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Article

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Forecasting European Union CO_2 Emissions Using Autoregressive Integrated Moving Average-autoregressive Conditional Heteroscedasticity Models

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ABSTRACT

In the past few decades, there are lot of discussions around global warming and climate change primarily due to the increased CO_2 emissions generated by the consumption of fossil fuels, such as oil and natural gas. After an enormous effort, the EU-28 managed to reduce CO_2 emissions in 2014 by 25.7% comparing to 1990 (Kyoto Protocol). This effort should continue in the future so that the EU-28 achieve a 40% reduction on CO_2 emissions by 2030. The current paper aims at investigating the optimum model to forecast CO_2 emissions in the EU-28. To achieve this aim an autoregressive integrated moving average (ARIMA) (1,1,1)- autoregressive conditional heteroscedasticity (ARCH) (1) model was used, combined with the linear ARIMA model and the conditional variance of the ARCH model. The estimation of parameter optimisation of ARIMA(1,1,1)-ARCH(1) model was done with the maximum likelihood approach using the Marquardt (1963), and Berndt-Hall-Hall-Hausman algorithms and the three distributions (normal, t-student, generalized error), whereas for the estimation of the covariance coefficient the reversed matrix by Hessian was used. Finally, in order to forecast the ARIMA(1,1,1)-ARCH(1) model, a dynamic as well as a static process was applied. The results of the forecasting revealed that the static procedure provides a better forecast comparing to the dynamic one.

Keywords: CO_2 Emissions, Autoregressive Integrated Moving Average (1,1,1)-Autoregressive Conditional Heteroscedasticity (1) Model, Forecasting, E.U

JEL Classifications: C22, C53, Q50

1. INTRODUCTION

During the last decades, the increase of the greenhouse gas emissions is considered the biggest threat for global warming. The economic growth of developed countries pushes the intensive use of energy and the consumption of fossil fuels, which results to more residues and waste leading to environmental decomposition.

Data from the 1960s and 1970s, show that the concentration of CO_2 in the atmosphere is increasing significantly. Hence, scientists put a lot of pressure to governments to take action. Unfortunately, it took the international community years to respond to this request. Back in 1988 the International Meteorology Organisation and the United Nations Environmental Program formed an intergovernmental committee for climate change. The evaluation report published in 1990, mentioned that the problem of temperature rise is an existing one and owes to be dealt with promptly. This outcome pushed governments to establish the United Nations Framework Convention on Climate Change (UNFCCC), which was signed in Rio de Janeiro in 1992. UNFCCC as well as the Kyoto Protocol that followed, form the only international frameworks for tacking climate change (United Nations Climate Change, 2019).

The Kyoto Protocol is an international treaty (signed on 11 December 1997, but entered into force on 16 February 2005), which sets the principles of reducing greenhouse gas concentrations in the atmosphere which cause temperature rise in the planet. Based on Kyoto Protocol, countries which have signed the treaty, are bound to reduce greenhouse gas emissions on average by 5.2% between 2008 and 2012, comparing to 1990 levels. The protocol is based on the principle of common responsibilities in tackling climate change but acknowledges the different capacity to achieve this based on each country's economic growth.

Negotiations for resolving the global temperature increase problem were tough due to clashing interests. Consequently, opposing country-teams with diverging views were generated. For example, countries producing carbon, such as Japan, USA, Canada, Australia, New Zealand, but also members of OPEK with Russia and Norway, which support the development of oil and natural gas production, are affected by Kyoto Protocol because they need to reduce their production and instead switch to alternative energy sources. In addition, emerging makers such as China and India could not commit to reducing greenhouse gas. On the contrary, the European Union was the earnest supporter of Kyoto Protocol, which committed to reduce greenhouse gas emissions by 6% for 2012 and reduction of fossil fuel consumption by 16%.

Kyoto Protocol followed a second phase during the period 2013-2020 known as Doha Amendment 2012. Thirty-eight developed countries participate among them 28 member states of the European Union. In this second phase, participating states commit to reduce their emissions to a level 18% lower than that of 1990. The EU also has committed to reduce by 20% for that period.

The Paris agreement for climate change took place in December 2015. This conference set two requirements for its application. The first one concerned the confirmation of the UNFCCC, by at least 55 country-members and the second one concerned the minimum amount of greenhouse gas emissions, which each country need to follow.

The Kyoto Protocol applies to six greenhouse gases: Carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulphur hexafluoride (SF_6). Carbon dioxide (CO_2) is a natural gas, which is defined by the photosynthesis into organic material. Most of the CO_2 emissions are due to fossil fuel consumption such as carbon, petroleum, natural gas and the burning of biomass. CO_2 emissions are also generated by the change in soil use, the car mobility and various others industrial activities. CO_2 is the main anthropogenic greenhouse gas that affects the radioactive balance of the earth. Moreover, CO_2 is the gas that form the basis in which other greenhouse gas are calculated, resulting in a dynamic overheating of the planet.

The majority of the countries, failed to achieve their commitments with regards to CO_2 emissions. The European Union is taking notable measures for reducing CO_2 emissions generated from the absorption of fossil fuels.

Given that there exists a two-way causal relationship between economic growth and CO_2 emissions, a reduction on the CO_2 emissions will have an unfavourable impact on the economic growth of European Countries Table A1. Table A2, presents the relationship between per capita CO_2 emissions and the per capita economic power of the 28 European Countries.

The amount of CO_2 emissions during the period 1990-2014 in EU, USA, China and the World is presented in the Figure 1.

From the Figure 1 we detect that since the Kyoto Protocol in 1990, the USA have reduced CO_2 emissions by 0.63 % pa and the EU by 1.19% pa. On the contrary, China has increased CO_2 emissions by 5.49% pa whereas the global CO_2 emissions are increasing by 0.73% pa.

The Table 1 presents the descriptive statistics for the per capita CO_2 emissions in the European Union, the USA, China and the World from 1990 (Kyoto Protocol) until 2014. The descriptive statistics mean, standard deviation (Std. Dev.) and coefficient of variation (CV) of these variables are recorded below in Table 1.

Table 1 shows that the variability in the per capita CO_2 emissions is greater in China and smaller in in the case of the USA.

The Figure 2 presents the rate of CO_2 emissions in the EU-28 countries.

The Figure 2 shows an overall downward trend of the CO_2 emissions between 1990 and 1999, with the exception of a peak in 1996, when an exceptional of a cold winter which led to increased demand for heating. From 1999 to 2006, the CO_2 emission for the EU-28 was relative stable. From 2006-2009 a sharp drop of CO_2 emissions was detected as result of the global financial and economic crisis leading to the decrease of industrial activity of the European Union. The CO_2 emissions increased again during the period 2009-2010 and dropped again between 2011 and 2014.

The remainder of the paper is organized as follows: Section 2 provides a brief literature review. Section 3 presents the analysis of methodology. Section 4 summarizes the data. The empirical results are provided in Section 5 and Section 6 proposes the forecasting results. Finally, the last section offers the concluding remarks.

2. LITERATURE REVIEW

The forecasting issues are important and are being applied in various scientific fields, such as economics, meteorology, medicine, mechanics, ecology and many more. The increasing trend of the CO_2 emissions in a global level due to human activity indicated the increased atmospheric concentration of CO_2. Climate change, because of global warming, is one of the most prolific issues during the last years. Reddy et al. (1995) suggest in their research that the total average temperature increase will reach 3-4°C, doubling the CO_2 emissions concentration, whereas in 2007 the intergovernmental committee for climate change reported an increase of the temperature between 1.1 to 6.4°C in the next 100 years.

Figure 1: Amount of carbon dioxide emissions (metric tons per capita) from consumption of energy over 1990-2014 in E.U, U.S.A, China and World

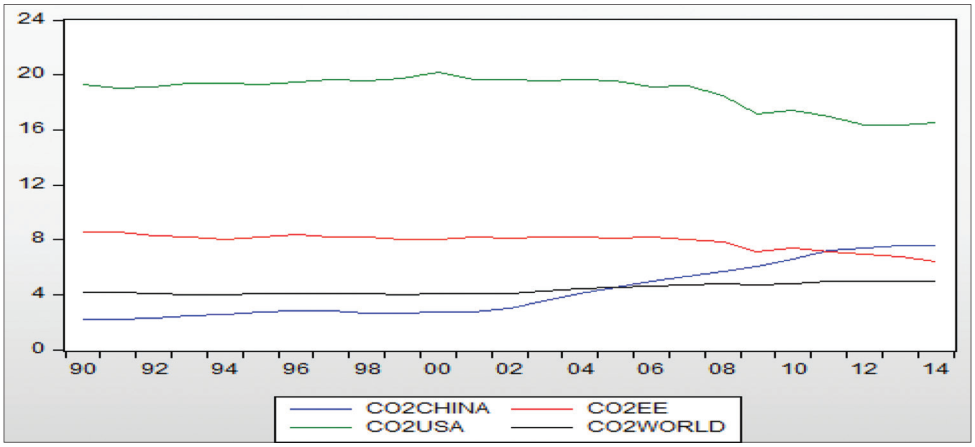


Figure 2: Amount of carbon dioxide emissions (metric tons per capita) from consumption of energy over 1990-2014 in E.U

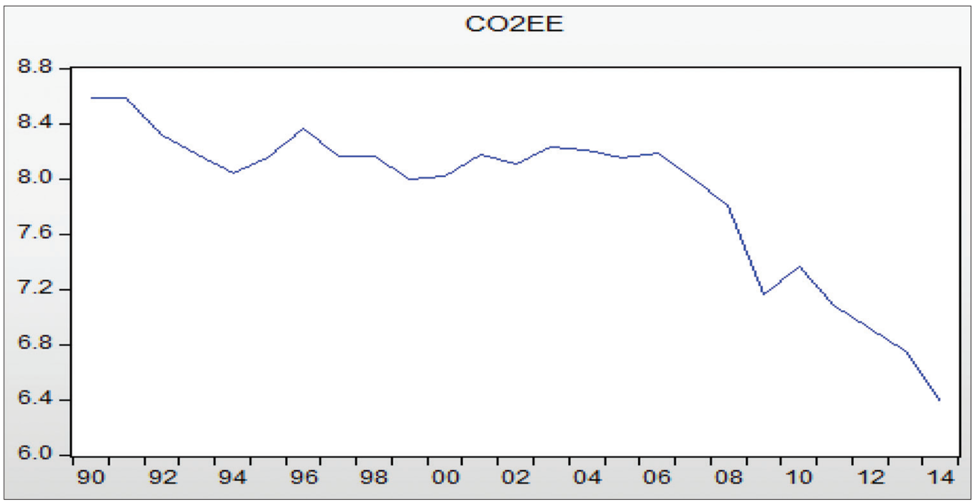


Table 1: Descriptive statistics for CO_2 emissions (1990-2014)

Variables	Mean	Std. Dev.	CV (%)	Minimum (year)	Maximum (year)
CO_2 E.U	7.880	0.585	7.42	6.379 (2014)	8.540 (1990)
CO_2 USA	18.789	1.209	6.43	16.310 (2012)	20.179 (2000)
CO_2 China	4.173	1.930	46.24	2.152 (1990)	7.557 (2013)
CO_2 World	4.384	0.377	8.59	3.986 (1999)	5.005 (2012)

Developed countries have a higher share of global CO_2 emissions comparing to developing countries. Nakicenovic back in 1994, studies the prospect of greenhouse gas emissions in a rural context. His findings suggest that developing countries are responsible for less than the 16% of the CO_2 concentration due to their previous consumption from mineral sources of energy. Developed countries have a higher share of global emissions. Researchers so far have investigated the forecasting of CO_2 emissions in various countries. Lotfalipour et al. (2013) have examined the economic aspects of CO_2 emissions and their consequences for the case of Iran. In their study they apply Grey and autoregressive integrated moving average (ARIMA) models to forecast CO_2 emission in the period between 1990 and 2011. Their results suggest that Grey models provided better results in terms of forecasting CO_2 emissions. Based on their estimated results, the quantity of CO_2 emissions will reach 925.680.000 tons in 2020, which indicated an increase of 66% compared to 2010, which is highly significant.

Rahman and Hasan (2017), investigated the CO_2 emissions between 1972 and 2015 in the case of Bagladesh. The optimum prognostic model for the CO_2 emissions in the period under investigation was the ARIMA(0, 2, 1) model. The results suggested that the CO_2 emissions for years 2016, 2017 and 2018 will be 83.94657, 89.90464 and 96.28557 metric tons respectively.

Pruethsan in 2007, analysed CO_2 emissions in Thailand using the VARIMAX approach during the period 2000-2015 and subsequently determined the VARIMAX(2, 1, 1) and VARIMAX(2, 1, 3) models as the optimal ones for the CO_2 forecast emissions in Thailand. The forecasting results (using the VARIMAX(2, 1, 1) model) show that CO_2 gas greenhouse emissions will increase steadily and will reach 25.17% until 2025 comparing to 2016, whereas using the VARIMAX(2, 1, 3) model the CO_2 gas greenhouse emissions will increase steadily and will reach 41.51% until 2040 comparing to 2016.

Nyoni and Mutongi (2019) are using annual data to investigate CO_2 emissions in the case of China from 1960 to 2017 using the Box-Jenkins approach. The ARIMA(1, 2, 1) model was shown to be the most suitable one to forecast CO_2 emissions in the period under investigation. The study results reveal that CO_2 emissions in China will increase and reach approximately 10.000.000 kt in 2024. This result forms a warning of the Chinese government with regards to clinical change and the overheating that China causes in the world.

Finally, Nyoni and Bonga (2019) use 1960-2017 data and a Box-Jenkins approach to forecast CO_2 emissions in China. The study proposes the ARIMA(2, 2, 0) as the optimum one to forecast CO_2 emissions. It further suggests that by 2025, the annual CO_2 emissions in India will reach 3.890.000 kt. The results is critical to the Indian government with respect its short-term and long-term planning of climate change and global overheating.

3. THEORETICAL BACKGROUND

3.1. ARIMA Models

An ARIMA model is a generalization of an autoregressive moving average (ARMA) used in econometrics. ARIMA is one of the type of models in the Box and Jenkins (1976) methodology for analysis and forecasting a time series.

The ARIMA(p,d,q,) can be expressed as:

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d\left(y_t-\mu\right)=\left(1-\sum_{j=1}^{q}\vartheta_j L^j\right)e_t \qquad (1)$$

where

$\phi_p(L)=1-\sum_{i=1}^{p}\phi_i L^i$ and $\vartheta_q(L)=1-\sum_{j=1}^{q}\vartheta_j L^j$ are polynomials in terms of L of degree p and q.

y_t is the time series, and e_t is the random error at time period t, with μ is the mean of the model.

d is the order of the difference operator.

$\phi_1,\phi_2,\ldots,\phi_p$ and $\vartheta_1,\vartheta_2,\ldots,\vartheta_q$ are the parameters of autoregressive and moving average terms with order p and q respectively.

L is the difference operator defined as $\Delta y_t = y_t - y_{t-1} = (1-L)y_t$.

3.2. Autoregressive Conditional Heteroscedasticity (ARCH)-GARCH Models

3.2.1. ARCH(q) model

Engle (1982) developed the ARCH model for testing the volatility of time series. The basic ARCH model consists of two equations, a conditional mean equation and a conditional variance equation. Both equations form a system that is estimated together with maximum likelihood (ML) method.

So, ARCH model is an ARMA and can be written as follows:

$$y_t=\mu_t+\varepsilon_t \text{ (conditional mean equation)} \qquad (2)$$

where u_t is conditional mean of y_t, and ε_t is the shock at time t.

The variance ε_t will be:

$$\varepsilon_t=u_t\sigma_t$$

where u_t is a white noise with zero mean and variance of one $u_t \rightarrow iid(0,1)$. u_t may or may not follow normal distribution.

$$\sigma_t^2=\omega+\sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 \text{ (conditional variance equation)} \quad (3)$$

where σ_t^2 is the conditional variance of y_t, ω is a constant term, and q is the order of the ARCH terms, $\omega>0$, $\alpha_i\geq 0$ and $i>0$.

3.2.2. GARCH(q,p) model

Bollerslev (1986) extended the ARCH model in a new one that allows the errors of variance to depend on its own lags as well as lags of the squared errors. In other words, it allows the extension of conditional variance to follow an ARMA process.

The GARCH model can be expressed as:

$$y_t=\mu_t+\varepsilon_t \text{ (conditional mean equation)} \qquad (4)$$

where u_t is conditional mean of y_t, and ε_t is the shock at time t.

$\varepsilon_t=u_t\sigma_t$

where u_t is a white noise with zero mean and variance of one $u_t \rightarrow iid(0,1)$.

$$\sigma_t^2=\omega+\sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2+\sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \text{ (conditional variance equation)} \qquad (5)$$

where

σ_t^2 is the conditional variance of y_t, ω is a constant term, q is the order of the ARCH terms, and p is the order of the GARCH terms. We assume that for every $p \geq 0$ and $q > 0$, the parameters are unknown and since the variance is positive, then the following relations must be positive too $\omega \geq 0$, and $\alpha_i \geq 0$ for every i=1,…, q and $\beta_j \geq 0$ for j = 1,…, p. If the parameters are constrained such that $\sum_{i=1}^{q}\alpha_i+\sum_{j=1}^{p}\beta_j<1$, they imply a weak stationarity. If p = 0, then GARCH model is becoming an ARCH model.

3.3. ARIMA-ARCH/GARCH Model

The ARIMA-ARCH/GARCH model is one model in which the variance of the error term of the ARIMA model follows an ARCH/GARCH process. In other words, the ARIMA-ARCH/GARCH model is a non-linear time series model which combined the lineal model ARIMA with the conditional variance of the ARCH/GARCH model.

For the ARIMA-ARCH/GARCH process to be suggested, the following two phases should be applied. The first one uses the best ARIMA model which fits the stationary and linear data of the time series, whereas the linear model residuals should contain the non-linear part of the data. The second phase uses the ARCH/GARCH model in order to include the non-linear patters of the residuals. The model combined the ARIMA model with the ARCH/GARCH which contains the non-linear patterns of the residuals (Dritsaki, 2018).

The process of parameter estimation of the ARIMA-ARCH/GARCH model is achieved through the logarithmic function of ML through nonlinear least squares using Marquardt's algorithm (1963). The latter is presentd by the following function:

$$\ln L\left[\left(y_t\right),\theta\right]=\sum_{t=1}^{T}\left\{\ln\left[D\left(z_t(\theta)\right),\upsilon\right]-\frac{1}{2}\ln\left[\sigma_t^2(\theta)\right]\right\} \quad (6)$$

where θ is the vector of the parameters that have to be estimated for the conditional mean, conditional variance and density function, z_t denoting their density function, $D(z_t(\theta),\upsilon)$, is the log-likelihood function of $[y_t(\theta)]$, for a sample of T observation. The ML estimator $\hat{\theta}$ for the true parameter vector is found by maximizing (8) (Dritsaki, 2017; 2019).

3.3.1. Conditional Distributions

Logarithmic function of ML used for parameters' estimation on volatility models for all theoretical distributions are the following: (Dritsaki, 2017; 2019).

- Normal distribution

$$\ln L\left[(y_t),\theta\right]=-\frac{1}{2}\left[T\ln(2\pi)+\sum_{t=1}^{T}z_t^2+\sum_{t=1}^{T}\ln(\sigma_t^2)\right] \quad (7)$$

where θ is the vector of the parameters that have to be estimated for the conditional mean, conditional variance and density function, T is observations.

- *t*-student distribution

$$\ln L\left[(y_t),\theta\right]=T\left[\ln\Gamma\left(\frac{\upsilon+1}{2}\right)-\ln\Gamma\left(\frac{\upsilon}{2}\right)-\frac{1}{2}\ln[\pi(\upsilon-2)]\right] \\ -\frac{1}{2}\sum_{t=1}^{T}\left[\ln(\sigma_t^2)+(1+\upsilon)\ln\left(1+\frac{z_t^2}{\upsilon-2}\right)\right] \quad (8)$$

where

$\Gamma(\upsilon)=\int_0^{\infty}e^{-x}x^{\upsilon-1}dx$ is the gamma function and υ is the degree of freedom.

- Generalized error distribution

$$\ln L\left[(y_t),\theta\right]=\sum_{t=1}^{T}\begin{bmatrix}\ln\left(\frac{\upsilon}{\lambda}\right)-\frac{1}{2}\left|\frac{z_t}{\lambda}\right|^{\upsilon}-\left(1+\upsilon^{-1}\right)\ln(2) \\ -\ln\Gamma\left(\frac{1}{\upsilon}\right)-\frac{1}{2}\ln\left(\sigma_t^2\right)\end{bmatrix} \quad (9)$$

where

$$\lambda=\left[2^{-2/\upsilon}\frac{\Gamma\left(\frac{1}{\upsilon}\right)}{\Gamma\left(\frac{3}{\upsilon}\right)}\right]^{1/2}$$

3.4. Diagnostic Checking of the Model ARIMA-ARCH/GARCH

Before we accept a fitted model and interpret its findings, it is essential to check whether the model is correctly specified, that is, whether the model assumptions are supported by the data. The diagnostic tests of ARIMA-ARCH/GARCH models are based on residuals. Residuals' normality test is employed with Jarque and Bera (1980) test. Ljung and Box (1978) (Q-statistics) statistic for all time lags of autocorrelation is used for the serial correlation test. Also, for the conditional heteroscedasticity test we use the squared residuals of autocorrelation function.

3.5. Forecasting Performance Measures

In order to compare the forecasting performance of ARIMA-ARCH/GARCH models we use the following statistics:

- Mean absolute error (MAE)

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|Y_i-\hat{Y}_i\right| \quad (10)$$

Y_i is the vector of observed values of the variable being predicted.

$\hat{Y}_i$ is the vector of n predictions.

It measures the average absolute deviation of forecasted values from original ones.

- Root mean squared error (MSE)

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i-\hat{Y}_i\right)^2} \quad (11)$$

- MSE has the following formula

$$MSE=\frac{1}{n}\sum_{i=1}^{n}\left(Y_i-\hat{Y}_i\right)^2 \quad (12)$$

MSE gives an overall idea of the error occurred during forecasting.

- The mean absolute percentage error (MAPE)

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i-\hat{Y}_i}{Y_i}\right| \quad (13)$$

This measure represents the percentage of average absolute error occurred. It is independent of the scale of measurement, but affected by data transformation.

4. DATA

Annual data for CO_2 emissions (CO_2) in the E.U (metric tons per capita), are downloaded from the World Bank's development indicators. The data is for the period from 1960 to 2014.

Figure 3 presents the course of the per capita CO_2 emissions in the European Union between 1960 and 2014 at the level.

Figure 3 shows that the CO_2 emissions at the EU present a random walk. Therefore, we will check for the stationarity of the series and its Figure 4 autocorrelation.

From Figure 4 shows that the auto-regression coefficients decline with rapid pace, which implied that the series is non-stationary.

We then apply the aforementioned tests afresh, in order to investigate the presence of stationarity in the first differences of the series. Figure 5, shows the first differences of the CO_2 emissions.

From Figure 5, we observe that the CO_2 emissions present intense fluctuations in their first differences, which is a possible indication of stationarity. We then test the stationarity with the auto-correlation Figure 6.

Figures 5 and 6 both show that the series is likely to be stationary in its first differences.

The confirmation of the series stationarity is achieved by applying the unit root tests Dickey and Fuller (1979; 1981) and Phillips and Perron (1998).

Figure 3: CO_2 emissions in E.U-28

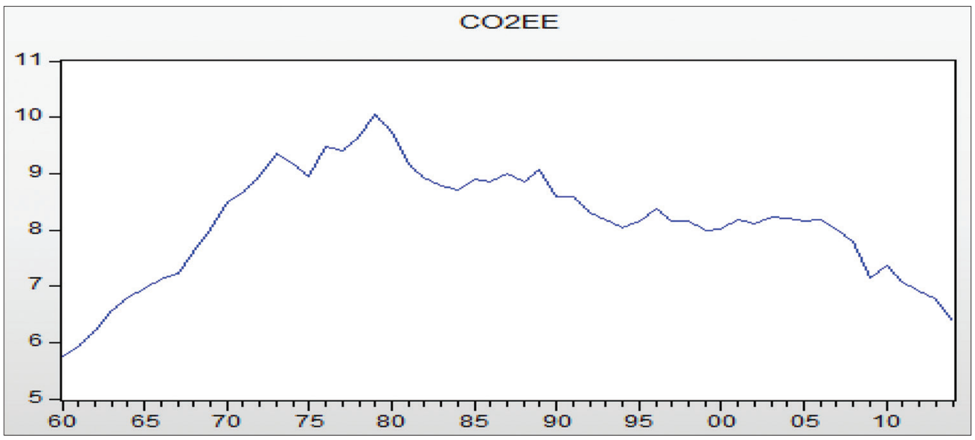
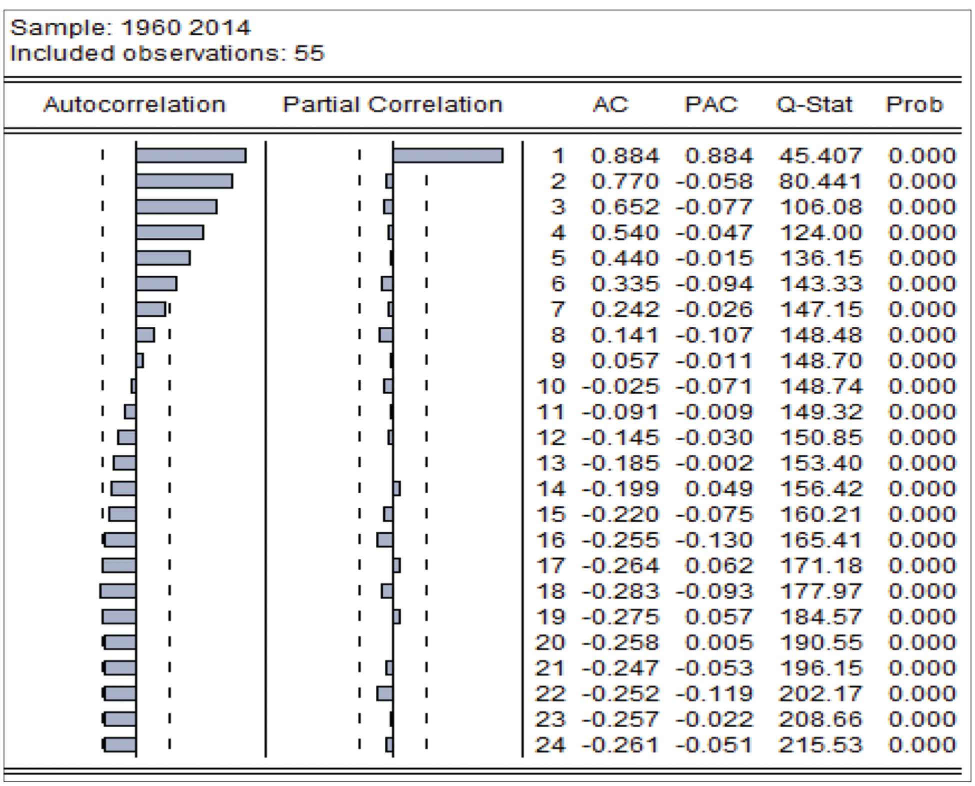


Figure 4: Auto-regression partial autocorrelation of CO_2 emissions on its level



Sample: 1960 2014
Included observations: 55

	AC	PAC	Q-Stat	Prob
1	0.884	0.884	45.407	0.000
2	0.770	-0.058	80.441	0.000
3	0.652	-0.077	106.08	0.000
4	0.540	-0.047	124.00	0.000
5	0.440	-0.015	136.15	0.000
6	0.335	-0.094	143.33	0.000
7	0.242	-0.026	147.15	0.000
8	0.141	-0.107	148.48	0.000
9	0.057	-0.011	148.70	0.000
10	-0.025	-0.071	148.74	0.000
11	-0.091	-0.009	149.32	0.000
12	-0.145	-0.030	150.85	0.000
13	-0.185	-0.002	153.40	0.000
14	-0.199	0.049	156.42	0.000
15	-0.220	-0.075	160.21	0.000
16	-0.255	-0.130	165.41	0.000
17	-0.264	0.062	171.18	0.000
18	-0.283	-0.093	177.97	0.000
19	-0.275	0.057	184.57	0.000
20	-0.258	0.005	190.55	0.000
21	-0.247	-0.053	196.15	0.000
22	-0.252	-0.119	202.17	0.000
23	-0.257	-0.022	208.66	0.000
24	-0.261	-0.051	215.53	0.000

The results of Table 2, confirm that the series is stationary in the first differences. The next step is to determine the ARIMA(p, q) model, based on the results from Figure 6. The parameters p και q of the ARIMA model could be determined rom the partial auto-correlation and auto-correlation coefficients comparing them respectively with the critical value $\pm\frac{2}{\sqrt{n}} = \pm\frac{2}{\sqrt{55}} = \pm 0.262$.

Moreover, to test for autocorrelation we use the Ljung and Box (1978) test determined by:

$$Q_{LB} = n(n+2)\sum_{k=1}^{m}\left[\frac{\hat{\rho}_k^2}{n-k}\right] \sim \chi^2_{\mathrm{m}} \qquad (14)$$

Looking at the values of the partial autocorrelation and autocorrelation coefficients (Figure 6) the value for p is between $0 < p < 1$ and respectively, the value for q will be between $0 < q < 2$. Using the values above, we chose the best ARIMA(p, d, q) model from the lowest values of AIC, SC, and HQ criteria. Table 3 shows the values for p and q.

Table 2: Augmented Dickey–Fuller and Phillips Perron unit root tests

Variable	ADF		P-P	
	C	C,T	C	C,T
CO_2EE	–1.700(0)	–1.787(0)	–1.884(4)	–1.786(1)
D CO_2EE	–5.284(0)*	–6.854(0)*	–5.502(4)*	–6.870(2)*

*,** and *** show significant at 1%, 5% and 10% levels respectively. (2) The numbers within parentheses followed by ADF statistics represent the lag length of the dependent variable used to obtain white noise residuals. (3) The lag lengths for ADF equation were selected using Schwarz information criterion. (4) Mackinnon (1996) critical value for rejection of hypothesis of unit root applied. (5) The numbers within brackets followed by PP statistics represent the bandwidth selected based on Newey and West (1994) method using Bartlett Kernel. (6) C=Constant, T=Trend. (7) Δ=First differences

Table 3: Comparing models using AIC, SIC and HQ tests

ARIMA model	AIC	SC	HQ
D CO_2EE			
(1,1,0)	0.167	0.240	0.195
(0,1,1)	0.192	0.265	0.220
(1,1,1)	0.111	0.221	0.153
(0,1,2)	0.170	0.280	0.213
(1,1,2)	0.147	0.294	0.204

Figure 5: CO_2 emission in their first differences

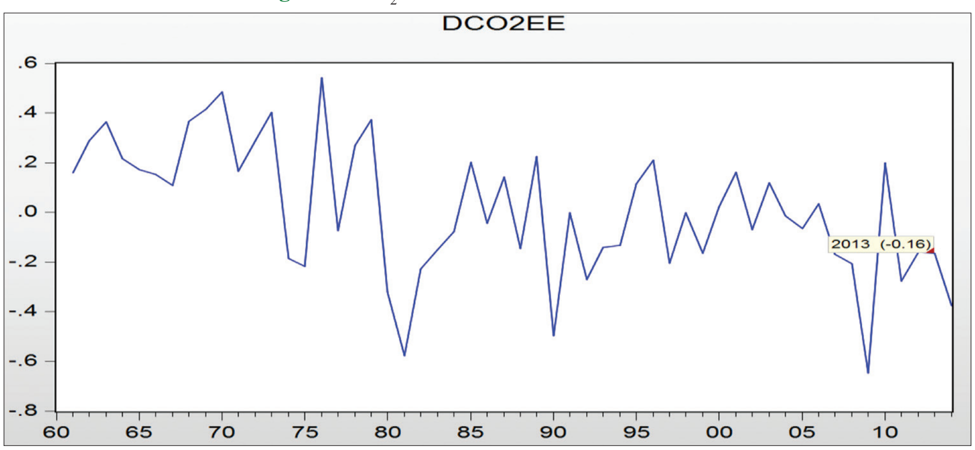
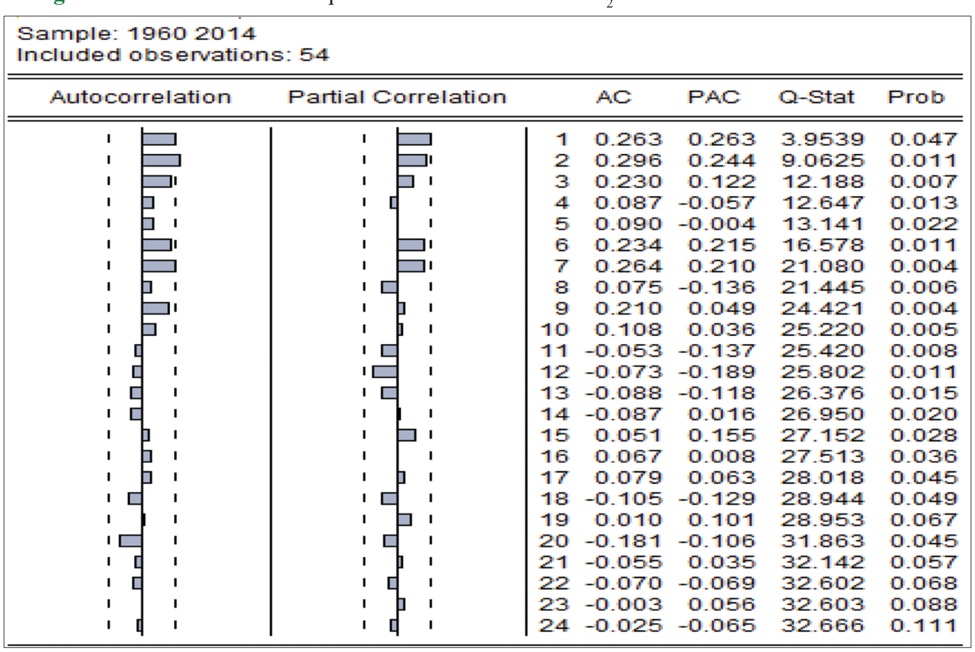


Figure 6: Autocorrelation and partial autocorrelation of CO_2 emissions in their first differences



	AC	PAC	Q-Stat	Prob
1	0.263	0.263	3.9539	0.047
2	0.296	0.244	9.0625	0.011
3	0.230	0.122	12.188	0.007
4	0.087	-0.057	12.647	0.013
5	0.090	-0.004	13.141	0.022
6	0.234	0.215	16.578	0.011
7	0.264	0.210	21.080	0.004
8	0.075	-0.136	21.445	0.006
9	0.210	0.049	24.421	0.004
10	0.108	0.036	25.220	0.005
11	-0.053	-0.137	25.420	0.008
12	-0.073	-0.189	25.802	0.011
13	-0.088	-0.118	26.376	0.015
14	-0.087	0.016	26.950	0.020
15	0.051	0.155	27.152	0.028
16	0.067	0.008	27.513	0.036
17	0.079	0.063	28.018	0.045
18	-0.105	-0.129	28.944	0.049
19	0.010	0.101	28.953	0.067
20	-0.181	-0.106	31.863	0.045
21	-0.055	0.035	32.142	0.057
22	-0.070	-0.069	32.602	0.068
23	-0.003	0.056	32.603	0.088
24	-0.025	-0.065	32.666	0.111

Results from Table 3, reveal that based on Akaike (AIC), Schwartz (SIC) and Hannan-Quinn (HQ) criteria, ARIMA(1,1,1) model is the most suitable one.

The estimation of the ARIMA(1,1,1) model is achieved by the ML method, whereas the optimisation of the model will be achieved using the Berndt-Hall-Hall-Hausman (BHHH), algorithm. The covariance coefficient will be estimated with the inverse Hessian matrix. Table 4, shows the results of estimating the ARIMA(1,1,1) model.

Results from Table 4, show that there aren't any problems with the significance of the coefficients. Also, the coefficient for the error variation estimation, shown as SIGMASQ, is $\rho_s = 0.058$ and is also statistical significant. The inverse roots of the model are AR = 0.94 and MA = 0.76 and are presented in the following Figure 7.

Figure 7 shows that the inverse roots of the model (inverted AR, MA roots), are within the inverted unit cycle, which confirms that the series under review is stationary.

We then test for heteroscedasticity (ARCH(q)) from the squared residuals of the model above. Table 5 shows the following results.

Table 5 reveals that both auto-correlation coefficients and partial autocorrelation coefficients after the first order, are not statistical significant. Therefore, the ARCH or GARCH procedures should be considered.

5. EMPIRICAL RESULTS

Since we found that there exists a first order ARCH-GARCH procedure (Table 5), we could move into the model specification followed by its estimation of the conditional mean and the

Table 4: Estimation of ARIMA(1,1,1) model

Dependent Variable: DCO2EE
Method: ARMA Maximum Likelihood (OPG - BHHH)

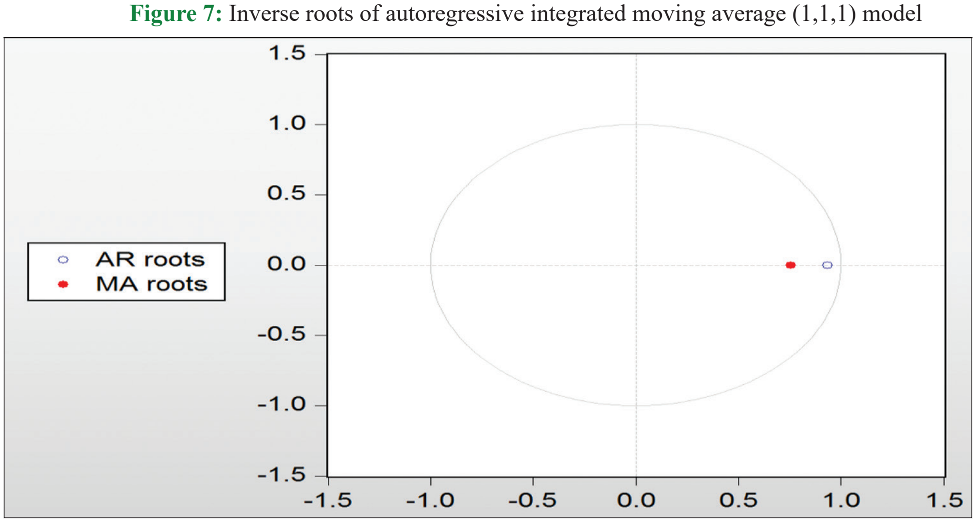
Sample: 1961 2014
Included observations: 54
Convergence achieved after 25 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.936118	0.089612	10.44635	0.0000
MA(1)	-0.758287	0.146692	-5.169241	0.0000
SIGMASQ	0.058056	0.011191	5.187797	0.0000

R-squared	0.160234	Mean dependent var	0.011370
Adjusted R-squared	0.127302	S.D. dependent var	0.265400
S.E. of regression	0.247933	Akaike info criterion	0.111355
Sum squared resid	3.134997	Schwarz criterion	0.221854
Log likelihood	-0.006582	Hannan-Quinn criter.	0.153970
Durbin-Watson stat	2.024627		

Inverted AR Roots	.94
Inverted MA Roots	.76

Figure 7: Inverse roots of autoregressive integrated moving average (1,1,1) model



conditional variance. Estimation of the ARIMA(1,1,1)-ARCH(1) or ARIMA(1,1,1)-GARCH(1,1) model is achieved with the ML method using the BHHH algorithm, the steps of the Marquardt method (1963), the three distributions (Normal, student's, generalized error), while for the co-variance coefficient the inverse matix by Hessian is applied. Coefficient estimation as well as residual tests with respect to normality, auto-regression and conditional heteroscedasticity, are presented in Table 6.

From Table 6 shows that the ARIMA(1,1,1)-ARCH(1) model with the GED distribution is the most appropriate one (as it has the highest LogL value). All model coefficients are statistical significant and do not present any issues at the diagnostic issues. Therefore, we could use this model for forecasting purposes. Table 7 presents the results of the estimation of this model.

The estimate of the regression in the ARIMA(1,1,1)-ARCH(1) model could be presented as:

$D\ CO_2EE_t = 0.933{*}D\ CO_2EE_{t-1} - 0.846e_{t-1}$ (conditional mean equation)

$\sigma_t^2 = 0.018 + 0.956\ e^2_{t-1}$ (conditional variance equation)

Figure 8 shows the actual and fitted values of the series, as well as the residuals of the fitted model at the 95% confidence interval.

Table 5: Autoregressive conditional heteroscedasticity (q) process test

Sample: 1960 2014
Included observations: 54

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.281	0.281	4.5148	0.034
		2	-0.040	-0.130	4.6093	0.100
		3	-0.209	-0.176	7.1996	0.066
		4	-0.036	0.082	7.2800	0.122
		5	0.175	0.162	9.1653	0.103
		6	0.092	-0.053	9.6966	0.138
		7	0.023	0.026	9.7298	0.204
		8	-0.115	-0.064	10.594	0.226
		9	0.053	0.134	10.782	0.291
		10	-0.071	-0.182	11.124	0.348
		11	-0.026	0.008	11.172	0.429
		12	-0.103	-0.083	11.933	0.451
		13	-0.084	-0.039	12.456	0.491
		14	-0.027	-0.050	12.511	0.565
		15	-0.080	-0.072	13.007	0.602
		16	-0.057	-0.050	13.267	0.653
		17	-0.128	-0.068	14.605	0.624
		18	-0.118	-0.134	15.784	0.608
		19	0.063	0.185	16.130	0.649
		20	0.034	-0.107	16.234	0.702
		21	-0.039	-0.048	16.371	0.748
		22	-0.068	0.018	16.811	0.774
		23	-0.167	-0.176	19.546	0.669
		24	-0.105	-0.081	20.654	0.659

Table 6: Estimation of ARIMA(1,1,1)-ARCH(1)/GARCH(1,1) models

Parameter	ARCH(1)			GARCH(1,1)		
	Normal	t-student	GED	Normal	t-student	GED
Mean equation						
AR(1)	0.938*	0.938*	0.932*	0.932*	0.932*	0.924*
MA(1)	–0.839*	–0.839*	–0.845*	–0.864*	–0.864*	–0.873*
Variance equation						
ω	0.019*	0.019*	0.017*	0.012	0.012	0.008
α	0.866**	0.866**	0.955*	1.024*	1.022*	1.212*
β	-	-	-	0.067	0.066	0.069
Persistence	-	-	-	1.091	1.088	1.281
	-	DOF=2201	PAR=2.609*	-	DOF=635.1	PAR=2.941*
LogL	6.172	6.170	6.510	6.330	6.321	7.008
Diagnostic tests						
$Q^2(24)$	21.316	21.302	23.714	22.188	22.153	24.806
ARCH-$X^2(1)$	0.304	0.303	0.636	0.550	0.542	1.461
Jarque-Bera	1.235	1.236	1.203	1.074	1.074	1.104

*, **, ***Show significant at 1%, 5% and 10% levels respectively. (2) ( ) is the order of diagnostic tests. (3) LogL is the value of the logarithmic-likelihood. (4) $Q^2(24)$ is the Q-statistic of correlogram of squared residuals at twenty-four lags. (5) ARCH-$X^2(1)$ for autoregressive conditional heteroskedasticity, (6) the persistence is calculated as $(\alpha_1+\beta_1)$ for the GARCH model

Table 7: Estimates of ARIMA(1,1,1)-ARCH(1) model

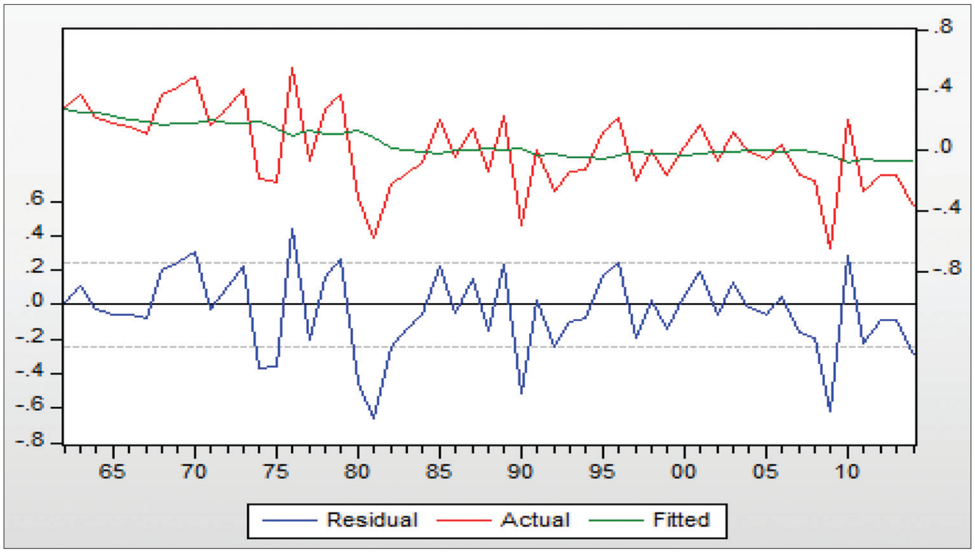
Dependent Variable: DCO2EE
Method: ML ARCH - Generalized error distribution (GED) (OPG - BHHH / Marquardt steps)

Sample (adjusted): 1962 2014
Included observations: 53 after adjustments
Convergence achieved after 30 iterations
Coefficient covariance computed using observed Hessian
MA Backcast: 1961
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.932913	0.033564	27.79469	0.0000
MA(1)	-0.845847	0.048850	-17.31504	0.0000
Variance Equation				
C	0.017907	0.006896	2.596807	0.0094
RESID(-1)^2	0.955557	0.377536	2.531034	0.0114
GED PARAMETER	2.609373	0.831499	3.138156	0.0017

R-squared	0.200663	Mean dependent var	0.008566
Adjusted R-squared	0.184990	S.D. dependent var	0.267131
S.E. of regression	0.241160	Akaike info criterion	-0.057013
Sum squared resid	2.966077	Schwarz criterion	0.128864
Log likelihood	6.510833	Hannan-Quinn criter.	0.014467
Durbin-Watson stat	1.950911		
Inverted AR Roots	.93		
Inverted MA Roots	.85		

Figure 8: Actual and fitted values, residuals of the model ARIMA(1,1,1)-ARCH(1) for D CO_2EE



Looking at Figure 8, the residuals show that there is an ARCH procedure in the data.

6. FORECASTING

In order to forecast the ARIMA(1,1,1)-ARCH(1,1) models we use both the dynamic (n-step ahead forecasts) and static (one step-ahead forecast) procedure. The dynamic procedure computes forecasting for periods after the first sample period, using the former fitted values from the lags of dependent variable and ARMA terms. The static procedure uses actual values of the dependent variable. In the following diagram, we present the criteria for the evaluation of forecasting using the dynamic and static forecast respectively (Dritsaki, 2019).

Figure 9: Dynamic and static forecast

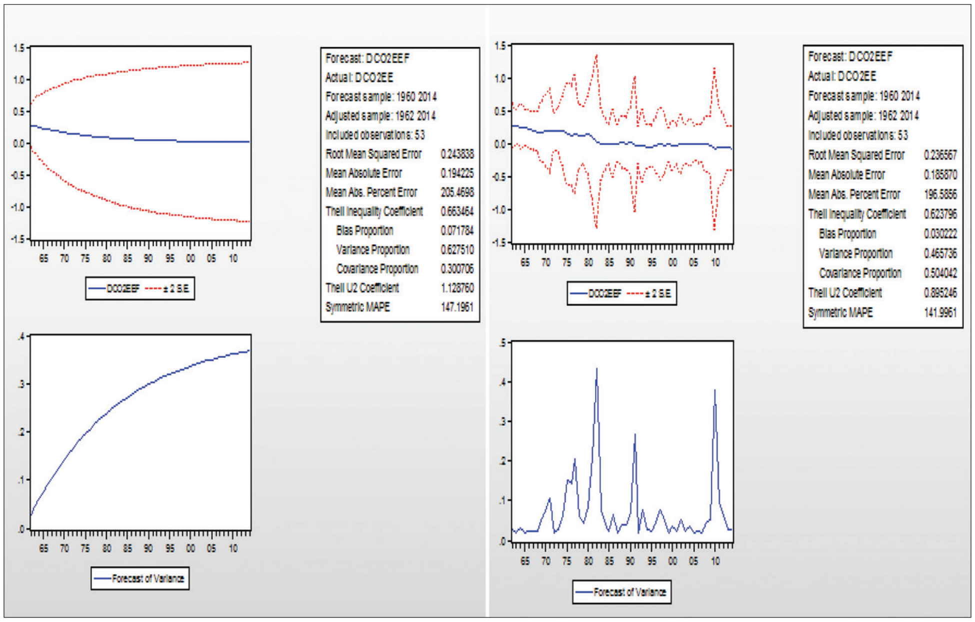


Figure 10: Time series plot for actual and forecasted D CO_2EE-28 values

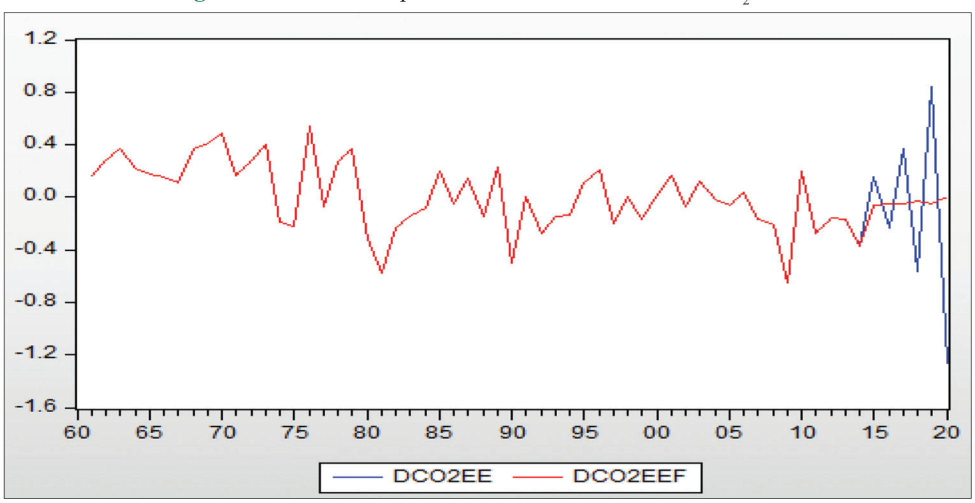


Table 8: Forecasted values of E.U-28 CO_2 emissions

Year	D CO_2EE	Forecasted CO_2EE	95% Confidence interval	
			Lower	Upper
2015	0.155	6.534	6.490	6.603
2016	–0.235	6.299	6.254	6.341
2017	0.371	6.670	6.627	6.712
2018	–0.564	6.106	6.055	6.172
2019	0.842	6.948	6.912	6.989
2020	–1.270	5.678	5.644	5.703

The Figure 9 indicate that the static procedure gives better results rather than the dynamic (MSE and MAE are lower in the static rather than the dynamic process). Since ARIMA(1,1,1)-ARCH(1,1) model is fit to the CO_2 data, therefore we can use to forecast values for the next 6 years out-of sample (from 2015 to 2020). The forecasted values of CO_2 are given in Table 8.

Figure 10 presents the trend of the actual and the forecasted D CO_2EE-28 values.

The forecasted values indicate that the CO_2 present fluctuations until the end of 2020. The great drop as shown by the results of the current study for 2020, is consistent with the commitment which the EU promised by the Kyoto protocol, as well as the amendment of Doha in 2012.

7. SUMMARY AND CONCLUSION

The degradation of environment becomes the recrudescence of the environment via the exhaustion of sources such as air, water and soil. This degradation is a consequence of a combination of an already big and constantly growing population, the continuing economic growth, the technological exhaustion of natural resources and the pollutant technology. The results of these damages to the human lifestyle and prosperity have caused a great amount of concern.

Many studies showed that there is an influence of economic growth to environmental degradation. The correlation between per capita GDP and CO_2 emissions is positive, implying that the increasing per capita GDP leads to increase of CO_2 emissions. No turning point is found at which emissions start to decrease. Market economy mechanisms according to studies' results are not sufficient in the decline of CO_2 emissions. For this reason, legal regulations are required to avoid further environmental degradation.

The purpose of this paper is to model and forecast CO_2 emissions of 28 member countries of EU based on annual data (from 1960 until 2014). Using ARIMA(1,1,1)-ARCH(1) model, ML methodology, Marquardt's algorithm methodology (1963) and BHHH, we forecasted CO_2 emissions for the next 6 years (2015-2020). The results of forecasting showed that CO_2 emissions will display fluctuations until the end of 2020. The year 2020 will present a considerable decrease of CO_2 emissions reaching 33.8% less than the year 1990 (Kyoto Protocol) and will cover by far the commitment of EU countries on the above Treaty. Moreover, after the biblical disasters worldwide (the burning of Amazon forest which covers 60% of the total rainforest, the lack of drinkable water) more countries such as USA, China, India and OPEC countries can adapt with last years' phenomena and decrease CO_2 emissions, avoiding planet's major disaster. According to our examined model, European Union will manage and reduce more CO_2 emissions by 40% in relation to 1990 and once more will be consistent with Kyoto protocol.

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APPENDIX

Table A1: CO_2 emissions (metric tons per capita) European Union, United States, China, World

ETH	E.U	U.S.A	China	World
1960	5.765	16.000	1.170	3.099
1961	5.925	15.681	0.836	3.070
1962	6.213	16.014	0.661	3.141
1963	6.578	16.482	0.640	3.245
1964	6.794	16.968	0.626	3.361
1965	6.966	17.452	0.666	3.440
1966	7.119	18.121	0.711	3.539
1967	7.227	18.598	0.574	3.578
1968	7.594	19.089	0.605	3.684
1969	8.008	19.858	0.725	3.824
1970	8.492	21.111	0.943	4.015
1971	8.658	20.980	1.042	4.074
1972	8.946	21.749	1.081	4.158
1973	9.348	22.511	1.098	4.299
1974	9.162	21.503	1.097	4.224
1975	8.944	20.402	1.250	4.121
1976	9.485	21.158	1.285	4.285
1977	9.411	21.532	1.389	4.343
1978	9.680	21.973	1.529	4.320
1979	10.053	21.780	1.543	4.482
1980	9.733	20.786	1.495	4.358
1981	9.156	19.767	1.460	4.150
1982	8.929	18.590	1.567	4.041
1983	8.780	18.572	1.629	3.954
1984	8.702	18.977	1.750	4.025
1985	8.904	18.882	1.871	4.074
1986	8.859	18.721	1.939	4.124
1987	9.002	19.350	2.038	4.152
1988	8.856	20.010	2.151	4.227
1989	9.080	20.076	2.153	4.244
1990	8.584	19.323	2.152	4.194
1991	8.583	19.056	2.229	4.173
1992	8.312	19.139	2.309	4.068
1993	8.171	19.347	2.443	4.002
1994	8.039	19.361	2.566	4.011
1995	8.153	19.277	2.756	4.036
1996	8.362	19.496	2.844	4.071
1997	8.157	19.690	2.821	4.082
1998	8.156	19.579	2.677	4.050
1999	7.992	19.727	2.649	3.986
2000	8.013	20.179	2.697	4.038
2001	8.175	19.637	2.742	4.081
2002	8.106	19.613	3.007	4.088
2003	8.225	19.564	3.524	4.258
2004	8.210	19.658	4.038	4.414
2005	8.145	19.592	4.523	4.528
2006	8.179	19.094	4.980	4.636
2007	8.010	19.218	5.335	4.671
2008	7.804	18.462	5.702	4.762
2009	7.157	17.158	6.010	4.662
2010	7.356	17.443	6.561	4.835
2011	7.079	16.977	7.242	4.975
2012	6.918	16.310	7.425	5.005
2013	6.754	16.323	7.557	4.998
2014	6.379	16.503	7.544	4.981

Source: World development indicators

Table A2: States in Europe by GDP (PPP) per capita, and CO_2 emissions

Country	CO_2 emissions (per capita)	GDP (PPP) per capita $
European Union	6.379	52.550
Austria	6.870	46.778
Belgium	8.328	43.338
Bulgaria	5.872	18.292
Croatia	3.974	21.240
Cyprus	5.260	32.373
Czech Republic	9.166	30.433
Denmark	5.936	46.223
Estonia	14.849	27.856
Finland	8.661	40.771
France	4.573	40.801
Germany	8.889	46.627
Greece	6.180	26.017
Hungary	4.266	25.553
Ireland	7.314	52.133
Italy	5.271	35.310
Latvia	3.498	23.487
Lithuania	4.378	27.537
Luxembourg	17.400*	99.738*
Malta	5.401	34.921
Netherlands	9.920	48.363
Poland	7.517	25.334
Portugal	4.332	27.218
Romania	3.498**	19.855**
Slovak Republic	5.662	28.641
Slovenia	6.214	29.879
Spain	5.034	33.285
Sweden	4.478	46.410
United Kingdom	6.497	40.762
World	4.981	15.332

Source: World development indicators, *Countries with large amount of CO2 emissions, and high GDP (PPP) (per capita), **Countries with small amount of CO2 emissions, and low GDP (PPP) (per capita)