	0.729
		8	-0.206	-0.265	6.9843	0.538
		9	0.102	-0.057	7.6208	0.573
		10	0.024	-0.065	7.6572	0.662
		11	0.029	-0.006	7.7108	0.739
		12	0.139	0.040	8.9939	0.703
		13	0.149	0.143	10.518	0.651
		14	-0.300	-0.270	16.869	0.263
		15	0.112	0.023	17.783	0.274
		16	0.095	0.058	18.459	0.298
		17	-0.168	-0.062	20.636	0.243
		18	0.130	0.122	21.986	0.233
		19	0.094	0.133	22.719	0.250
		20	-0.149	0.014	24.634	0.216

Figure 4: Correlogram of Greek GDP series (second difference)

The results of the Augmented Dickey-Fuller (ADF) test and Phillips-Perron test on the level, first and second differences are also depicted in Table 1. Results indicate that the GDP is stationary in the second differences. So, our ARIMA(p, d, q) model will have the value d=2, or it will be integrated of order two, I(2).

Table 1: ADF and PP test on level, first and second differences of GDP

	Level		**First differences**		**Second differences**	
	t statistic	**5% level**	**t statistic**	**5% level**	**t statistic**	**5% level**
ADF	-1.632463	-2.923780	-2.895410	-2.923780	-6.949054	-2.925169**
PP	-1.827559	-2.922449	-2.912292	-2.923780	-6.919983	-2.925169**

*MacKinnon (1996) one-sided p-values.
**denote statistically significant at 5% significance levels.

3.3 Model identification

ARIMA model requires the identification of the three parameters p, d and q, where p is the order of auto regressive terms , d is the order of integration or number of differences and q is number of moving average terms. From the previous step, we defined the value of d=2. For the identification of the ARMA(p, q), p and q parameters, we used the ACF and PACF plots for tentative values and next used the Akaike information criterion (AIC) for the selection of the optimum model. In order to select the appropriate values, we perform a comparison of tentative models, within the range of the values we calculate from the critical value $\pm 2/\sqrt{n} = \pm 2/\sqrt{50} = \pm 0.282$. From the values of the ACF and PACF on Fig. 2, we define the value of q between 0 and 10 and the value of p between 0 and 2. So, we create a comparison table for the combination of all the models in this range (Table 2). From the results, we can conclude that the most suitable ARMA model is the ARMA(1, 1). Given that the model is stationary on second differences (d=2), the ARIMA model will be ARIMA(1, 2, 1).

Table 2: Comparison of models using AIC, BIC and HQ

Model Selection Criteria Table
Dependent Variable: DDGDPGRCM
Date: 08/10/22 Time: 20:27
Sample: 1971 2021
Included observations: 48

Model	LogL	AIC*	BIC	HQ
(1,1)(0,0)	-488.108242	20.504510	20.660443	20.563438
(1,2)(0,0)	-488.078997	20.544958	20.739875	20.618618
(2,1)(0,0)	-488.080943	20.545039	20.739956	20.618699
(0,4)(0,0)	-487.416502	20.559021	20.792921	20.647412
(0,0)(0,0)	-491.582674	20.565945	20.643911	20.595408
(2,2)(0,0)	-487.583461	20.565978	20.799878	20.654369
(0,2)(0,0)	-489.868951	20.577873	20.733806	20.636800
(0,1)(0,0)	-490.954626	20.581443	20.698393	20.625638
(0,3)(0,0)	-489.053746	20.585573	20.780490	20.659232

3.4 Model estimation

Next, we estimate the above ARIMA(1, 2, 1) model and the results are depicted in Table 3. The results show that both coefficients are significant at 1% level of significance. The iterative process used by EViews converged after 32 iterations. The roots are 0.64 and 0.94, both inside the unit circle, indicating stationarity and invertibility respectively. Also, the residual plot in Fig. 5, shows the fitted, actual and residuals of the selected model ARIMA(1, 2, 1).

Table 3: Comparison of models using AIC, BIC and HQ

Dependent Variable: D(GDPGRCM,2)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 1973 2020
Included observations: 48
Convergence achieved after 32 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.637188	0.156030	4.083750	0.0002
MA(1)	-0.936530	0.151644	-6.175851	0.0000
SIGMASQ	41068898	6704390.	6.125673	0.0000

R-squared	0.107718	Mean dependent var	-597.9036
Adjusted R-squared	0.068061	S.D. dependent var	6856.099
S.E. of regression	6618.672	Akaike info criterion	20.51030
Sum squared resid	1.97E+09	Schwarz criterion	20.62725
Log likelihood	-489.2472	Hannan-Quinn criter.	20.55450
Durbin-Watson stat	1.750587		

Inverted AR Roots	.64
Inverted MA Roots	.94

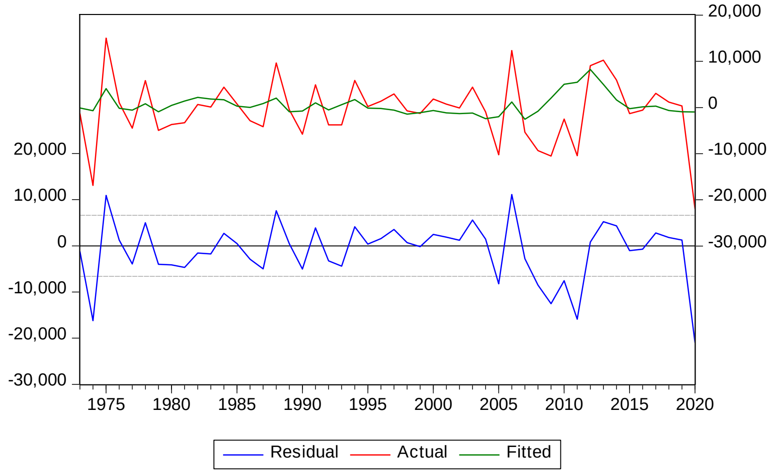


Figure 5: Residual plot of the ARIMA(1, 2, 1)

3.5 Diagnostic checking

The diagnostic checking of the model allows us to check the goodness of fit of the model. In general, we examine the plot of the residuals and look for outliers, autocorrelation or periods where the model does not fit well. From the results of Fig. 6, we note that the autocorrelation coefficients and the partial autocorrelation coefficients are not statistical significant in all lags. So, we can conclude that the residuals are not autocorrelated. From the diagnostics, we can conclude that the ARIMA(1, 2, 1) can be considered as an appropriate model.

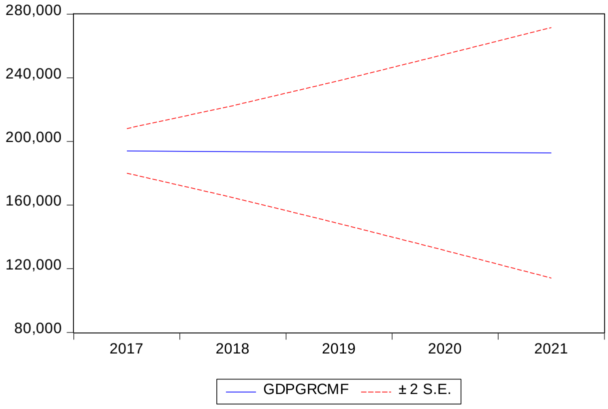
Sample: 1973 2020
Included observations: 48
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.006	-0.006	0.0021	
		2	-0.034	-0.034	0.0625	
		3	0.078	0.077	0.3846	0.535
		4	-0.107	-0.108	1.0045	0.605
		5	-0.152	-0.150	2.3005	0.512
		6	0.009	-0.006	2.3049	0.680
		7	-0.104	-0.101	2.9381	0.710
		8	-0.167	-0.167	4.6049	0.595
		9	0.120	0.080	5.4945	0.600
		10	0.041	0.025	5.6031	0.692
		11	0.045	0.054	5.7368	0.766
		12	0.113	0.047	6.5930	0.763
		13	0.099	0.083	7.2634	0.777
		14	-0.286	-0.285	13.044	0.366
		15	0.085	0.076	13.573	0.405
		16	0.050	0.055	13.760	0.468
		17	-0.166	-0.071	15.883	0.390
		18	0.095	0.086	16.612	0.411
		19	0.064	0.042	16.953	0.458
		20	-0.144	-0.108	18.734	0.408

Figure 6: Correlogram of residuals

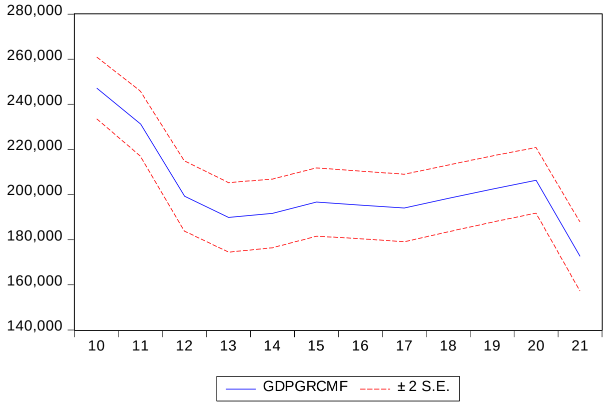
3.6 Forecasting and forecast evaluation

After the selection of the ARIMA(1, 2, 1) model, we depict the actual and forecasted values, as well as the statistical values of the forecasting (Fig. 7, 8, 9). The accuracy of forecasting is checked by root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and the inequality coefficient of Theil (U). From the results, we can see that for the period later than 2010, the dynamic and static forecasts perform well. The MAPE is relatively low for both and the U-Theil inequality index has a value close to zero.



Forecast: GDPGRCMF	
Actual: GDPGRCM	
Forecast sample: 2017 2021	
Included observations: 5	
Root Mean Squared Error	7382.692
Mean Absolute Error	6849.986
Mean Abs. Percent Error	3.483108
Theil Inequality Coefficient	0.018929
Bias Proportion	0.166004
Variance Proportion	0.775613
Covariance Proportion	0.058383
Theil U2 Coefficient	0.774304
Symmetric MAPE	3.511684

Figure 7: Dynamic forecast of GDP for 2017-2021



Forecast: GDPGRCMF	
Actual: GDPGRCM	
Forecast sample: 2010 2021	
Included observations: 12	
Root Mean Squared Error	8589.909
Mean Absolute Error	5675.143
Mean Abs. Percent Error	2.818009
Theil Inequality Coefficient	0.021056
Bias Proportion	0.100709
Variance Proportion	0.155846
Covariance Proportion	0.743445
Theil U2 Coefficient	0.816908
Symmetric MAPE	2.741326

Figure 8: Static forecast of GDP for 2010-2021

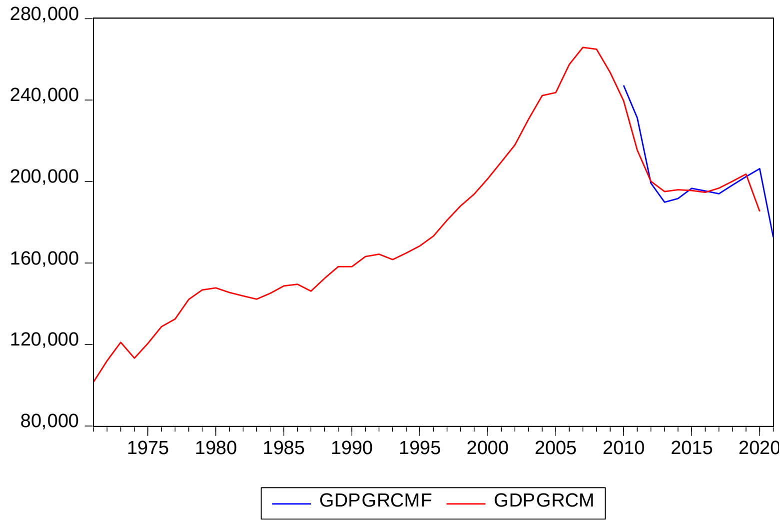


Figure 9: Residual plot of the ARIMA(1, 2, 1)

IV. CONCLUSION

The aim of this work was to model the Greek GDP and examine its forecasting capability, applying the BoxJenkins approach, based on annual data from 1971 to 2020. The four stages of Box-Jenkins approach were conducted in order to select an appropriate ARIMA model, and time series and the correlogram plots were used for testing the stationarity of the data. Using the different goodness-of-fit measures (AIC, and BIC), the various ARIMA models with different order of autoregressive and moving-average terms were compared to find the appropriate ARIMA (p, d, q) process. Finally, an ARIMA (1, 2, 1) model was selected and estimated. The results from static and dynamic forecasting show that they model provides some realistic and accurate values for the period after 2010. Despite the inherent limitations of forecasting, form this work it looks that the ARIMA model is adequate for GDP modeling and forecasting.

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