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Kontakt/Contact ZBW – Leibniz-Informationszentrum Wirtschaft/Leibniz Information Centre for Economics Düsternbrooker Weg 120 24105 Kiel (Germany) E-Mail: *rights[at]zbw.eu* https://www.zbw.eu/econis-archiv/

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# **Forecasting European Union CO<sub>2</sub> Emissions Using Autoregressive Integrated Moving Average-autoregressive Conditional Heteroscedasticity Models**

# Melina Dritsaki<sup>1\*</sup>, Chaido Dritsaki<sup>2</sup>

<sup>1</sup>University of Oxford, Oxford, UK, <sup>2</sup>Department of Accounting and Finance, University of Western Macedonia, Kozani, Greece. \*Email: melina.dritsaki@ndorms.ox.ac.uk

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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<sub>2</sub> 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).

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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 the case of the USA.

The Figure 2 presents the rate of  $\text{CO}_2$  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 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, emissions (1990-2014)

Variables	Mean	Std. Dev.	CV (%)	Minimum (year)	Maximum (year)
CO <sub>2</sub> E.U	7.880	0.585	7.42	6.379 (2014)	8.540 (1990)
CO <sub>2</sub> USA	18.789	1.209	6.43	16.310 (2012)	20.179 (2000)
CO, China	4.173	1.930	46.24	2.152 (1990)	7.557 (2013)
$CO_2^2$ World	4.384	0.377	8.59	3.986 (1999)	5.005 (2012)

Developed countries have a higher share of global CO<sub>2</sub> 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<sub>2</sub> 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<sub>2</sub> emissions in various countries. Lotfalipour et al. (2013) have examined the economic aspects of CO<sub>2</sub> 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<sub>2</sub> emission in the period between 1990 and 2011. Their results suggest that Grey models provided better results in terms of forecasting CO2 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<sub>2</sub> 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:

$$\left(1-\sum_{i=1}^{p}\phi_{i}L^{i}\right)\left(1-L\right)^{d}\left(y_{t}-\mu\right)=\left(1-\sum_{j=1}^{q}\vartheta_{j}L^{j}\right)e_{t}$$
(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  $\mu$  is the mean of the model.

d is the order of the difference operator.

 $\phi_1, \phi_2, ..., \phi_p$  and  $\vartheta_1, \vartheta_2, ..., \vartheta_q$  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:

$$y_t = \mu_t + \varepsilon_t$$
 (conditional mean equation) (2)

where  $u_t$  is conditional mean of  $y_t$ , and  $\varepsilon_t$  is the shock at time t.

The variance  $\varepsilon_t$  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.

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

where  $\sigma_t^2$  is the conditional variance of  $y_t$ ,  $\omega$  is a constant term, and q is the order of the ARCH terms,  $\omega > 0$ ,  $\alpha_i \ge 0$  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:

$$y_t = \mu_t + \varepsilon_t$$
(conditional mean equation) (4)

where  $u_t$  is conditional mean of  $y_t$ , and  $\varepsilon_t$  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  $u_t \rightarrow iid(0,1)$ .

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

where

 $\sigma_t^2$  is the conditional variance of  $y_t$ ,  $\omega$  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  $p \ge 0$  and q > 0, the parameters are unknown and since the variance is positive, then the following relations must be positive too  $\omega \ge 0$ , and  $\alpha_i \ge 0$  for every i=1,..., q and  $\beta_j \ge 0$  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 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:

$$\ln L\left[\left(y_{t}\right),\theta\right] = \sum_{t=1}^{T} \left\{ \ln\left[D\left(z_{t}(\theta)\right),\upsilon\right] - \frac{1}{2}\ln\left[\sigma_{t}^{2}(\theta)\right] \right\}$$
(6)

where  $\theta$  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,  $D(z_t(\theta), v)$ , 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

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

where  $\theta$  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

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

where

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

Generalized error distribution

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

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

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

• MSE has the following formula

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

MSE gives an overall idea of the error occurred during forecasting.
 The mean absolute percentage error (MAPE)

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

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

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# 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 4: Auto-regression partial autocorrelation of CO<sub>2</sub> emissions on its level

Autocorrelation         Partial Correlation         AC         PAC         Q-Stat         Prob           I         I         0.884         0.884         45.407         0.000           I         I         0.884         0.884         45.407         0.000           I         I         0.652         -0.077         106.08         0.000           I         I         I         3         0.652         -0.077         106.08         0.000           I         I         I         I         4         0.540         -0.047         124.00         0.000           I         I         I         I         5         0.440         -0.015         136.15         0.000           I         I         I         I         5         0.440         -0.015         136.15         0.000           I         I         I         I         I         5         0.440         -0.015         136.15         0.000           I         I         I         I         I         9         0.057         -0.011         148.74         0.000           I         I         I         I         10         -0.025         -0.071 <th colspan="9">Sample: 1960 2014 Included observations: 55</th>	Sample: 1960 2014 Included observations: 55								
1       0.884       0.884       45.407       0.000         1       1       0.884       0.884       45.407       0.000         1       1       0.652       0.077       106.08       0.000         1       1       1       3       0.652       0.077       106.08       0.000         1       1       1       5       0.440       -0.015       136.15       0.000         1       1       1       5       0.440       -0.015       136.15       0.000         1       1       1       6       0.335       -0.094       143.33       0.000         1       1       1       7       0.242       -0.026       147.15       0.000         1       1       1       9       0.057       -0.011       148.74       0.000         1       1       1       10       -0.025       -0.071       148.74       0.000         1       1       1       10       -0.025       -0.071       148.74       0.000         1       1       10       -0.025       -0.071       148.74       0.000         1       1       11       -0.091 <td< td=""><td>Autocorrelation</td><td>Partial Correlation</td><td>AC</td><td>PAC</td><td>Q-Stat</td><td>Prob</td></td<>	Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob			
Image: Constraint of the constraint			1         0.884           2         0.770           3         0.652           4         0.540           5         0.440           6         0.335           7         0.242           8         0.141           9         0.057           10         -0.025           11         -0.091           12         -0.145           13         -0.185           14         -0.200           16         -0.255           17         -0.264           18         -0.283           19         -0.275           20         -0.258           21         -0.247           22         -0.252           23         -0.257	0.884 -0.058 -0.077 -0.047 -0.015 -0.094 -0.026 -0.107 -0.011 -0.071 -0.011 -0.071 -0.009 -0.030 -0.002 0.049 -0.075 -0.130 0.062 -0.093 0.057 0.005 -0.053 -0.053 -0.022	45.407 80.441 106.08 124.00 136.15 143.33 147.15 148.48 148.70 148.74 149.32 150.85 153.40 156.42 160.21 165.41 171.18 177.97 184.57 190.55 196.15 202.17 208.66	0.000 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  $p \kappa \alpha i$  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:

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

Looking at the values of the partial autocorrelation and autocorrelation coefficients (Figure 6) the value for p is between 0 and respectively, the value for <math>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		
	С	C,T	С	C,T	
CO,EE	-1.700(0)	-1.787(0)	-1.884(4)	-1.786(1)	
D CO2EE	-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)  $\Delta$ =First differences

Table 5. Comparing models using AIC, SIC and HO lest	Table 3:	Comparing	models	using	AIC,	SIC	and HC	) tests
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ARIMA model	AIC	SC	HQ
D CO,EE			
(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 6: Autocorrelation and partial autocorrelation of CO<sub>2</sub> emissions in their first differences

Sample: 1960 2014 Included observations: 54									
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob			
		1 2 3 4 5 6 7 8 9 0 1 1 1 2 3 4 5 6 7 8 9 0 1 1 1 2 3 4 5 6 7 8 9 0 1 1 1 2 3 4 5 6 7 8 9 0 1 1 1 2 3 4 5 6 7 8 9 0 1 1 1 2 3 4 5 6 7 8 9 0 1 1 1 2 3 4 5 6 7 8 9 0 1 1 1 2 3 4 5 6 7 8 9 0 1 1 1 2 3 4 5 6 7 8 9 0 1 1 1 2 3 4 5 6 7 8 9 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	AC 0.263 0.296 0.230 0.087 0.090 0.234 0.264 0.264 0.264 0.263 -0.073 -0.073 -0.088 -0.087 0.051 0.067 0.079 -0.105 0.010 -0.181 -0.055	0.263 0.244 0.122 -0.057 -0.004 0.215 0.210 -0.136 -0.137 -0.189 -0.118 0.016 0.155 0.008 -0.129 0.101 -0.106 0.025	3.9539 9.0625 12.188 12.647 13.141 16.578 21.080 21.445 24.421 25.220 25.420 25.420 25.420 25.420 25.420 26.376 26.950 27.152 27.513 28.018 28.944 28.953 31.863 32.2142	0.047 0.011 0.007 0.013 0.022 0.011 0.004 0.004 0.005 0.008 0.015 0.020 0.028 0.036 0.045 0.045 0.045 0.045			
		22 23 24	-0.070 -0.003 -0.025	-0.069 0.056 -0.065	32.602 32.603 32.666	0.068 0.088 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) MA(1) SIGMASQ	0.936118 -0.758287 0.058056	0.089612 0.146692 0.011191	10.44635 -5.169241 5.187797	0.0000 0.0000 0.0000			
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	0.160234 0.127302 0.247933 3.134997 -0.006582 2.024627	Mean dependent var0.S.D. dependent var0.Akaike info criterion0.Schwarz criterion0.Hannan-Quinn criter.0.		0.011370 0.265400 0.111355 0.221854 0.153970			
Inverted AR Roots Inverted MA Roots	.94 .76						





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)

 $\sigma_t^2 = 0.018 + 0.956 e_{t-1}^2$  (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.

<b>Table 5: Autoregressive</b>	conditional heteroso	cedasticity (q)	process test

Sample: 1960 2014 Included observation	s: 54					
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 4	0.281 -0.040 -0.209 -0.036 0.175 0.092 0.023 -0.115 0.053 -0.053 -0.0026 -0.103 -0.084 -0.027 -0.080 -0.057 -0.128 -0.118 0.063 0.034 -0.039 -0.068 -0.167 -0.105	0.281 -0.130 -0.176 0.082 -0.053 0.026 -0.064 -0.064 -0.182 0.008 -0.083 -0.039 -0.050 -0.072 -0.050 -0.053 -0.053 -0.053 -0.053 -0.053 -0.053 -0.053 -0.053 -0.054 -0.053 -0.054 -0.053 -0.054 -0.053 -0.054 -0.054 -0.054 -0.054 -0.054 -0.054 -0.054 -0.054 -0.054 -0.054 -0.055 -0.055 -0.054 -0.055 -0.056 -0.056 -0.056 -0.056 -0.056 -0.056 -0.056 -0.134 -0.185 -0.107 -0.056 -0.134 -0.185 -0.107 -0.058 -0.107 -0.056 -0.134 -0.185 -0.107 -0.058 -0.107 -0.056 -0.107 -0.056 -0.107 -0.050 -0.056 -0.107 -0.056 -0.107 -0.056 -0.107 -0.056 -0.078 -0.078 -0.078 -0.078 -0.078 -0.078 -0.078 -0.078 -0.078 -0.078 -0.078 -0.078 -0.078 -0.078 -0.078 -0.077 -0.078	4.5148 4.6093 7.1996 7.2800 9.1653 9.6966 9.7298 10.594 10.594 10.782 11.124 11.124 11.172 11.933 12.456 12.511 13.007 14.605 15.784 16.371 16.811 19.546 20.654	0.034 0.100 0.066 0.122 0.103 0.138 0.204 0.226 0.291 0.348 0.429 0.451 0.491 0.565 0.602 0.653 0.624 0.608 0.649 0.702 0.748 0.774 0.669

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

Parameter		ARCH(1) GARC		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<sup>2</sup>(1) for autoregressive conditional heteroskedasticity, (6) the persistence is calculated as  $(\alpha_i + \beta_i)$  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) MA(1)	0.932913 -0.845847	0.033564 0.048850	27.79469 -17.31504	0.0000 0.0000
	Variance I	Equation		
C RESID(-1) <sup>4</sup> 2	0.017907 0.955557	0.006896 0.377536	2.596807 2.531034	0.0094 0.0114
GED PARAMETER	2.609373	0.831499	3.138156	0.0017
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	0.200663 0.184990 0.241160 2.966077 6.510833 1.950911	Mean depend S.D. depende Akaike info cri Schwarz criter Hannan-Quin	ent var nt var terion ion n criter.	0.008566 0.267131 -0.057013 0.128864 0.014467
Inverted AR Roots Inverted MA Roots	.93 .85			

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



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, EE-28 values



 Table 8: Forecasted values of E.U-28 CO<sub>2</sub> emissions

Year	D CO <sub>2</sub> EE	Forecasted CO <sub>2</sub> EE	95% Confidence interv	
			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<sub>2</sub>EE-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<sub>2</sub> 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<sub>2</sub> emissions for the next 6 years (2015-2020). The results of forecasting showed that CO<sub>2</sub> emissions will display fluctuations until the end of 2020. The year 2020 will present a considerable decrease of CO<sub>2</sub> 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, emissions, avoiding planet's major disaster. According to our examined model, European Union will manage and reduce more CO<sub>2</sub> emissions by 40% in relation to 1990 and once more will be consistent with Kyoto protocol.

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# APPENDIX

Table A1:	CO,	emissions	(metric	e tons p	er capita)
European	Unio	on, United	States,	China.	, World

ETH         E.U         U.S.A         China           1960         5.765         16.000         1.170           1961         5.925         15.681         0.826	<b>World</b> 3.099
1960         5.765         16.000         1.170           1961         5.925         15.691         0.826	3.099
1061 5.025 15.601 0.026	2 070
1701 3.723 13.001 0.030	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
1065 6066 17.452 0.666	3.301
1903 $0.900$ $17.432$ $0.000$	2 520
1900 /.119 10.121 0./11 10(7 7.227 19.509 0.574	2.239
1907 7.227 18.398 0.374 1009 7.504 10.090 0.005	3.3/8
1968         7.594         19.089         0.605           1060         0.000         10.050         0.705	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 9733 20786 1495	4 358
1981 9156 19767 1460	4 1 5 0
1982 8 929 18 590 1 567	4 041
1982 8780 18 572 1 629	3 05/
1983 8.760 16.572 1.627 1084 8.702 18.077 1.750	4 025
1005 0000 1000000	4.023
1965 0.904 10.002 1.071 1086 9.950 19.721 1.020	4.074
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	4.124
1987 9.002 19.550 2.058 1088 9.856 20.010 2.151	4.152
1988         8.850         20.010         2.151           1080         0.080         20.076         2.152	4.227
1969         9.080         20.070         2.155           1000         9.594         10.222         2.152	4.244
1990         8.384         19.323         2.132           1001         8.582         10.056         2.220	4.194
1991         8.383         19.030         2.229           1002         8.212         10.120         2.200	4.1/3
1992         8.312         19.139         2.309           1002         0.171         10.247         2.442	4.068
1993         8.1/1         19.34/         2.443           1004         0.020         10.2(1)         2.5(6)	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

Country	CO, emissions	GDP (PPP)
	(per capita)	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)

Source: World development indicators