UNIVERSITY OF MACEDONIA

MASTER THESIS

Economic Growth, Energy Consumption and Carbon Emissions a Panel VAR Approach

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Abstract

This study utilizes a panel-VAR approach to examine the nexus among economic growth, energy use and carbon emissions, a subject which employed many studies in the past. In a sample of 113 countries over the period 1990-2015, the PVAR approach has been used along with impulse response functions, Granger-causality tests and variance decompositions. The results indicate unilateral causality from both economic growth and energy use to carbon emissions, as well as unilateral causality from economic growth to energy use which supports the conservative hypothesis. Traces of the Environmental Kuznets Curve hypothesis have also been detected.

Keywords:

Economic growth; Energy use; carbon emissions; panel data; Panel vector autoregressive model; Impulse response functions; Granger causality

Table of contents

List of tables

List of Figures

1. Introduction

Most people nowadays are aware of the fact that climate change and global warming are solemn problems which, if left unresolved by international organizations and governments, may lead to disastrous consequences for the environment and for the wellbeing of future generations. These problems may also be harmful for the economy as a whole, since they are deemed responsible for existing issues like slower economic development, unforeseen inflation, business shutdowns and real estate devalues. Carbon emissions have been found to be the main cause of global warming, along with other anthropogenic activities. Global warming could rise to a threat to all life on Earth if the concentration of carbon dioxide, methane and other greenhouse gases increases dramatically over the next 150 years or so.

According to Antonakakis et al. (2017), the Intergovernmental Panel on Climate Change (IPCC, Climate Change 2014, Synthesis Report, Summary for Policymakers. 2014) reported that the increasing levels of greenhouse gases[1] (GHG) which are mainly responsible for global warming, are mainly driven by increased economic activity and energy consumption throughout the world.

Taking the above unpleasant facts into consideration, we became eager to find how these three variables react on each other. This led us to conduct this particular research. In the past, many academics have been devoted to reveal any causality evidence between the separate pairs of energy – growth and environment - growth. Because of that, the literature regarding the energy consumption – economic growth – environmental degradation relationship is both extensive and various, in terms of empirical procedures and dataset structures. In general, there are three strands of literature that are related with the examination of economic growth, energy consumption and environmental degradation. The first one is all about the relationship between economic growth and energy consumption. The second one concerns the relationship between economic growth and the environment which is embedded as the

[1] This category mainly includes carbon dioxide, methane, nitrous oxide, water vapor and fluorinated gases.

Environmental Kuznets Curve (EKC) hypothesis, according to the economic theory.

As for the EKC hypothesis, Dinda (2004) claims that it represents the relationship between income per capita and environmental degradation which is displayed as an inverted "U" shape, i.e. environmental degradation increases with growing income up to a threshold level, beyond which environmental quality improves with higher income per capita.

The past two decades, the third strand of research which is the consolidated examination of these two relationships in a single framework has sparkled the interest and the scientific curiosity of a growing number of policy makers and researchers. This erupting interest may be due to the fact that in the past, many scholars have highlighted the significance of the causal interconnectedness among economic growth, energy consumption and environmental degradation (see Ang, 2007; Haggar, 2012; Soytas and Sari, 2009). Since these scholars claim that the aforementioned variables are inter-related, understanding the relationship among these three variables will contribute in solving any conflicting impact of economic, environmental and energy conservation policies on one another.

Although both the relations between energy consumption and economic growth, as well as that of economic growth and environment have been thoroughly examined separately in the past, relatively few empirical works have been devoted in the enrichment of the third related strand of research, reflected as the combination of the first two separate streams of literature, for the purpose of examining the causal relationships among all three variables (Acheampong, 2018; Ozcan, 2019). Furthermore, according to Acheampong (2018), he reports that "there are only a limited number of studies which have examined the Granger causality link between economic growth and environmental degradation (Soytas et al. (2007)" (page 678).

In this study, we have two major objectives to achieve. One is to explore what causal relationship exists among economic growth, energy use and carbon emissions for a number of 113 countries, collectively. For this exploration to happen, concerning the methodology to be performed, we estimate a Panel Vector Auto Regression (PVAR) model, containing the three variables under examination (economic growth, energy use and carbon emissions). The PVAR approach was originally developed by Holtz-Eakin et al. (1988) as an equation-by-equation estimator, which was later extended by Binder et al. (2005) as an estimator for a PVAR model with only endogenous variables that are lagged by one period. As an additional methodological application, we compute panel impulse response functions (IRF), panel Granger causality tests and variance decompositions in order to explore in depth the interconnectedness among the examined variables.

The other of our objectives is to compare our results with those by Ozcan et al. (2019) while following their study, which is also devoted in examining the three-way linkage among economic growth, energy consumption and environmental degradation. We are willing to make this comparison to distinguish if there are any similarities between the different findings.

Most of our findings cannot be deemed unforeseen, someone could say. It is found that economic growth and energy consumption both cause increases in carbon emission levels worldwide. In addition, economic growth also impacts energy consumption levels in a positive way. From the above, we can conclude that economic growth and rising levels of economic consumption can lead to more air pollution for the countries under examination, which most of them seem to be dependent on traditional non-renewable energy sources such as oil and coal.

The rest of the paper is organized as follows: section 2 discusses the relative literature. Section 3 consists of some key features and differences of the paper (by Ozcan et al., 2019) that we follow, as well as contributions of our study. Section 4 describes our data in details and compares them with the followed paper`s data. Section 5 discusses the empirical steps taken. Section 6 presents the empirical results as well as the findings by Ozcan et al. (2019) compared to mine. Section 7 concludes the paper and discusses potential avenues for further research.

2. Literature Review

Over the past two decades, many researchers have made relevant empirical studies, in order to visualize the interdependence of factors like economic growth, energy consumption and the environment. According to the relevant existing broad literature, like I mentioned in the introductory section, there are many studies which concern the growth-environment (Environmental Kuznets Curve or EKC hypothesis) linkage and others which concern the energy consumption-growth linkage, separately. Nevertheless, there is not much to tell regarding the economic growth-energy consumption-environment relationship, due to the quite small number of related studies.

It is argued that there are two reasons why both the growth-environment and energy-growth relationships should be studied in a single framework more often. Firstly, any new research examining the connection between energy consumption and economic growth, without considering CO_2 emissions, no longer provide any new insight to the literature (Adewuyi and Awodumi, 2017). Secondly, it has been observed that energy consumption has a direct impact on the level of environmental pollution from carbon emissions (Acheampong 2018, p.679).

In the following subsections, we are about to present some studies with similar and contradictive results regarding all three strands of literature separately, which all together constitute the energy consumption-economic growth-environment literature. The following studies are multi-country studies for the most part, since this particular study falls in the same category.

2.1. Economic Growth – Environment Nexus

In most cases related to this category of the literature, similarly to this particular study, Carbon emissions (CO_2) were used as a means of measuring environmental pollution, since CO_2 is one of the main factors responsible for global warming. The economic growth-environment relationship represents the Environmental Kuznets Curve (EKC) hypothesis. As it is referred in Magazzino (2017), "the relationship between carbon dioxide emissions, energy consumption, and real output is a synthesis of the Environmental Kuznets Curve (EKC) and the energy consumption-growth literatures (Kuznets, 1955)" (cited in the 2nd paragraph in the Literature review).

According to Stern (2003), this hypothesis shows the relationship between income and environmental quality, which is being displayed as an inverted "U"-shaped curve. In other words, income and environmental degradation both rise conjointly, until the level of the peak of the curve. From that point on, environmental degradation falls as income levels continue to rise.

Sarkodie and Strezov (2019) support that the EKC hypothesis attracted much attention in the nineties, after the seminal work of Grossman and Krueger (1991), which revealed that concentrations of air pollutants (sulfur dioxide and smoke) rise along with income level, but decline when even higher income levels occurred.

In early studies that were officially recorded, panel estimation was mainly utilized. Regarding the economic growth-carbon emissions nexus, Waheed et al. (2019) claims that "most of the studies have confirmed a unidirectional relationship from economic growth to carbon emissions" (cited in p. 1110), as it is confirmed in this study as well. As for the EKC hypothesis validity, the conclusions differ. Some studies have confirmed the EKC hypothesis (for example Arouri et al., 2012; Fuji and Managi,2013; Galeotti et al. ,2009; He et al., 2017; Saboori et al., 2012; Wang and Liu, 2017). Other studies have found a monotonic rising curve (see Azam, 2016; Antonakakis et al., 2017; Holz-Eakin and Seden, 1995), while there are those where no relationship between GDP and CO_2 has been found (for example Agras and Chapman, 1999; Richmond and Kaufmann, 2006). In recent detailed reviews of the related literature (see Al-Mulali et al., 2015; Dinda, 2004; Furuoka, 2015; Kijima et al, 2010; Stern, 2004), it is also claimed that the findings, being country or region specific, are generally inconclusive.

2.2. Energy Consumption – Economic Growth Nexus

Moving on with the second strand under study, which is the economic growth-energy consumption relationship, many authors have conducted multiple in-depth investigations of how these two variables affect each other. Throughout the entire related literature, we see how energy consumption and economic growth affect each other, through miscellaneous country and multi-country panel based studies, utilizing various econometric methods. Because of that, mixed and conflicting results have been mainly reported (Apergis and Payne, 2009). The directions of the causal relationship between energy consumption and economic growth fall into four distinct categories, each of which has important implications for energy policy. These four types of causalities are displayed in Table 2.1 bellow.

Table 2.1: Economic growth-energy consumption causality hypotheses

Neutrality hypothesis	• No causality between energy consumption and GDP • It is supported by the absence of a causal relationship between energy consumption and GDP
Conservation hypothesis	• Unidirectional causality running from GDP to energy • It is supported if an increase (decrease) in GDP causes an increase (decrease) in energy consumption
Growth hypothesis	• Unidirectional causality running from energy to economic growth • It is supported if increases in energy consumption contribute to growth process
Feedbag hypothesis	• Bidirectional causality between energy consumption and economic growth • It implies that energy consumption and economic growth are jointly determined and affected at the same time

The studies based on this nexus, were pioneered by Kraft and Kraft (1978). In some recent and relative literature surveys (see Mutumba et al., 2021; Narayan and Smyth, 2014; Tiba and Omri, 2017) it has been reported that Granger causality test procedure has been the empirical tool with the highest frequency usage for investigating this particular nexus and that the results archived from this method are also mixed. In Mutumba et al. (2021), it has been calculated that the number of studies so far, concerning Granger causality between energy consumption and economic growth, is at least 351.

Except for country datasets and empirical procedures, the related literature consists of many studies that are devoted in examining the energy-growth nexus, in terms of various energy types as well. For example, Apergis and Payne (2010) investigated the relationship between renewable energy consumption and economic growth, based on a sample of 20 OECD countries with the help of Panel cointegration analysis and Error correction model for the period 1885-2005. They found that there is bidirectional Granger-causality between these 2 variables in both the short-and long-run. In addition, Wolde-Rufael and Menyah (2010) study if and how nuclear energy and economic growth affect each other, in a sample of 9 developed countries for the period 1971-2005, using a modified version of Granger causality test developed by Toda and Yakamoto (1995). The results of their work were mixed, depending on the country. Furthermore, Ucan and Yusel (2014) in their paper analyzed the relationship between renewable and non-renewable energy consumption and economic growth for a panel of 15 European Union countries over the period 1990-2011, using panel cointegration and panel causality approach. Through his work, the author concluded that renewable energy consumption affects positively real GDP, while non-renewable energy consumption affects negatively real GDP.

2.3. Energy Consumption – Economic Growth – Environment Nexus

Examining the causal relationship between energy consumption and GDP within a bivariate framework can produce biased results. According to some Energy Economics reviews (for example Mutumba et al., 2021; Narayan and Smyth, 2014) in these frameworks, the omitted variables problem occurs (Lutkepohl, 1982). This is one of the reasons that triggered the development of the third and most important strand of research in the literature, which concerns the economic growth, energy consumption and environment nexus. According to Ozcan et al. (2019), Ang (2007) and Soytas et al. (2007) were the first to conduct the consolidated examination among economic growth, energy consumption and environmental degradation. Regarding this combined nexus, various studies have been made and different econometric methods have been applied.

My findings are similar to most of relative studies, which have also reported unidirectional causality running from economic growth and energy consumption separately, towards CO_2. On average, regarding studies examining developing countries, the conservative hypothesis between economic growth and energy consumption has been mainly supported, just as it is in this study as well.

As for the multi-country studies on economic growth-energy consumption-environmental degradation relationship, in which the P-VAR approach was mostly used, a few of the examples are of Magazzino`s publications. In three of his papers, he studied the relationship of these three macroeconomic variables, for different sets of countries, using the panel-VAR approach with system Generalized Methods of Moments (Magazzino 2014, 2016, 2017). Specifically, in Magazzino (2014), he studied this relationship for 6 ASEAN countries, 1971-2007, and found out that there is a positive response of CO_2 to real GDP, more energy use equals increased economic activity and shocks to energy supply may sabotage economic growth (Ozturk, 2010). In Magazzino (2016), he studied for 6 GCC and 4 Middle East countries, from 1971 to 2006. He found out that for the six GCC countries, the growth hypothesis holds while for the non-GCC countries, the neutrality hypothesis holds. More recently, in Magazzino (2017), he studied the same relationship for 19 APEC countries, 1960-2013, using Panel VAR estimation with Mean Group estimators, as well as panel Co-integration and panel Granger Causality tests. His results support the neutrality hypothesis, since no causal relationship emerged between real GDP and energy use.

Continuing with the other similar studies based on the energy-environment-growth nexus, Ozkan et al. (2019) applied a panel-VAR estimation for 35 OECD countries, from 2000 to 2014, along with orthogonal impulse response functions (IRF) and panel Granger Causality test. They found that there is positive effect of GDP and energy consumption on the environment, complementarity among GDP and energy consumption and a negative effect of economic growth in the environment by overusing the finite natural resources in order to produce more output. Moreover, Acheampong (2018) investigated if there is any evidence of causal relationship among energy consumption, economic growth and the environment for a panel of 116 countries, using a panel-VAR model, along with system-Generalized Method of

Moments (system-GMM), Granger causality tests, variance decomposition and impulse response functions. In this study, the global panel is disaggregated into regional subpanels, in order to examine the causal relationship among the three variables both in a global and regional scale. Concerning the global panel, there has been found unidirectional causality running from energy consumption to economic growth and from carbon emissions to energy consumption, as well as bidirectional causality between economic growth and carbon emissions.

Antonakakis et al. (2017) investigated the causal relationships among output-energy-environment for a sample of 106 countries for the time period 1971-2011. The results of this study suggest that there is bidirectional causality between the pairs of growth-emissions and growth-energy consumption (feedbag hypothesis), as well as unilateral causality running from energy consumption towards carbon emissions. Traces of the EKC hypothesis have also been found in the impulse response functions. Wang et al. (2017) studied for a panel of 170 countries, divided into 4 subpanels categorized by income groups, for the period 1980-2011. The results of the global panel show that there is bidirectional Granger causality for the pairs of GDP-CO_2, EC-CO_2 in the short as well as long run, a unidirectional Granger causality from GDP to EC for the short run, and finally a bidirectional Granger causality between GDP and energy consumption in the long run.

Table 2.2: Recent studies of the EC-EG-CO_2 literature with PVAR approach

Author	Period	Countries	Relationship
Magazzino (2014)	1971-2007	6 ASEAN	GDP→CO_2 GDP←EC
Magazzino (2016)	1971-2006	6 GCC + 4 Middle East	For the GCC: GDP←EC For the non GCC: GDP≠EC
Antonakakis et al. (2017)	1971-2011	106	GDP←→CO_2 U shaped curve GDP←→EC EC→CO_2

Magazzino (2017)	1960-2013	19 APEC	GDP≠EC GDP→CO_2
Wang et al. (2017)	1980-2011	170	<u>For the global panel</u>: GDP←→CO_2 GDP←→EC EC←→CO_2
Acheampong et al. (2018)	1990-2014	116	<u>For the global panel:</u> GDP←EC GDP←→CO_2 EC←CO_2 EKC validity
Ozcan et al. (2019)	2000-2014	35 OECD	GDP→CO_2 EC→CO_2 GDP←→EC

Notes: ASEAN: Association of Southeast Asian Nations, **APEC:** Asia-Pacific Economic Cooperation, **GCC:** Gulf Cooperation Council**, OECD:** Organization for Economic Co-operation and Development, **EC**: Energy consumption, **GDP**: Per capita gross domestic product, **EKC**: Environmental Kuznets curve, → indicates unidirectional relationship, ←→ indicates bidirectional relationship, ≠ indicates no causal relationship.

3. Discrepancies of the Followed Paper and our Contributions

Given that this study follows the work of Ozcan et al. (2019), in this section we argue how their work differs from ours and how our study contributes to the relative literature. In subsection 3.1., we discuss about some important discrepancies and facts about the paper of Ozcan et al. (2019), which are worth mentioning and in subsection 3.2., we discuss this study`s contribution.

3.1. Discrepancies of Ozcan et al. (2019)

Although in the study of Ozcan et al. (2019) the panel-VAR method has being also utilized, there are still some critical differentiations in their data, methodology and even variables compared to mine. Following the work of Sigmund and Ferstl (2017), Ozcan et al. (2019) applied a panel vector autoregressive (PVAR) model in a Generalized Method of Moments (GMM) framework, in order to examine the three-way linkage among economic growth, energy consumption and environmental degradation. They make a more in depth examination of environmental pollution by estimating three panel-VAR models including three environmental indexes respectively (ecological footprint, environmental performance index[2] and carbon emissions) in their analysis as indicators of environmental damage. In order to make the relevant comparison of the results between the two papers, we take into consideration the model which includes CO_2 as environmental index, since we also include it in our model. We discuss about this comparison in section 6.

3.2. Contributions

Through this study we are willing to fill in some of the gaps by providing new empirical evidence concerning the causal linkage among economic growth, energy consumption and carbon emissions, using a multivariate framework. The main contribution of this study to the literature is the

[2] Ecological footprint measures the pressure imposed the environment, coming from human consumption, while Environmental performance index identifies countries` scores of compliance for several core environmental policy objectives. For more information, see Ozcan et al. (2019).

application of the panel Vector Autoregressive (PVAR) methodology for the examination of these three macroeconomic variables, using a long panel of 113 cross-sectional units (countries) and 26 time-series (years). So far, few are the related studies that apply the same methodology as I do, and even fewer are those who do it with such an extensive country sample such as mine. While in some similar studies, this causality relationship has been examined in a regional or country-group level (for example Acheampong, 2018; Ozcan et al., 2019; Wang et al., 2017), I aim to reveal any possible interconnectedness among these variables in an intercontinental scale.

4. Data

This section describes the dataset employed in this study. We utilize annual data over the period 1990-2015 for 113 countries. Subsection 3.1 describes our variables and in subsection 3.2, a comparison is being made between my dataset and the one by Ozcan et al. (2019).

4.1. Our Dataset

Since the aim of this study is to capture the relationship among the energy consumption, economic growth and CO_2 emissions we extracted data for three variables that represent indexes of the consumption levels of energy, aggregate income state and air pollution respectively. These corresponding variables are: EU (energy use in kg of oil equivalent per capita), GDP (gross domestic product per capita at Purchasing Power Parity, in constant 2017 international $) and CO_2 (CO_2 emissions in metric tons per capita).

These data have been derived exclusively from World Development Indicators[3]. We chose our data so that they are purposely strongly balanced with as few missing values in the data as possible. Both the time and cross-sectional dimensions would be more extensive if there were not so many missing values regarding the energy use and carbon emissions data for a reasonable number of these countries.

For our sample, 113 countries were collected in total, from various regions all around the globe. Specifically, our sample contains:

- 9 European countries: Albania, Bulgaria, Belarus, Cyprus, Georgia, Malta, North Macedonia, Romania, Ukraine
- 31 countries of OECD: Australia, Austria, Belgium, Chile, Columbia, Costa Rica, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden, Switzerland, Turkey, UK and USA

[3] The data can be acquired from World Development Indicators | DataBank (worldbank.org).

- 21 countries of Sub-Saharan Africa plus 1 of Africa: Angola, Benin, Botswana, Cameroon, Congo (Brazzaville), Congo (Democratic Republic), Cote d`ivoire, Ethiopia, Gabon, Ghana, Kenya, Mauritius, Mozambique, Namibia, Nigeria, Senegal, South Africa, Sudan, Tanzania, Togo, Zambia and Zimbabwe
- 12 of MENA region: Algeria, Bahrain, Egypt, Iran, Iraq, Jordan, Lebanon, Morocco, Oman, Saudi Arabia, Tunisia and United Arab Emirates
- 9 Asian: Armenia, Azerbaijan, Kazakhstan, Kyrgyz Republic, Myanmar, Nepal, Tajikistan, Turkmenistan and Uzbekistan
- 15 of Asian-Pacific region: Bangladesh, Brunei Darussala, China, India, Indonesia, Malaysia, Mongolia, Pakistan, Peru, Philippines, Russian Federation, Singapore, Sri lanka, Thailand and Vietnam
- 15 of Latin America and Caribbean region: Argentina, Bolivia, Brazil, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Nicaragua, Panama, Paraguay, Trinidad and Tobago, and Uruguay

For our analysis, we mostly use the first difference of the logged form of these variables (logGDP, logEU and $logCO_2$). According to Stock and Watson (2011), this conversion of the variables is necessary for the elimination of the non-stationarity and heteroscedasticity phenomena which are frequently detected in time series of variables.

4.2. Data Comparison

Correspondingly, for their analysis, Ozcan et al. (2019) acquired data for 35 OECD countries, over the period 2000 to 2014. With the same variables which are measured similarly to ours (except for GDP which in the case of Ozcan et al.,2019, is measured in constant 2011 international $, PPP[4]) they aimed to capture any kind of relationship that exists among these variables, as we are willing to do. Table 4.1 bellow shows a summary of the two distinct datasets.

Table 4.1: Comparison of the two datasets

Data comparison		
	My data	**Ozcan`s data**
Countries	113	35 OECD
Time span	1990-2015	2000-2014
Variables	**Real GDP per capita at PPP** → in constant 2017 international $	**Real GDP per capita at PPP** → in constant 2011 international $
	Energy use → in kg of oil equivalent per capita	**Energy consumption** → in kg of oil equivalent per capita
	CO_2 → in metric tons per capita	**CO_2** → in metric tons per capita

The 35 OECD countries included in the sample of Ozcan et al. (2019) for their analysis, are these: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, UK and USA.

By observing the countries from the two datasets separately, we can understand that Ozcan et al. (2019) selected quite developed countries for their sample, in contrast to our sample which contains many

[4] He also used two other variables (Ecological Footprint and Environmental Performance Index) in order to study how environmental degradation in all levels affects GDP and EC, not just air pollution like I do with CO_2 emissions only. For the same reason, he described three empirical models in total (see Ozcan, 2019).

countries that are still in a developing path. It is important to keep that in mind, when considering how the results differ from one another (ours versus those of Ozcan et al., 2019).

5. Methodology

In this section, we discuss about the empirical methodology. Concerning our econometric work and analysis, we tried to follow as close as possible the methodological structure of Ozcan et al. (2019). In subsection 5.1, we talk about the panel unit root tests implemented. In subsection 5.2, we describe the Generalized Methods of Moments panel VAR (GMM-PVAR) model that we employ for this study. Subsection 5.3 presents the impulse response functions (IRF). Subsection 5.4 includes the panel Granger causality test and variance decompositions, extra tools to assess the robustness of the GMM-PVAR model. In each of these subsections there is a brief reference to the corresponding procedure followed by Ozcan et al. (2019) in their work.

Regarding the panel VAR estimation and its robustness tests, all of the econometric steps for our analysis are mainly taken based in the work of Abrigo and Love (2016), who constructed *st455*, a package which enables the estimation of a homogeneous PVAR in the STATA software.

5.1. Panel Unit Root Tests

Before estimating our 3-variable panel VAR model, it is essential to make sure that our variables are stationary or in other words, do not possess unit roots. For the purpose of checking whether our variables contain panel unit roots or not, this study employs panel unit root tests developed by Im et al. (2003) (hereafter IPS). The IPS unit root test considers the following panel Augmented Dickey-Fuller (ADF) specification:

$$\Delta lnYit = \rho_i Y_{it-1} + \sum_{j=1}^{pi} \delta_{ij}\, \Delta lnY_{it-j} + \varepsilon_{it} \tag{1}$$

where $\boldsymbol{Y_{it}}$ is a vector of my key endogenous variables: real GDP per capita, carbon emissions in metric tons per capita and energy consumption in kg of oil equivalent per capita.

The IPS assumes that the persistence parameters ρ_i are heterogeneous across cross-sections. It tests if the null hypothesis H_0: $\rho_i < 0$ is valid, against the alternative hypothesis H_1: $\rho_i < 0$,
($i = 1, \ldots, N_1$); $\boldsymbol{\rho}\rho_i = 0$, ($i = N_1, \ldots, N$) for all i. If the alternative hypothesis is accepted, then the individual series are allowed to be integrated.

Correspondingly, Ozcan et al. (2019) applied two panel unit root tests as suggested by Im et al (2003) and Pesaran (2007).

The IPS test is executed twice: on data in levels as well as in first differences of the natural logarithms. The results are reported in **Table 6.3** and show that all of the variables are stationary in first differences, while the existence of a unit root is indicated in the level results.

5.2. Generalized Method of Moments (GMM) Panel Vector AutoRegressive Regression (PVAR)

A (time series) Vector autoregressive model (VAR) is a system regression model which typically treats all variables as endogenous and includes more than one dependent variable. In macro-econometrics, VAR models regarding time series data, was firstly introduced by Sims (1980), as an alternative tool of multivariate simultaneous equation models. A Vector Autoregressive Regression consists of the same number of endogenous variables as equations. All of these equations of the system contain lags of all the endogenous variables. For a better comprehension, consider the simplest case of a bivariate VAR model with one lag for each endogenous variable, as presented below:

$$
\begin{aligned}
y_{1t} &= \beta_{10} + \beta_{11} y_{1t-1} + a_{11} y_{2t-1} + u_{1t} \\
y_{2t} &= \beta_{20} + \beta_{21} y_{2t-1} + \alpha_{21} y_{1t-1} + u_{2t}
\end{aligned}
\qquad (2)
$$

For our empirical strategy, we use a panel Vector AutoRegression (PVAR) methodology in a Generalized Method of Moments (GMM) framework. According to Acheampong (2018) “this technique combines the traditional VAR approach, which treats all variables in the system as endogenous, with the panel data approach, which allows for unobserved individual heterogeneity (Love and Zicchino, 2006, p.193)”. A PVAR model is a combination of a single equation dynamic panel model (DPM) and a vector autoregressive model (VAR). In other words, the PVAR approach is a merger of two distinct approaches: the panel data and the VAR approach. With the panel data approach, the problems of over-parameterization and biases from omitted variables can be solved, given that we focus on a group of countries. Hence, according to Antonakakis et al. (2017) “PVARs are explicitly designed to address the endogeneity problem, which is one of the most serious challenges of the empirical research on economic growth, energy consumption and CO_2 emissions” (p. 809).

There are several other advantages which accompany this empirical method. One of them is the inclusion of lags among the dependent and independent variables. According to Koop and Korobilis (2016), this can deal with the potential heterogeneity that may exist in the estimated coefficients on the variables under examination, as well as It” . . . allows for static or dynamic dependencies that may occur among the examined countries” (Ozcan et al., 2019, p.2). Moreover, country fixed-effects as well as time fixed-effects can also be included in a PVAR. The first capture time-invariant components that may affect energy consumption and growth, while the latter can account for any global (macroeconomic) shocks that may have a similar impact in all countries without exception.

The panel-VAR model, in its general form, can be written as follows:

$$\Delta lnY_{it} = A_0 + A_1 \Delta lnY_{it-1} + A_2 \Delta lnY_{it-2} + \cdots + A_j \Delta lnY_{it-j} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where $\mathbf{Y}_{it}$ is a (1 x 3) vector of dependent variables (GDP, EU and CO_2). Δln denotes the first difference of the natural logarithm. The autoregressive structure allows all endogenous variables to enter the model with a number of j lags. μμ_i, λ_t and ε_{it} are country fixed-effects, time fixed-effects and idiosyncratic errors respectively. The (3 x 3) matrices $\mathbf{A}_1$, $\mathbf{A}_2$… $\mathbf{A}_{j-1}$, $\mathbf{A}_j$ are parameters to be estimated. Since our data is annual, we decided to insert one lag of each variable in my model.

Given that the data we use for this study are panel, estimating our model with Ordinary Least squares (OLS) would definitely lead to biased results because of the existence of this country-specific fixed and time effect. A common problem which plagues models like ours is the correlation between unobserved panel fixed effect and the lag of the independent variable. To obtain desired estimates under this circumstance, the Generalized Method of moment (GMM) ought to be employed, developed by Arellano and Bond (1991). With this method, the lag of the dependent variable is used as an instrument to overcome the problem of this correlation. However, according to Blundell and Bond (1998), the GMM is found to produce inconsistent results when examining dynamic panel data models "where the autoregressive parameter is moderately large and the number of time series observations is moderately small" (p. 115).

When applying the VAR method to panel data, we must impose the constraint that the underlying structure is the same for each cross-section unit. Since this constraint is likely to be violated in practice, one way to overcome the parameter constraint is to account for "individual heterogeneity" in the levels of the variables by introducing fixed effects into the model. In general, according to the literature, there are two ways in order to eliminate the fixed effects: the first difference (FD) and the forward orthogonal transformation (FOD). When there are gaps in the data, using the FD procedure may magnify them (Abrigo and Love, 2016). Besides that, Hayakawa (2009) suggested that the forward orthogonal transformation has a better adjustment.

Another reason that we are applying the FOD approach is that regarding the STATA code presented by Abrigo and Love (2016) which we exclusively use for our empirical work, the FOD option specifies that the panel-specific fixed effects be removed using the forward mean differentiation, also known as "Helmert transformation" or "Helmert procedure" (see Arellano and Bover, 1995), in order to reduce the fixed effects. As Magazzino (2016) suggests, "to avoid the problem of correlation between fixed effects and regressors, we use forward mean differencing, [also referred to as Helmert transformation] (Holtz Eakin et al., 1988; Arellano and Bover, 1995), which removes only the forward mean" (p.963). The forward mean is the mean of all available future observations for each country-year. The "Helmert transformation" preserves the orthogonality between the transformed variables and the lagged regressors, which allows us to use these regressors as instruments and estimate the coefficients by system-GMM. The system-GMM, developed by Blundell and Bond (1998), can provide more consistent and robust results, since it uses the lagged differences of the dependent variable as instruments for equations in levels and also includes the lagged levels of the dependent variable as instruments for equations in first differences.

For the estimation of the panel-VAR model, we follow Abrigo and Love (2016) on how to estimate a homogeneous panel-VAR in a generalized method of moments (GMM) framework, in STATA. Their work is an extension of the work of Love and Zicchino (2006) work. Love and Zicchino (2006), through their published article, were the first to provide the academic community with an unofficial STATA code relative to panel VAR models. The extension of PVAR by Abrigo and Love (2016) is illustrated as the package *st0455* for STATA software, which we use in our entire analysis for building our panel-VAR model with fixed effects and executing all of the necessary tests.

In correspondence, concerning the panel-VAR model construction and estimation, Ozcan et al. (2019) followed Sigmund and Ferstl (2017) who used a quite different code for estimating panel-VAR models in R. They suggested a PVAR model with fixed effects as:

$$x_{i,t} = \left(L_n - \sum_{l=1}^{p} A_t\right) n_i + \sum_{l=1}^{p} A_l x_{i,t-1} + Z x_{i,t} + V f_{i,t} + u_{i,t} \qquad (4)$$

In the above expression, $x_{i,t}$ is the endogenous variable with time t, $x_{i,t-1}$ indicates the lagged of endogenous variable, L_n shows an $n*n$ identity matrix and A,Z and V are homogeneity parameters. The letter $f_{i,t}$ displays a vector of exclusively exogenous covariates with f=1,…,T. Lastly, $u_{i,t}$

denotes the idiosyncratic error postulated to be well-behaved and independent. Based on the exhibition by Ozcan et al. (2019), the fixed effects elimination with either the FD or the FOD procedure can be omitted by using the GMM framework. Following Binder et al. (2005), Sigmund and Ferstl (2017) identified the first difference of the GMM estimator as:

$$\Delta x_{i,t} = \sum_{l=1}^{p} A_l \, \Delta x_{i,t-1} + Z\Delta x_{i,t} + V\Delta f_{i,t} + \Delta u_{i,t}$$
(5)

In the above expression, the letter Δ denotes the first difference (FD) or the forward orthogonal transformation (FOD). For the same reasons as we do, Ozcan et al. (2019) applied the FOD approach.

5.3 Impulse Response Functions

Another important advantage of the PVAR approach is that it allows for the assessment of the effect of orthogonal shocks, i.e., the effect of a shock of one variable on another variable while holding all other variables constant. This is accomplished through the use of panel impulse response functions (IRF). We compute IRF in order to see how each variable reacts separately to shocks on all other variables separately.

According to Love and Zicchino (2006), the impulse response functions [IRF] describe the reaction of one variable to the innovations in another variable in the system, while holding all other shocks equal to zero. [For each variable from each equation separately, a shock is applied to the error term, and the effects upon the time series-VAR system over time are noted.] However, since the actual variance-covariance matrix of the errors is unlikely to be diagonal, to isolate shocks to one of the variables in the system it is necessary to decompose the residuals in such a way that they become orthogonal. [It is necessary for the residuals to be decomposed in a way that they transform into orthogonalized residuals, in order to isolate shocks to one of the VAR errors. For the IRFs, the ordering of the variables inside the VAR system is of high importance.] The usual convention is to adopt a particular ordering and allocate any correlation between the residuals of any two elements to the variable that comes first in the ordering. The identifying assumption [which is commonly used in many similar studies], is that the variables that come earlier in the ordering, affect the following variables contemporaneously, as well as with a lag, while the variables that come later affect the previous variables only with a lag (p.194).

To put it differently, the variables that appear earlier in the systems are more exogenous and the ones that appear later are more endogenous. For this study, we assume that current shocks to per capita GDP affecting per capita energy use and CO_2 emissions, as well as with a lag, while energy use and CO_2 emissions can affect GDP only with their lag(s). This is rational since current environmental pollution and energy consumption would not have a direct impact on current economic growth but they will have an impact on future economic growth. Thus, current economic growth is affected by previous environmental pollution and energy consumption.

We reckon the simple impulse response functions (IRF), expressed by Abrigo and Love (2016). The simple IRF Φ_i can be calculated by changing the expression to an infinite vector moving-average (VMA), and Φ_i are the VMA parameters, as follows:

$$\Phi_i = \begin{cases} \mathrm{I}_k \\ \sum_{j=1}^{i} \Phi_{t-j} \mathrm{A}_j \end{cases} \qquad (6)$$

where Φ_i is the simple IRF rewritten as an infinite vector moving average (VMA) with VMA parameters[5] and A_j are reduced-form parameters to be estimated. The forecasting horizon of my impulse responses is 2 years.

On the contrary, for the needs of their paper, following Lutkepohl (2005), Ozcan et al. (2019) reckoned the orthogonal impulse response

[5] According to Abrigo and Love (2016), given the existence of stability, the panel VAR has an infinite-order vector moving-average (VMA) representation.

functions (OIRF), in order to capture the response among the endogenous variables. The computation function can be expressed as:

$$OIRF(p, c) = \frac{dx_{i,t+p}}{d(u_{i,t})_c} \qquad (7)$$

where $x_{i,t}$ denotes the endogenous variable (energy consumption, GDP, CO_2 emissions) whereas p denotes the shock number of each period to the c-th component of $u_{i,t}$. The confidence intervals of the above IRF and OIRF were computed using the Monte Carlo simulations.

5.4. Panel Granger Causality Tests and Variance Decompositions

According to Anil Seth, 2007 (Scholarpedia), Granger causality is a statistical concept of causality that is based on prediction. According to Granger (1969) causality, if a variable X_1 "Granger-causes" (or "G-causes") a variable X_2, then past values of X_1 should contain information that helps predict X_2 above and beyond the information contained in past values of X_2 alone. Its mathematical formulation is based on linear regression modeling of stochastic processes (Granger, 1969).

To put it simply, in equation (1), y_2 does not Granger-cause y_1 if, and only if, $a_{11} = 0$. In other words, y_2 does not Granger-cause y_1 if, and only if, lagged values of y_2 do not appear in the reduced form equation for y_1.

For our Granger causality analysis, we deploy the *`pvargranger`* command for executing panel Granger causality test, which accompanies the panel vector autoregression (PVAR) approach as introduced by Abrigo and Love, 2016. This test performs a set of pair wise Granger causality Wald Chi-squared (χ^2) tests for each equation of the underlying PVAR model, after its estimation. The relative test statistic is defined as the cross-section average of individual Wald statistics associated with the standard Granger causality tests based on single time series and follows chi-squared (χ^2) distribution. According to the null hypothesis of these Wald tests, the coefficients on all the lags of an endogenous variable are jointly equal to zero; thus, the coefficients may be excluded in an equation of the panel VAR model.

Correspondingly, Ozcan utilized the panel Granger causality test by Dimitrescu and Hurlin (2012) who proposed two tests[6] in order to check for the validity of panel Granger causality. This panel Granger causality test can be obtained from:

$$w_{i,t} = n_i + \sum_{i=1}^{b} c_i^{(b)} w_{i,t-b} + \sum_{i=1}^{b} l_i^{(b)} v_{i,t-b} + u_{i,t} \quad (8)$$

where n_i is the constant term, $ci^{(b)}$ displays the lag parameter and $li^{(b)}$ denotes the coefficient slope. Furthermore, *w* and *v* signify each time two of the examined variables (GDP, EC, CO_2) enabling any tester to check the causality as a pair. The null hypothesis implies the validity of no panel Granger causality for the models, whereas the alternative hypothesis signifies panel causality among the covariates.

According to Wang et al. (2017), since "Granger causality tests only have the ability to identify the direction of casual links among variables", it is important to utilize variance decomposition analysis in order to "determine the importance of the causal effect of one variable on the other and to estimate how each variable responds to changes in the other variables" (cited in p. 8).

This is why we present forecast error variance decompositions (FEVD), which show the percentage of change in one variable that is explained by the shock to another variable, accumulated over time. In other words, this tool provides its user with the proportion of the movements in the dependent variables of a system. This proportion is due to a dependent variable`s separate "own" shocks, versus shocks to the other variables correspondingly. The variance decompositions display the magnitude of the total effect. Just like in the IRF, shocks on variables that occur earlier in the ordering affect subsequent variables simultaneously, while shocks on variables that occur later in the ordering affect only earlier variables with a lag of one period. We report the total

[6] The first panel test stems from the Wald statistics (Z_{wald}) and the second is adapted from the estimated moments for limit T datasets (Z_{bar}).

effect accumulated over 10 and 20 years, as longer time horizons produced equivalent results. For the computation of FEVD, the following expression of the h-step ahead forecast error is used, obtained from the paper of Abrigo and Love (2016):

$$\mathbf{Y}_{it+h} - \mathbf{E}(\mathbf{Y}_{it+h}) = \sum_{\mathrm{i}=0}^{\mathrm{h}-1} \mathbf{e}_{i(t+h-i)} \boldsymbol{\Phi}_{\boldsymbol{i}} \qquad (9)$$

where $\mathbf{Y}_{it+h}$ is the observed vector at time $t+h$ and $\mathbf{E}(\mathbf{Y}_{it+h})$ is the h-step ahead predicted vector made at time t.

6. Empirical Findings

This section includes three subsections. In subsection 6.1, he first some basic descriptive statistics of our variables are presented as well as some information approximating to how `our` countries are listed depending on their own GDP, EU and CO_2 scores. In the second one, we present all the results that we extracted from our personal empirical work, in this specific order:

i. Panel unit root tests
ii. GMM-Panel VAR model estimation
iii. Impulse response functions (IRF)
iv. Panel Granger-causality test
v. Forecast Error Variance Decompositions (FEVD)

In the third, a comparative analysis is being carried out between our results and those of Ozcan et al. (2019), following the same structure as the one above (except for FEVD which have not been calculated in Ozcan et al., 2019).

6.1. Preliminary Analysis

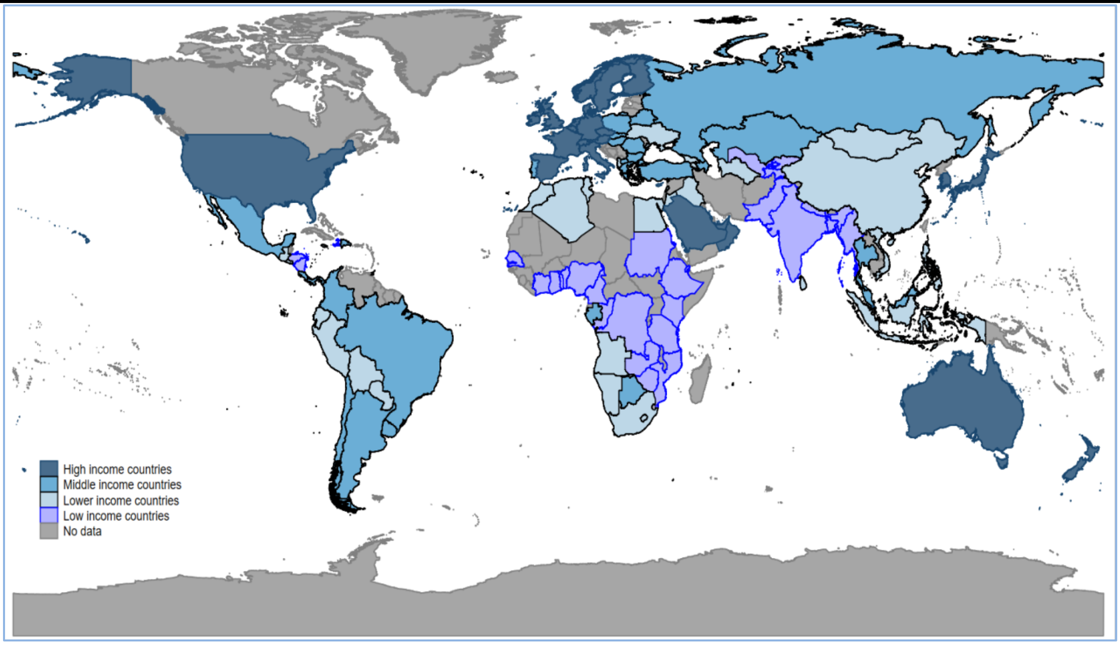
Since we are dealing with GDP, EU (energy use) and $CO_{2,}$ let us have an overview of how the countries of our sample perform, in terms of these variables. Have in mind that GDP is measured as per capita at Purchasing Power Parity in constant 2017 international $, energy use as kg of oil equivalent per capita and CO_2 is measured as metric tons per capita.

6.1.1 GDP, Energy Use and CO_2: A Multi Country Overview

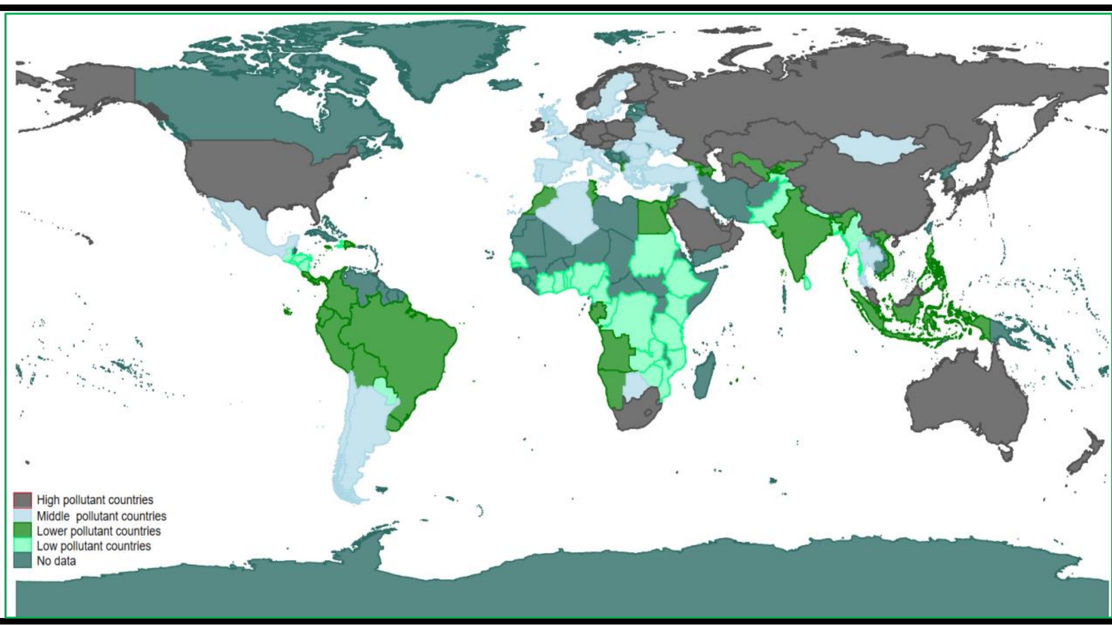
Figure 6.1 as shown bellow, contains two subfigures displaying two maps of our country sample in terms of GDP level and carbon emission pollution levels, correspondingly. For the purpose of the creation of these two maps, data of GDP and CO_2 were used from year 2015, since this is the most recent one from the time span of our data (1990-2015).

Fig. 6.1: GDP and CO_2 intensity of our country sample

***Sub-figure 1**:* Lay out of our country sample based on GDP



***Subfigure 2**:* CO_2 emitters of our country sample.



In addition, we calculated the means of our three variables from 1990 until 2015, which represents the time dimension of our data and made the following lists based on them. Thus, Table 6.1 bellow shows the first ten countries with the highest values of GDP, EU and CO_2 separately.

Some notable facts here are that in total, four countries are mutually referred in both EU and CO_2 lists (Bahrain, Trinidad and Tobago, Brunei Darussalam and Australia), two countries in both GDP and CO_2 lists (Norway and US) while two are those who fall under all three lists (Luxembourg and United Arab Emirates).

Table 6.1: Top 10 countries with higher GDP, EU and CO_2 respectively

GDP		EU		CO_2	
Country	**Value**	**Country**	**Value**	**Country**	**Value**
Luxembourg	94465.135	Bahrain	1114.487	UAE	25.6615
UAE	86790.705	UAE	9886.411	Bahrain	22.7880
Brunei Darussalam	69580.505	Trinidad and Tobago	9767.719	Luxembourg	22.5794
Singapore	61910.477	Luxembourg	8204.169	United States	18.6472
Switzerland	60494.373	Brunei Darussalam	7605.788	Australia	16.9770
Norway	56430.555	United States	7561.403	Brunei Darussalam	15.4153
United States	49969.506	Finland	6312.057	Trinidad and Tobago	13.3331
Denmark	47862.324	Norway	5758.165	Saudi Arabia	13.3287
Austria	46719.543	Sweden	5487.038	Czech Republic	11.6291
Netherlands	46591.716	Australia	5482.280	Kazakhstan	11.6168

Notes: UAE stands for United Arab Emirates.

The above facts may indicate a connection among all three variables and a possibly stronger one between energy use and carbon emissions.

Table 6.2 given bellow, shows the top 10 countries with the lowest GDP, EU and CO_2 respectively. Similar assumptions can apply in this case as well, since four countries are found to be mutually referred in all three lists (Democratic Republic of Congo, Myanmar, Nepal and Bangladesh). In addition, four are the countries which are mentioned in both GDP and EU lists. Therefore, the connection between economic growth and energy use is probably more solid in lower and low income countries.

Table 6.2: Top 10 countries with the lowest GDP, EU and CO_2 respectively

GDP		EU		CO_2	
Country	**Value**	**Country**	**Value**	**Country**	**Value**
Mozambique	773.387	Bangladesh	162.941	Congo (Dem. Rep.)	0.034
Ethiopia	952.490	Senegal	249.538	Ethiopia	0.068
Congo (Dem. Rep.)	969.060	Myanmar	283.998	Mozambique	0.099
Tanzania	1663.375	Haiti	295.217	Tanzania	0.125
Togo	1679.416	Congo (Dem Rep.)	318.087	Nepal	0.129
Myanmar	1858.763	Ghana	331.472	Haiti	0.186
Tajikistan	2117.711	Congo (Rep.)	338.883	Myanmar	0.187
Nepal	2265.099	Nepal	344.743	Zambia	0.231
Bangladesh	2283.577	Benin	347.688	Bangladesh	0.232
Zambia	2454.567	Cameroon	381.921	Kenya	0.253

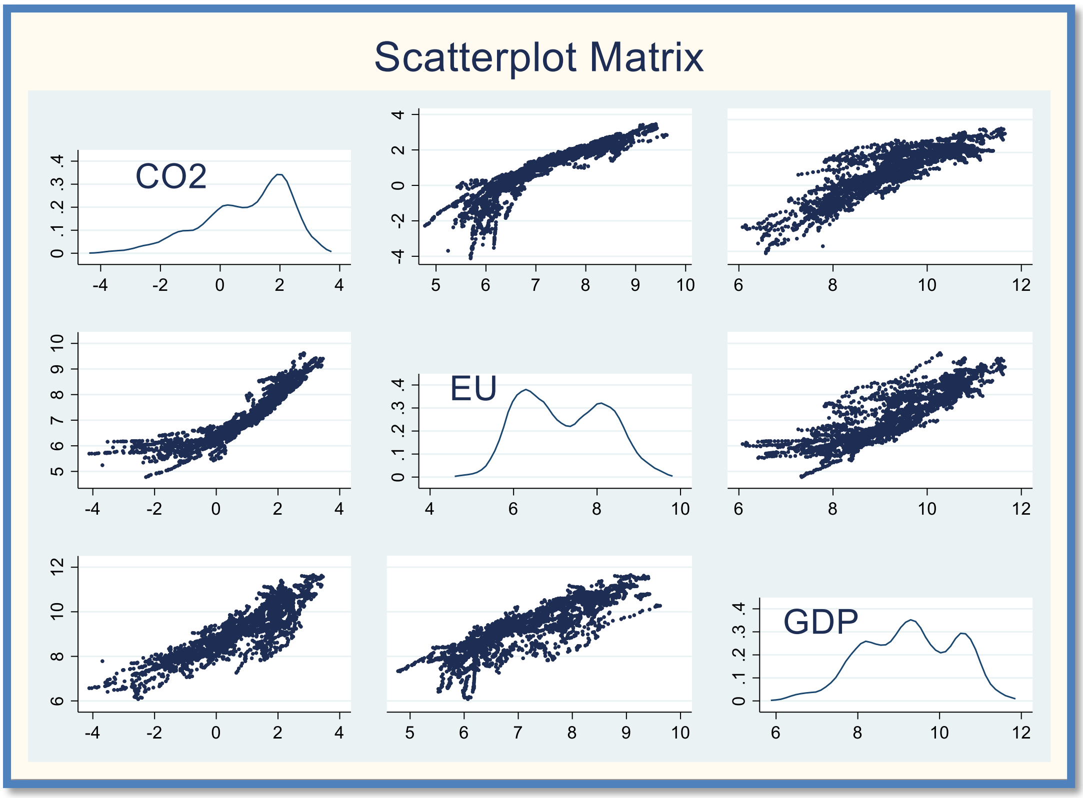
6.1.2 Descriptive Statistics

Fig. 6.2 depicts how the variables are laid out. Specifically, a scatterplot matrix is presented between the examined variables, as well as the density plots of the variables, which reveal the distribution of each one throughout the entire period. Looking at the distribution plots of EU and GDP, we can see a bimodal distribution, which is highlighted by two distinct peaks in the estimated probability density function. This is an expected observation, since our sample includes a great deal of both developing and developed countries. On average, developed countries possess physical and human capital at a superior level, compared to those of developing countries. Thus, less energy is required in the production process of goods and services, in the developing countries. Table 6.3 shows the summary statistics of all the variables used in this study. Table 6.4 presents diachronically the descriptive statistics of our variables, compared to those by Ozcan et al (2019). In the case of the latter one, different patterns unfold between the variables. For example, CO_2 emissions have a positive trend with GDP, which is a fact that can be observed in my case as well.

Table 6.3: Summary statistics

	CO_2	EU	GDP
Observations	2,937	2,849	2,935
Mean	4.935895	2214.282	18523.34
Std	5.294088	2320.279	19382.07
Min	0.0163127	118.8983	436.7204
Max	31.74752	15108.69	114889.2

Fig. 6.2: Scatterplot of the variables



Note: the variables are displayed in logarithmic form

Table 6.4: Descriptive statistics comparison

Our Descriptive Statistics						
	CO_2		EU		GDP	
Year	Mean	Std	Mean	Std	Mean	Std
1990	5.140	4.983	2123.05	2225.33	15216.00	18512.03
1991	5.831	5.400	2201.77	2377.45	17286.39	20052.48
1992	5.065	5.015	2118.75	2263.45	15226.34	19123.08
1993	5.801	5.395	2243.59	2394.57	17266.92	20414.59
1994	4.907	5.017	2058.49	2270.11	15179.87	19570.39
1995	5.525	5.355	2197.25	2402.25	17624.00	20449.56
1996	4.874	5.181	2051.02	2342.24	15181.86	20229.11
1997	5.507	5.491	2194.59	2495.03	17179.50	20782.26
1998	4.925	5.157	2052.14	2349.42	15112.76	20863.75
1999	5.552	5.315	2228.08	2502.60	17533.27	21044.55
2000	4.787	5.144	2052.07	2363.00	15741.96	20993.35
2001	5.365	5.317	2199.45	2500.79	17835.63	20512.46
2002	4.856	4.888	2086.85	2251.07	16096.77	20270.82
2003	5.445	5.012	2223.78	2351.07	18049.78	19375.20
2004	4.827	5.018	2099.98	2340.96	16526.47	20799.55
2005	5.382	5.122	2254.07	2468.01	18491.63	19775.72
2006	4.778	5.009	2095.91	2321.83	16789.60	21196.19
2007	5.280	5.012	2248.86	2434.50	18561.87	19953.37
2008	4.758	4.987	2100.91	2320.52	17134.30	21378.49
2009	5.209	4.983	2239.15	2390.36	18955.28	19861.80
2010	4.775	4.912	2112.97	2301.62	17788.72	21657.41
2011	5.191	4.984	2239.30	2360.93	19785.01	19947.17
2012	4.852	4.810	2156.97	2336.96	17917.11	22023.74
2013	5.329	4.850	2333.27	3790.22	19750.25	20218.35
2014	4.851	4.785	2154.23	3686.00	18163.16	22496.44
2015	5.315	4.765	2320.91	1499.75	19831.86	20776.03

Descriptive Statistics by Ozcan et al. (2019)						
	CO_2		EU		GDP	
Year	Mean	Std	Mean	Std	Mean	Std
2000	354753.5	966779.4	137.0878	52.7525	703418.9	913121.1
2001	353178.5	950151.3	135.9043	49.5841	1051013	2289261
2002	354387.6	957754.7	133.2919	49.2492	1068376	2325605
2003	359741.9	963104.2	133.1565	48.1615	1082218	2385449
2004	363744.7	977393.4	129.4952	44.8035	1121263	2472156
2005	364597.8	981691.5	125.0832	41.4273	1167693	2553479
2006	363742.9	966549.1	122.6357	45.7304	1207933	2618252
2007	366148.5	981488.1	119.1581	49.1157	1251456	2667114
2008	359275.0	952283.9	119.7954	53.9586	1258075	2655886
2009	336093.0	892181.3	120.7983	60.1260	1221994	2576973
2010	344787.9	915946.0	123.5665	63.9264	1261182	2646308
2011	338805.2	899845.0	119.1184	67.0299	1290306	2685123

2012	333217.1	870643.9	117.5182	63.9264	1311030	2739679
2013	334228.5	882754.6	116.2558	64.2476	1336242	2781692
2014	335216.4	885414.5	115.8542	64.6821	1345952	2824923

6.2. Our Empirical Findings

The results of panel unit root tests are mentioned in Table 6.3. The test statistics for the log levels of GDP, EU (Energy Use) and CO_2 are statistically insignificant at 1%, 5% or 10% level of significance. Thus, the log values of the variables GDP and CO_2 emissions at levels suggest that the variables are panel non- stationary. However, whilst this panel unit root test is carried out to the first differences of the variables, the null hypothesis of non-stationarity is rejected for all variables at 1% level of significance. Thus, from the whole test we can conclude that all the variables include a panel unit root at levels, although the variables are stationary at first difference. In other words, our variables are integrated of order one or I(1).

Table 6.5: Panel unit root tests

	logGDP	logEU	$\log CO_2$
Level			
W-t-bar statistic	7.6343	2.9232	1.7213
p-value	(1.00)	(0.99)	(0.96)
First difference			
W-t-bar statistic	-19.0974	-20.9958	-22.3162
p-value	(0.00)	(0.00)	(0.00)

After the declaration of our variables as I(1), we use the first difference of each of the variables to estimate the panel-VAR model. The results are reported in Table 6.5. Our findings reveal that there is statistically significant and positive causality relationship among the pairs of GDP-EU, GDP-CO_2 and EU-CO_2.

For our sample of 113 countries, we observe that GDP is depended only by its past values. In fact, in its equation, the one and only significant coefficient is that of its first lag (t-1), meaning that this variable seems to be driven only by its own past values. EU (Energy Use) is only affected by GDP. From Table 6.5, it is suggested that GDP may increase by 0.1857% when energy use increases by 1%. Furthermore, the results of the same table indicate that GDP causes CO_2 positively. To be more precise, a 1% increase in CO_2 may lead to a GDP increase by 0.2528 %. This causal relationship states that an increase in the aggregate income may lead to negative environmental externalities. Similar to GDP, energy use (EU) can also affect CO_2 emissions positively. According to the corresponding statistically significant coefficient, a 1% increase in CO_2 emissions can lead to an energy increase by 0.2052 %. This finding is supported by Antonakakis et al. (2017) but contradicts that of Tiwari et al. (2013). These positive relationships of GDP and EU with CO2 emissions indicate that increasing countries` energy consumption levels and economic growth rates create more air pollution, concerning the countries of this sample. These findings are in line with previous studies (see Apergis and Payne, 2009, 2010; Ozcan 2013, 2019). The overall findings of the panel-VAR model suggest that on average, these economies create air pollution in order to grow. In addition, increase in economic growth leads to more energy consumption, which means that an increase in aggregate income creates further demand for energy. Similar findings have been reported in the studies of Chen et al. (2016) and Kais and Sami (2015).

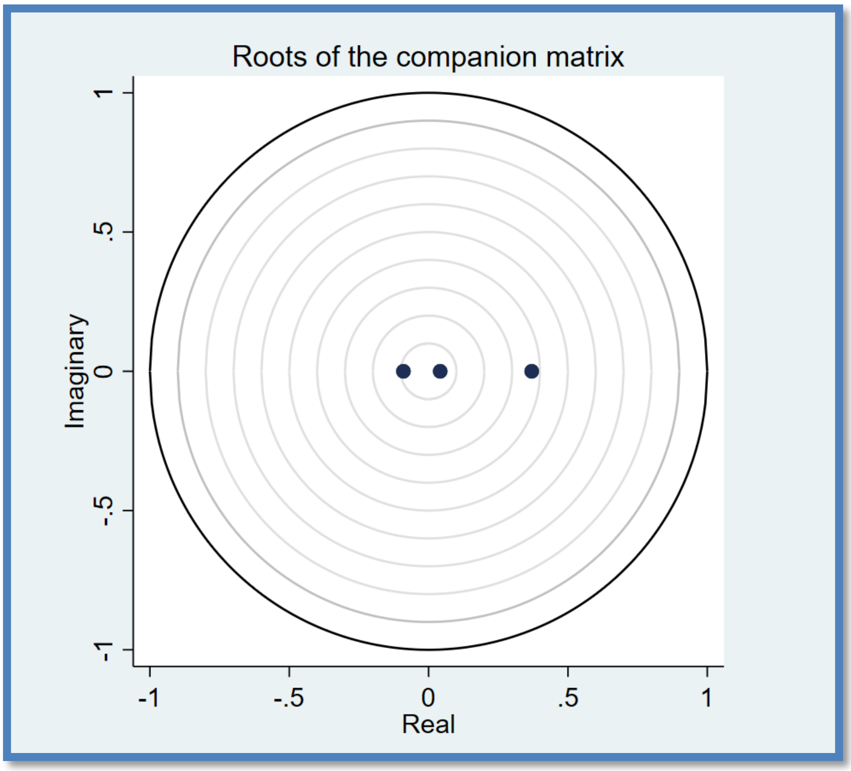
Table 6.6: Results for the GMM-PVAR model

	coefficient	se	*p*-value	min95	max95
logGDP (t)					
logGDP (t-1)	.3311***	.1078	.0021	.1198	.5425
logEU (t-1)	.0355	.0277	.2001	-.0188	.0899
logCO2 (t-1)	.0186	.0155	.2302	-.0118	.0490
logEU (t)					
logGDP (t-1)	.1857*	.1062	.0803	-.0224	.3938
logEU (t-1)	.0624	.0544	.2511	-.0442	.1689
logCO2 (t-1)	.0134	.0211	.5269	-.0281	.0548
logCO2 (t)					
logGDP (t-1)	.2528**	.1198	.0348	.0180	.4877
logEU (t-1)	.2052**	.1018	.0439	.0056	.4048
logCO2 (t-1)	-.0722	.1044	.4888	-.2768	.1323

Note: *, ** and *** indicate rejection of the null hypothesis at the 10, 5 and 1 percent levels of significance, respectively.

Moving on, we apply a stability test for our model in order to check whether it is stable or not (Fig. 6.3). The covariates of our estimated model are all inside the perimeter of the unit circle. Indisputably, this fact confirms the stability condition.

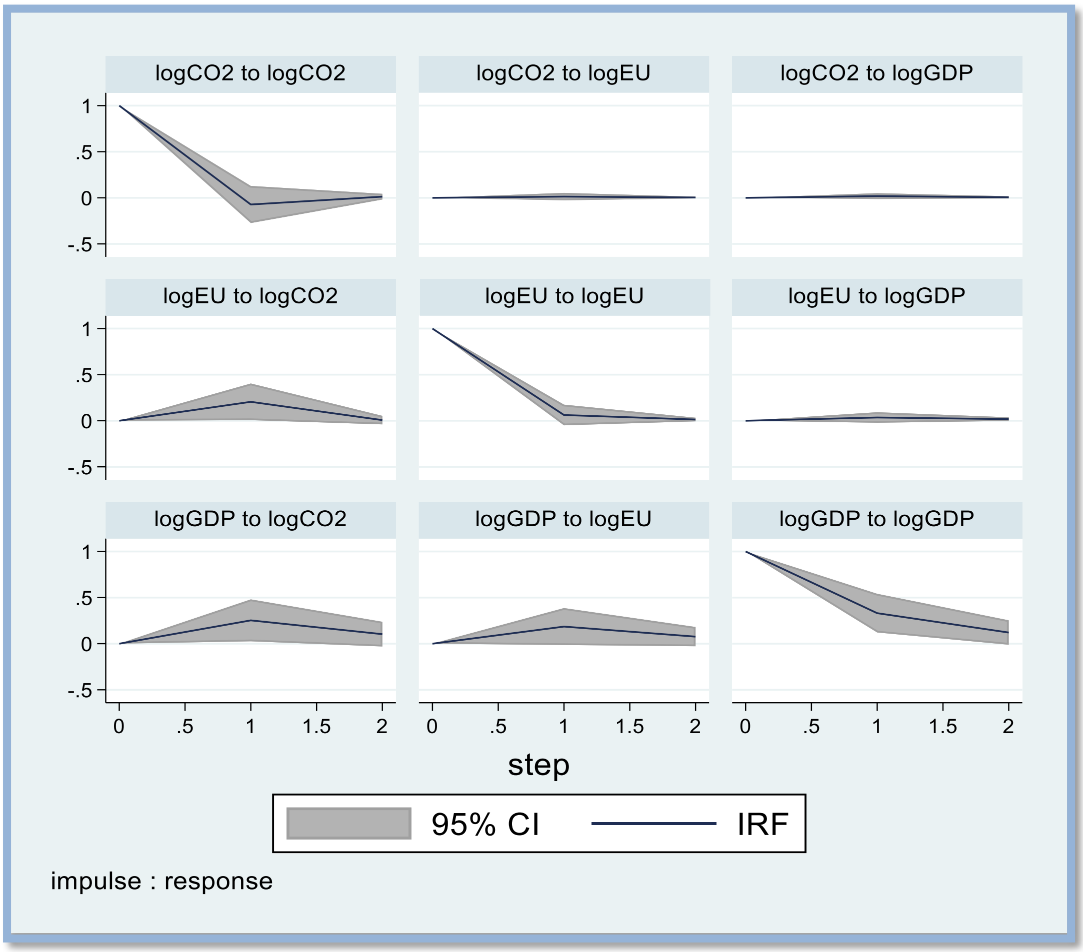
Fig. 6.3: Stability test



As a next procedure, we evaluate the IRF chart for our model. Fig. 6.3 displays the responsive shocks of each dependent variable to the three endogenous covariates measured for two years. In the figures, the gray area represents the confidence bands, while the dark blue line inside each band indicates the response functions. Below, we are about to analyze the results as categories, comprehensively.

When we examine the linkage between EU (energy use) and GDP, we realize that a shock on GDP can make EU respond positively. Concerning the relationship between CO_2 and GDP, CO_2 increases to a shock on GDP and then stabilizes. This is an interesting finding because it suggests that higher economic activity implies more air pollution, a fact which indicates that traces of the EKC hypothesis exist throughout the country sample that we chose for our research. When it comes to the linkage between CO_2 emissions and energy use, a shock on energy use causes a rise in CO_2 emissions. According to the graph, all of these escalations, which occurred after the shock, happen in short term (1 year) and the variables of the system in all cases, start to be stabilized after that.

Fig. 6.4: Impulse response functions



In order to have a better understanding of the interconnectedness among the variables, I also apply the panel Granger causality test, inserted in the *st0455* package for the STATA software (see Abrigo and Love, 2016). Table 6.7 exhibits the results of the panel Granger causality test. These results do not differ from those of the IRF and of the GMM-PVAR model. In particular, unidirectional Granger causality has been detected between the bellow pairs:

- From GDP to EU
- From GDP to CO_2
- From EU to CO_2

Table 6.7: Panel Granger-causality results

Dependent variable	Sources of causation (independent variables)		
	logGDP	logEU	$logCO_2$
logGDP	-	1.642 (0.200) -----	1.439 (0.230) -----
logEU	3.059* (0.080) ⇐	-	0.400 (0.527) -----
$logCO_2$	4.454** (0.035) ⇐	4.060** (0.044) ⇐	-

Chi-squared are reported while numbers in parentheses are P values. ***, **,* Statistical significance at 1%, 5% and 10% levels of significance, respectively. The symbol ⇐ represents the presence of Granger causality, while ----- represents that Granger causality does not exist.

The unilateral causality between economic growth and energy use supports the conservative hypothesis, which means that major portions of energy consumption require economic development. This finding is supported by studies of Mehrara (2007) and Chen et al. (2016).

From Table 6.7 we can see that GDP Granger causes CO_2 emissions. This means that growth in economic activity can hurt the environment. Likewise, this finding is confirmed by studies of Kais and Sami (2016) (who also confirmed the inverted `U`-shaped curve), Narayan et al. (2016), Chen et al. (2016) and Pao and Chen (2019). There is also observed unidirectional Granger-causality from EU to CO_2 emissions, as it is also found in Esso and Keho (2016).

As a final empirical step, we compute the Forecast Error Variance Decompositions (FEVD). The results between the 10-step and 20-step horizon are identical and presented in Table 6.8. The variation of GDP is due to its own disturbances, while the variation of EU depends on GDP by 14%. The errors in predicting the CO_2 emissions are the most sensitive ones, compared to those of GPD and EU, since 38% of the error variance in CO_2 forecasts is divided to two unequal contributions from shocks to the GDP (10%) and energy use (27%) equations. These findings are in line with the rest of the aforementioned empirical tools.

Table 6.8: Variance decompositions

Variable	logGDP	logEU	$logCO_2$
10 periods ahead			
logGDP	0.9940	0.0049	0.0009
logEU	0.1359	0.8637	0.0002
$logCO_2$	0.1028	0.2730	0.6241
20 periods ahead			
logGDP	0.9940	0.0049	0.0009
logEU	0.1359	0.8637	0.0002
$logCO_2$	0.1028	0.2730	0.6241

Percent of variation in the row variable explained by column variable.

Overall, from the analysis of the nexus between economic growth, energy use and CO_2 emissions, the findings suggest that economic growth has a statistically significant effect on all three variables. To be more accurate, economic growth`s impact on carbon emission levels seems to be more statistically significant than the impact it has on energy consumption. The fact that there has been found unilateral impact from GDP to carbon emissions implies that economic growth affects air quality negatively. The unidirectional causality found between economic growth and energy consumption, supports the conservation hypothesis.

Moreover, there has also been found unidirectional impact from energy consumption to carbon emissions. This could possibly mean that for a large number of countries in the sample, because of the need to accelerate the process of economic growth, excessive exploitation of fossil fuel is implemented resulting in rising carbon emission levels. For many countries, renewable energy sources should replace traditional energy sources, for the production process, given that environmental pollution is an issue that needs to be taken into account, in a global scale.

6.3. Comparative Analysis of the Results

In this section, we will execute a comparative analysis between the findings from our work and that from Ozcan et al. (2019), since this current paper is devoted to following theirs. In summary, comparing these two studies, several similarities as well as differences have been detected. It would be critical to remind and highlight the differences between the two datasets first, before proceeding to a more detailed analysis of the findings.

Table 4.1, located in the data section, summarizes the common and the dissimilar characteristics of the two datasets. One fact that must be taken into account before processing the partly different results which are provided in the following pages is that for their work, Ozcan et al. (2019) used a sample (35 OECD countries) that contains many countries which have already reached at least a decent economic potential. In the meantime, a great number of the countries that we have included in my sample, can be categorized as low and middle income countries. This peculiarity may play a key role in justifying the differentiations between the two sets of results.

Firstly, we present Table 6.9 which summarizes the causality relationships among GDP, EU (Energy Use) and CO_2 discovered in our study and the study by Ozcan et al. (2019).

Moving on to the comparison between the two panel vector autoregressive models, from Table 6.10 we can notice that for the most part, the two models are pretty similar, in terms of statistical significant coefficients. In both models it is mutually found that only past values of GDP affect GDP, as well as EU and GDP both cause CO_2 emissions[7]. As for the dissimilar results, it seems that in the model by Ozcan et al. (2019), EU and CO_2 are both significantly affected by their lagged values respectively, while this is not the case in our model. There is one of our findings which is contradictive with the other findings and that is the causality running from GDP to EU, a finding that supports the conservative hypothesis.

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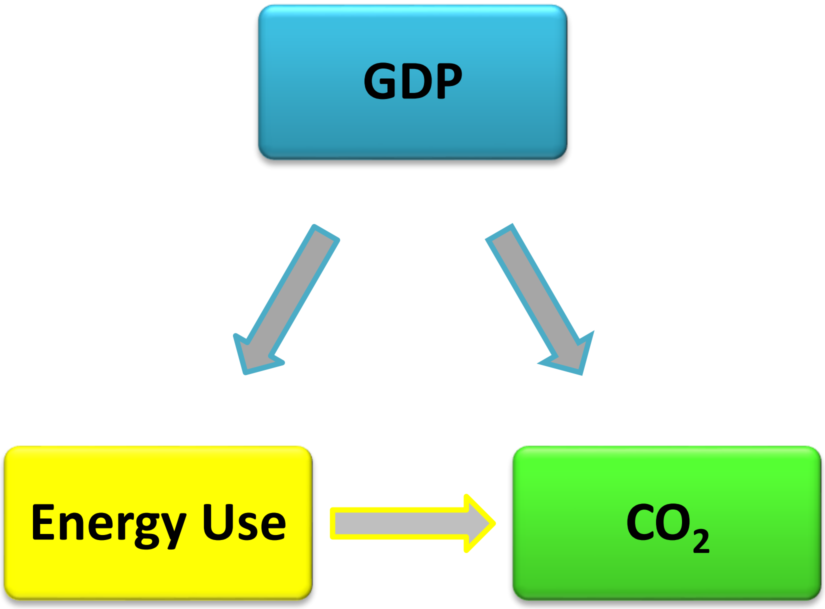
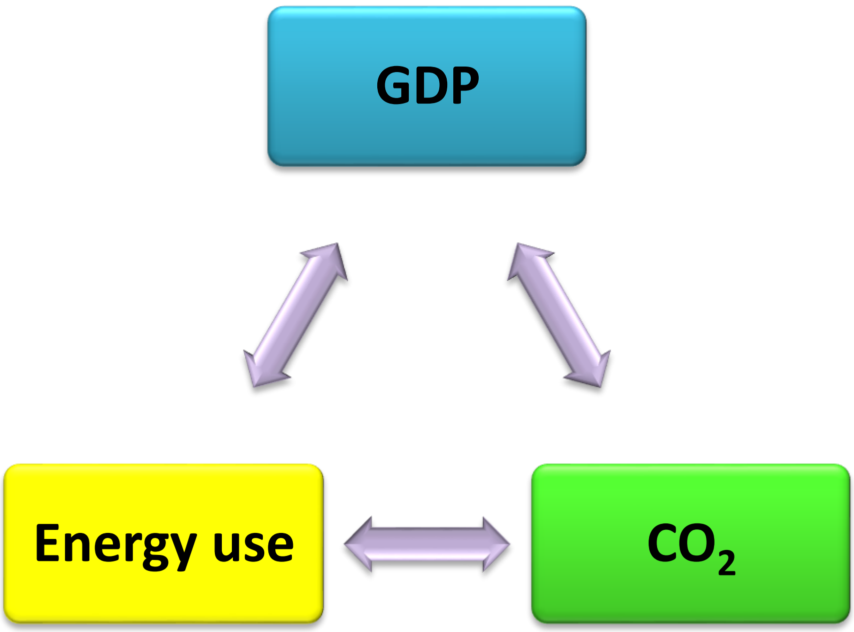
[7] The original table of the model with the GMM-PVAR results by Ozcan et al. (2019) can be found in the appendix section.

Table 6.9 Summary of causality relationships from both studies

Subtable A: *Causality relationships of our work*



Subtable B: *Causality relationships of the work of Ozcan et al. (2019)*



Notes: all arrows in subtable A represent unilateral causality, while all arrows in subtable B represent bidirectional causality respectively.

Table 6.10: Panel-VAR coefficient comparison

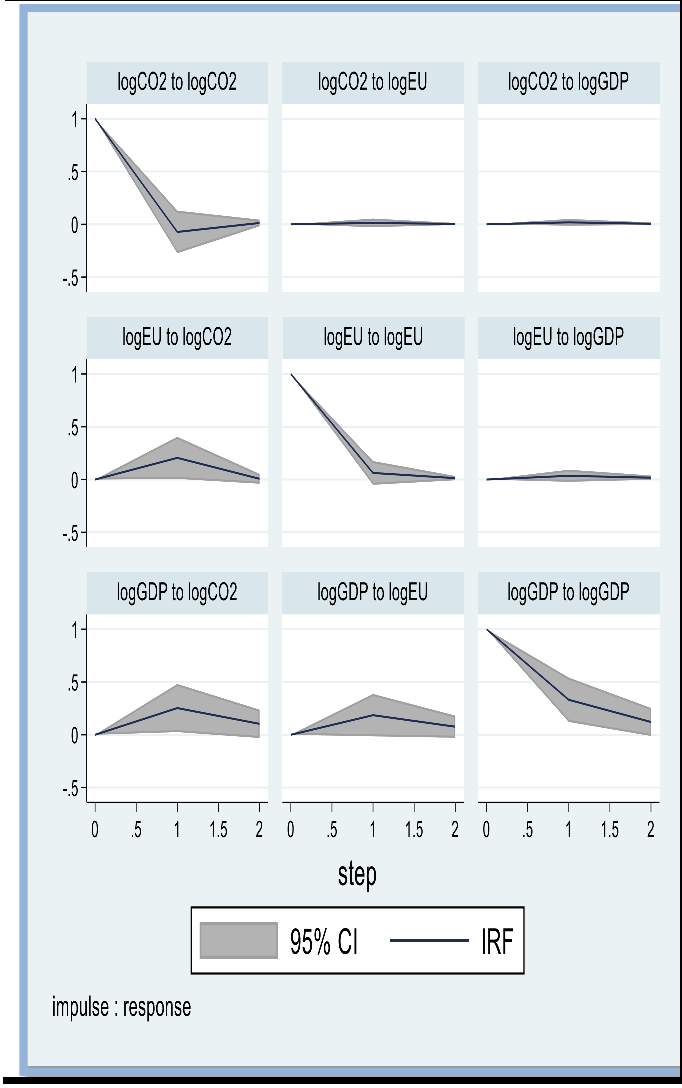
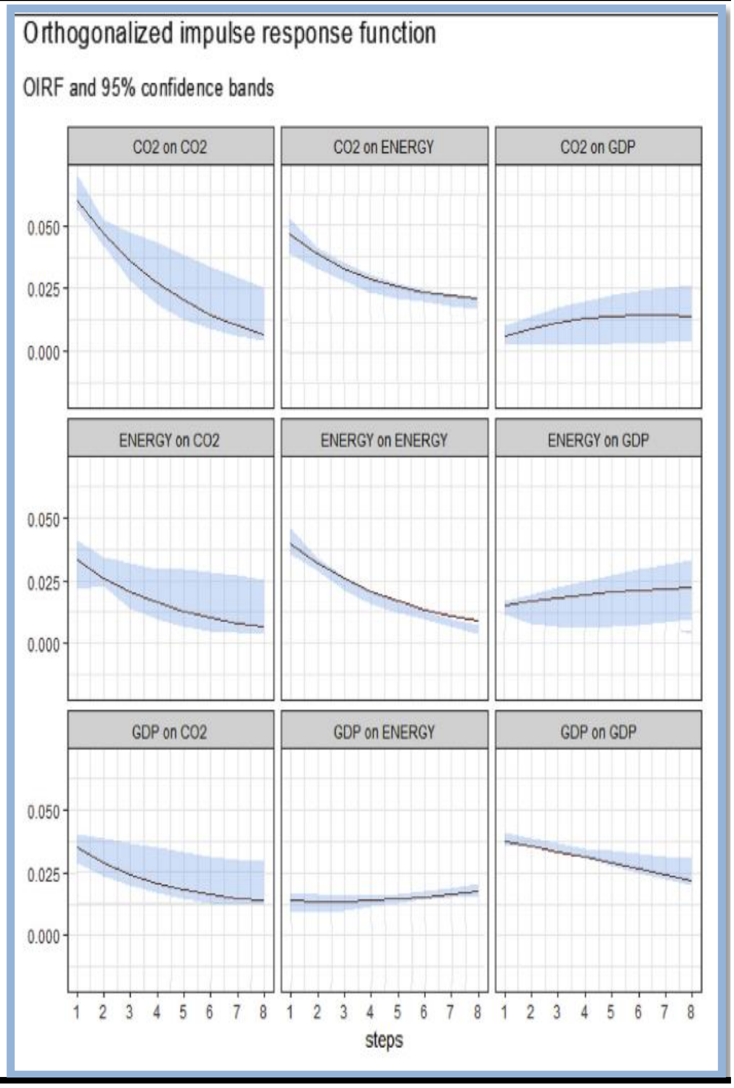
	Panel-VAR coefficients	
	My model	Ozcan`s model
logGDP (t)		
logGDP (t-1)	.331 ***	.701***
logEU (t-1)	.035	.042
logCO2 (t-1)	.018	.142
logEU (t)		
logGDP (t-1)	.185 *	.033
logEU (t-1)	.062	.051***
logCO2 (t-1)	.013	.051
logCO2 (t)		
logGDP (t-1)	.252 **	.098 **
logEU (t-1)	.205 **	.089 **
logCO2 (t-1)	- .072	.912*

Notes: ***, ** and * indicate statistical significane in 1%, 5% and 10% respectively

From Table 6.10, it is important to distinguish the variant of the coefficients corresponding to each variable, between the two models. With a glance, we can notice that most coefficients of the EU and CO_2 equations of our model are bigger, compared to those of the model by Ozcan et al. (2019), while in the GDP equation, the opposite is true. This implies that in our case, a 1% increase in GDP or EU will lead an increase in CO2 emissions, which is double in comparison to the CO_2 increase in the other case. This may be due to the fact that our dataset contains way more countries than their dataset (113 countries Vs 35 countries), although it can also indicate that "our" countries, through various economic activities and fuel-based production processes, create more environmental pressure than those of the other dataset.

From the IRF point of view, more differentiations rather than similarities have been found by comparing the results of the two different impulse response function graphs. In terms of the linkage between GDP and CO_2, it is important to note that in our case, traces of the EKC hypothesis are confirmed, while this does not happen in the case of Ozcan et al. (2019). Again, this may be due to the fact that their sample consists of developed countries (35 OECD countries), like I mentioned in the previous pages, which means that these economies might have crossed the peak point of EKC curve. On the contrary, since our sample includes a great portion of countries that are yet in a developing path, they are more likely to undergo environmental degradation along with economic development. The only similarity detected between the two graphs is the positive response of energy use in a GDP shock. According to the graph by Ozcan et al. (2019), GDP responds positively to both shocks in energy use and CO_2 emissions, while the response of energy use to a CO_2 shock is also positive. Regarding our graph, a shock on energy use can cause an increase in CO_2 emissions.

Fig. 6.5: Impulse Response Functions comparison

Impulse Response Functions	
My Impulse Response Functions	Ozcan`s Impulse response functions
	

As we mentioned in section 5, for the Granger causality analysis we apply Granger causality Wald tests in each equation of the panel VAR model (see Abrigo and Love, 2016). On the contrary, for their analysis, Ozcan et al. (2019) applied the panel Granger causality test introduced by Dumitrescu and Hurlin (2012) who proposed two tests (Z_{wald}) and (Z_{bar}) in order to check the validity of panel Granger causality. The results they found between the Z_{wald} and Z_{bar} are almost identical.

In Table 6.11 bellow, we display the Z_{wald} statistics obtained from the Granger causality tests that were executed in both studies separately.

Table 6.11: Panel Granger causality test comparison

Source of causation	logGDP		logEU		logCO2	
	My Zwald	Ozcan`s Zwald	My Zwald	Ozcan`s Zwald	My Zwald	Ozcan`s Zwald
logGDP	----	----	3.059*	6.165***	4.454**	10.433***
logEU	1.642	2.731*	----	----	4.060**	5.853***
logCO2	1.439	2.269*	0.400	5.239***	----	----

Notes: ***, ** and * significant at the 1, 5, and 10 levels, respectively.

In Ozcan et al. (2019), bidirectional Granger causality was found between the pairs GDP-EC and EC-CO_2. On the contrary, we find unidirectional Granger causality running from GDP to EC and from EC to CO_2 correspondingly. All tests verify the unilateral Granger causality from GDP to CO_2 emissions.

Overall, although our findings show unidirectional positive causality running from both economic growth and energy consumption separately towards carbon emissions, in the case of Ozcan et al. (2019), these causalities were found to be bidirectional, nominating a complementarity among the above causality pairs. Moreover, a notable difference detected between the two studies is the fact that my impulse response functions (IRF) indicate traces of the Environmental Kuznets Curve (EKC) hypothesis, in contrast to those of Ozcan (et al. 2019). In addition, their findings support the feedbag hypothesis (complementarity between economic growth and energy consumption), while ours support the conservative hypothesis (unidirectional causality from economic growth to energy consumption).

7. Conclusions

In this research we aim to examine the causal relationship between economic growth, energy consumption and carbon emissions for a panel of 113 countries from different regions across the globe, over the period 1990-2015. We do this by applying the Generalized Method of Moments (GMM) panel Vector Autoregressive Regression approach (PVAR) in STATA. In addition, we check the robustness of this model and its results by implementing impulse response functions (IRF), Granger causality tests and forecast error variance decompositions (FEVD). Since this study follows the work of Ozcan et al. (2019), we compare our results to theirs, in order to check for any similarities and differences between them.

The findings of the IRF, Granger causality tests and FEVD are aligned with the causality relationships found due to the GMM-PVAR model estimation, which denotes that there is significant and unilateral impact of GDP to both energy use (EU) and carbon emissions. This implies that policies aiming to increase the aggregate economic growth rate may impact energy consumption as well as degrade the air. The weak unilateral causality found running from GDP to energy use signifies that any structural policies, which aim to contribute to economic improvement of the countries in a multi-region scale, may cause a rise in global energy consumption. There has also been found a unilateral causal relationship from EU (energy use) to CO_2 emissions. This suggests that energy conservation policies will decrease carbon emission levels. This finding is a reminder that there is need of global awareness on the use of renewable and cleaner energy sources. Concerning the discovered positive and unilateral causalities running from GDP to CO_2 emissions and from EU (energy use) to CO_2 emissions, most of the relative studies have confirmed these relationships (Waheed et al., 2019). These relationships point out the fact that on average, the selected economies for my dataset depend on fossil-based energy sources such as oil and coal. Statistically significant and positive interconnectedness among carbon emissions and energy consumption and among carbon emissions and GDP were also reported in Ozcan et al. (2019), after the estimation of their own GMM-PVAR model.

Moreover, the impulse response functions provide evidence of the traditional EKC hypothesis. This may be due to the fact this study concerns many countries with a relatively poor economical background. Regarding the corresponding results of Ozcan et al. (2019), no indication of the EKC hypothesis has been found, possibly due to the fact that their analysis is based on developed countries mainly, according to their exhibition. Thus, a possible explanation for this particular antithesis is that either our sample contains considerably more underdeveloped than developed countries or that the aggregate lagging economic growth of the underdeveloped overwhelms the economic growth of currently developed countries in my sample, when comparing these economies in total.

The unidirectional causality running from GDP to EC supports the conservative hypothesis which incurs when an increase in real GDP causes an increase in energy consumption. The prevailing of this hypothesis means that energy conservation policies, aiming to reduce carbon dioxide emissions (CO_2) and consequently global warming will not decelerate the process of economic development. Most previous studies associated with mainly developing countries, also support the conservative hypothesis between economic growth and energy consumption (Waheed et al. , 2019).

On the other hand, according to Mutumba et al. (2021) “conservation hypothesis is majorly in those economies that have gained growth beyond a certain threshold that can drive growth with declining energy use (Kamah et al. 2021)” (p. 9224).

Given that this relationship, although significant, is also found to be partly weak (at 10% level of significance) and that our data contains approximately 70% of world countries, this may be an indication that these countries on average have made progress in terms of economic development, but there is still enough ground to cover to reach a quite satisfying level of economic condition. In addition, this might also be a signal for these economies to consider making use of cleaner and more efficient energy sources, as well as achieving energy goals of sustainability and renewability (Chen, 2012).

Overall, from our point of view, since this study is devoted to the examination of the relationship among the three aforementioned variables and follows the study by Ozcan et al. (2019), which is also devoted to the same examination, although using partly different empirical procedures in a noticeably different panel dataset, the different results of these two studies may highlight the convergence gap that incurs among the countries categorized in various income groups, in terms of production process needs and what externalities these needs bring to the environment. Another remark that needs to be taken into consideration is that the results of this study underline the necessity of replacing non-renewable with renewable sources of energy, in many states all around the globe, i.e., a remark that has been also confirmed by many past studies.

One limitation of this study that needs to be taken into consideration is that its conclusions and the interpretation of its results apply at the global level and not on each country individually. For single-country analysis, the empirical steps that would need to be followed should be based on time series data.

8. Appendix

Table 8.1: Results from GMM-PVAR (model 1) by Ozcan et al. (2019)

	$GDP_{(t-1)}$	$EC_{(t-1)}$	$CO_{2\,(t-1)}$
GDP	0.701 (0.025)	0.042 (0.133)	0.142 (0.172)
EC	0.033 (0.183)	0.051 (0.008)	0.051 (0.232)
CO_2	0.098 (0.050)	0.089 (0.050)	0.912 (0.060)

Notes: *p* values in parenthesis

Table 8.2: The countries included in the data by Ozcan et a. (2019)

Ozcan`s sample		
Region/continent	***Countries***	
	Number	**Name**
OECD	35	Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, UK, USA

Table 8.3: Countries included in my data sample

My sample		
Region/continent	***Countries***	
	Number	**Name**
Europe	9	Albania, Bulgaria, Belarus, Cyprus, Georgia, Malta, North Macedonia, Romania, Ukraine
OECD	31	Australia, Austria, Belgium, Chile, Columbia, Costa Rica, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden, Switzerland, Turkey, UK, USA
Sub-Saharan Africa + Africa	22	Angola, Benin, Botswana, Cameroon, Congo (Brazzaville), Congo (Democratic Republic), Cote d`ivoire, Ethiopia, Gabon, Ghana, Kenya, Mauritius, Mozambique, Namibia, Nigeria, Senegal, South Africa, Sudan, Tanzania, Togo, Zambia, Zimbabwe
MENA	12	Algeria, Bahrain, Egypt, Iran, Iraq, Jordan, Lebanon, Morocco, Oman, Saudi Arabia, Tunisia, United Arab Emirates
Asia	9	Armenia, Azerbaijan, Kazakhstan, Kyrgyz Republic, Myanmar, Nepal, Tajikistan, Turkmenistan, Uzbekistan
Asia-Pacific	15	Bangladesh, Brunei Darussala, China, India, Indonesia, Malaysia, Mongolia, Pakistan, Peru, Philippines, Russian Federation, Singapore, Sri lanka, Thailand, Vietnam
Latin America and Caribbean	15	Argentina, Bolivia, Brazil, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Nicaragua, Panama, Paraguay, Trinidad and Tobago, Uruguay

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