ERF 2020

26TH Annual Conference

Exploring the Relationship between Electricity Consumption and Drivers of Climate Change: A Functional Data Analysis Approach

Amira Elayouty and Hala Abou-Ali

ECONOMIC RESEARCH FORUM

منتدى البحوث الاقتصادية

Exploring the relationship between electricity consumption and drivers of climate change: a functional data analysis approach

Amira Elayouty[*,†] **and** **Hala Abou-Ali**[**‡]

[*] Department of Statistics, Faculty of Economics and Political Science, Cairo University.

[†] Department of Statistics, School of Mathematics and Statistics, University of Glasgow.

[**] Department of Economics, Faculty of Economics and Political Science, Cairo University.

[‡] Research Fellow, Economic Research Forum.

1 Introduction:

The Sustainable Development Goal 13 (SDG13) is concerned with taking urgent action to combat climate change and its impacts. Climate change is an inevitable global challenge with long-term environmental, social and economic implications and damages. The year 2017 was one of the three warmest years on record; it was 1.1 degrees Celsius above the pre-industrial period. Concurrently, the world continues to experience rising sea levels, extreme weather conditions as well as increasing concentrations of greenhouse gases (IPCC, 2018). This calls for urgent and accelerated action by countries to mitigate the impacts of climate change on food production, health, energy consumption and production, increasing sea levels, etc, as they implement their commitments to the Paris Agreement on Climate Change. To undertake appropriate actions, researchers are interested in understanding and quantifying the impacts of the different anthropogenic activities on the drivers of climate change (Pachauri et al., 2014).

Greenhouse gases warm the earth's climate through creating what is known by the 'greenhouse effect'. These gases, including carbon dioxide (CO2), nitrous oxide, methane, and others, are essential in sustaining a suitable temperature for the planet. However, since the Industrial Revolution, these greenhouse gas emissions have rapidly increased simultaneously with energy-production leading to climate change. Carbon dioxide (CO_2) is the primary greenhouse gas emitted through human activities. Pal and Eltahir (2016) suggested that by 2070, the Middle East and North Africa (MENA) region could suffer heatwaves beyond the limit of human survival. CO_2 emissions stem mainly from burning oil, coal and gas for energy use, burning wood and waste materials, and from industrial processes such as cement production. China is the world's largest emitter, emitting more than one-quarter of the global emissions, followed by the United States of America and Europe, emitting 17-18%

of global emissions each, and finally Africa and South America, emitting 3-4% of global emissions each (Ritchie and Roser, 2019).

Electricity has been identified as the main source of global CO_2 emissions. For example, electricity production is accountable to about 27.5% of total CO2 emissions in Europe (EEA, 2018). Therefore, the electricity sector in Europe is a highly regulated market due to its large abatement potential. However, this is mainly attributed to the methods used to produce electricity, such as coal, natural gas, uranium, sum or renewable resources. For this reason, the choice of electric generation technology plays a decisive role in reducing its environmental impacts. For instance, China relies primarily on coal for electricity, which has carbon impact 20 times greater than renewables (IEA, 2016). Therefore, although one may expect a strong positive relationship between income, economic growth and industrial development and CO_2 emissions, many developed and rich countries have reached relatively lower carbon footprint. In an illustration of the Environmental Kuznets Curve (EKC) Model named after Kuznets (1955), which was first observed by Grossman and Krueger (1991, 1995) when they were exploring the influence of the North American Free Trade Agreement (NAFTA) on the environment. For instance, Portugal, France and the United Kingdom have per capita emissions that are lower than their neighbours with similar standards of living such as Germany, the Netherlands, or Belgium (Ritchie and Roser, 2019). This is because a much higher share of electricity in those countries is produced from nuclear and renewable sources. Thus, although prosperity is regarded a primary driver of CO_2 emissions, policy and technological choices definitely make a difference.

The link between global climate change and emissions generated from non-renewable energy resources is proved by Khan and Arsalan (2016). Following from this, it is important to investigate the changes over time in the CO_2 emissions across countries and how the relationship between CO_2 emissions and electricity consumption including both residential and industrial sectors and the countrys economic growth and development has changed over the years. This will help providing insights about the future trends of CO_2 and its potential impacts on climate change. This in turn should help the plan for action towards reducing the greenhouse gases resulting from electricity production.

This paper aims at (1) assessing the variations in the trends of CO_2 emissions and electricity consumption across countries worldwide and the changes over time, (2) investigating the changes over time in the impact of electricity consumption on CO_2 emissions worldwide with a particular focus on the countries in the MENA region, and (3) evaluating the differences in the trends of CO_2 emissions across the different income groups of countries. To achieve these aims, functional data analysis methods are employed. Functional data analysis has grown into a comprehensive and useful field of statistics which provides a convenient framework to describe, model and analyse time series data for different individuals. Up to our knowledge, functional data analysis has not been employed before to study the patterns and relationships of CO_2 emissions across the globe.

The rest of the paper is organised as follows. Section 2 describes the data available for the study. Section 3 motivates and explains the functional data methods used in the analysis of the CO_2 emissions and the electricity consumption data described in Section 2. This is followed by a discussion of the results in Section 4. Finally, in Section 5, the paper concludes with the main findings and policy implications of the study.

2 Data Description:

As mentioned above, this paper aims at investigating the variations in the trends of CO_2 emissions across the globe over time as well as studying the nature of the changes in the relationship between electricity consumption and the carbon dioxide emissions over time across the globe in general and in the Middle East and North Africa (MENA) region in particular. Following from this, annual data on the carbon dioxide emissions (kt), electric power consumption (kWh) per capita [1], population size and percentage growth rate of gross domestic product (GDP) per capita are obtained from the World Bank data (https://data.worldbank.org/) for almost each country across the globe over the period 1975 - 2014. In addition, information on the World Bank country classifications based on income level is obtained from (https://datahelpdesk.worldbank.org/knowledgebase/articles/906519). However, only 108 countries worldwide have a reasonable amount of data available for the analysis. Countries were selected on the basis of having at most one third of the data for each variable missing.

3 Methodology:

Linear trends are often used to model the rate of change in the CO_2 emissions (Hosseini, et al., 2019) and linear regression model is one of the common methods used to explain the correlation between CO_2 emissions and related economic sector variables (Choi and Abdullah, 2016). To examine the effect of economic sector growth on CO_2 emission changes across countries Aye and Edoja (2017) employed a panel data analysis. Unfortunately, the linear trend appears not to be always a sensible summary of the trend. A linear trend can miss important features of the trend, such as curvature, and is very sensitive to the start and finish times (Henderson, 2006). In addition, when a linear trend is used universally to model the trends in large number of individuals there will always be some subjects where it performs well and others where it is less adequate which makes the results incomparable (Henderson, 2006). Following from this, smooth functions have been now widely used for modelling non-linear trends. One objective of this paper is to explore the potential of using functional data analysis to analyse the variations and the differences in CO_2 emissions over time and facilitate comparisons in trends across the different countries.

In econometrics, data collected over time on the same individuals are often analysed using panel data analysis. Recently, functional data analysis (FDA) has grown into a compre-

[1] According to the world bank, the electric power consumption per capita (kWh) is the production of power plants and combined heat and power plants less transmission, distribution, and transformation losses and own use by heat and power plants, divided by midyear population.

hensive and useful field of statistics that can provide a sensible alternative to panel data analysis in many situations (Kneip, et al., 2004). FDA is a very popular technique used for analyzing data collected as multiple time series. In FDA, each time series is viewed as observations of a continuous function collected at a finite series of time points (Ramsay and Dalzell, 1991). In this setting, the fundamental unit of interest is the entire function or curve constructed from the observations collected over time without being concerned about the temporal correlations between the measurements of the same individual.

In FDA, the underlying curves (functions) are assumed to be smooth. However, in practice, data are observed discretely in time (for instance, here, data are observed annually) and hence the first and most crucial step in FDA is to construct the smooth functional curves from their corresponding discrete observations. A popular method to represent smooth functions $y(t)$ over time $t \in \mathcal{T}$ is through linear combinations of known basis functions as follows:

$$y(t) = \sum_{k=1}^{K} c_k \phi_k(t) = \mathbf{c}^\top \mathbf{\Phi}(t)$$

where $\phi_k(t)$ are known basis functions that are defined over the same range as $y(t)$ and the coefficients c_k are estimated by minimising the sum of squared distances to the set of discrete points $y_1, \ldots, y_n$ observed at the the time points $t_1, \ldots, t_n$ that underlie the continuous curve $y(t)$. In the vector-matrix notation, $\mathbf{\Phi}(t)$ is the vector of all K basis functions and $\mathbf{c}$ is a vector that contains all K coefficients. There are multiple choices if basis functions including polynomials, regression splines, Fourier series and wavelets. The choice of the basis function is based on the characteristics of the data and the nature of the smooth curve (Ramsay and Silverman, 1997). For instance, a Fourier basis is particularly designed for periodic data, whereas a B-splines basis (De Boor, 2001) is a very popular choice for smoothing non-periodic data with strong local features. The degree of smoothness imposed on the curve $y(t)$ is controlled by the number K of basis functions. A large K implies more flexibility and smoothness in the estimated curve. Selecting the optimal number of basis functions is a complicated discrete process. In contrast, a roughness penalty approach may offer greater control of the smoothness through seeking a smooth function $y(t)$ that minimises the sum of squared distances to the observed $y_1, \ldots, y_n$ subject to a roughness penalty on $y(t)$ that ensures that the function is suitably smooth (Wood, 2006).

Most of the classical statistical methods like the principal component analysis, cluster analysis, factor analysis and linear regression have been extended to the context of functional data. Ramsay and Silverman (1997) describe and provide many examples of the functional data formulation to these common statistical analysis methods. In this paper, we shall describe briefly the functional principal component analysis and functional linear regression which we will use to describe the trends in CO_2 emissions and its relationship with electricity consumption and analyse their variations across the globe.

3.1 Functional principal component analysis

Functional principal components analysis (FPCA) is a very useful exploratory tool for summarising and extracting the features and primary sources of variation in a set of curves $y_i(t), i = 1 \ldots, N$ after adjusting for the average smooth curve $\bar{y}(t)$. We focus on the mean corrected curves $z_i(t) = y_i(t) - \bar{y}(t), i = 1 \ldots, N$ as we are interested in characterising the main deviations of the $y_i(t)$ from the average curve. The first principal component $\xi_1(t)$ is considered as a loading function for the $z_i(t)$ that exists over the same range $\mathcal{T}$ and accounts for the maximum variation. With analogy to tradition PCA, $\xi_1(t)$ is chosen so that it yields the maximum variability in the functional principal component (FPC) scores:

$$s_{1i} = \int_{\mathcal{T}} \xi_1(t) z_i(t) dt, \qquad i = 1, \ldots, N$$

subject to the normalisation constraint $\int_{\mathcal{T}} \xi_1(t)^2 dt = 1$. Subsequent FPCs are defined in a similar way subject to extra orthogonality constraints. For example, the second FPC must be orthogonal to the first FPC in the sense that $\int_{\mathcal{T}} \xi_1(t)\xi_2(t)dt = 0$.

With analogy to traditional PCA, the loadings' functions $\xi(t)$ correspond to the eigenvectors of the variance-covariance matrix of the raw data. Thus, each $\xi(t)$ represents a solution to the following eigen-equation:

$$\int v(s,t)\xi(t)dt = \rho\xi(s) \tag{1}$$

where $v(s,t)$ is the covariance function defined by:

$$v(s,t) = \frac{1}{N}\sum_{i=1}^{N} z_i(s) z_i(t) \tag{2}$$

Representing the eigenfunctions $\xi(t)$ and the curves $y_i(t)$ or equivalently $z_i(t)$ in terms of their basis expansions reduces the covariance function (2) and the eigen-equation (1) to matrix form that yields a tractable solution, see Ramsay and Silverman (1997) for more details.

3.2 Functional linear regression

With analogy to classical linear models, functional linear regression and analysis of variance are useful techniques for explaining the variability in a variable in terms of other observed quantities. A linear model is considered functional if the response variable is functional and the explanatory variables are scalar, or if the response variable is scalar and one or more explanatory variables are functional, or if both the response and one or more explanatory variables are functional. In all these cases, the regression coefficients, say β_j, are no longer scalar but functions, denoted by $\beta_j(t)$. In this paper, we will be interested in two of these cases. The first case is where we have a functional response and we aim at investigating whether we can describe variation in the curves through country-level covariates. That is, we are interested in models of the form:

$$\mathbf{y}(t) = \mathbf{X}\boldsymbol{\beta}(t) + \boldsymbol{\epsilon}(t), \tag{3}$$

where $\mathbf{y}(t)$ is the vector of the response functions $(y_1(t), \ldots, y_N(t))^\top$, $\boldsymbol{\epsilon}(t)$ is the vector of the residual functions and $\mathbf{X}$ denotes the design matrix of q covariates that describe the N countries. These might include the overall mean and single or various grouping variables. $\boldsymbol{\beta}(t)$ is thus a vector of the q functional objects defined over the same range as the $y_i(t)$. If the overall mean profile is of interest then the design matrix $\mathbf{X}$ will include a column of ones and hence $\beta(t)$ will include a functional object that describes the average profile $\mu(t)$. At a given time point t, this model is similar to a traditional one-way ANOVA model.

In this paper, we will use the above model (3) such that $\mathbf{y}(t)$ is the vector of the estimated CO_2 emissions' functions $(y_1(t), \ldots, y_N(t))^\top$ over the period 1975-2014 for the N countries across the globe; whereas $\mathbf{X}$ is an $N \times 4$ design matrix with a column of ones corresponding to an overall mean profile and three columns corresponding to the three income groups identified by the world bank labelled as low, middle and high income groups. Thus, $\boldsymbol{\beta}(t)$ is a vector of length 4 such that $\beta_1(t)$ describes the overall mean profile of CO_2 emissions and $\beta_j(t),\ j = 2, 3, 4$ is the specific effect of group j measuring the deviations of group j from the overall mean.

With analogy to linear regression, the vector of functional regression coefficients $\boldsymbol{\beta}(t)$ can be estimated through the minimisation of the following least squares criterion:

$$\int_{\mathcal{T}} \|\mathbf{y}(t) - \mathbf{X}\boldsymbol{\beta}(t)\|^2 dt$$

Using the same basis expansion for the original curves $\mathbf{y}(t)$ and the estimated coefficients functions $\boldsymbol{\beta}(t)$ is useful for reducing the functional linear model to a tractable matrix form, see Ramsay and Silverman (1997).

Statistical inference about the model parameters including F-test and R-squared values have also been extended to the functional context. Such inferential diagnostics are useful for identifying the significance of covariates and explaining how the variation in the set of curves changes over time.

The second case of interest in this paper is the concurrent model where both the response and the covariates are functional such that:

$$\mathbf{y}(t) = \mathbf{X}(t)\boldsymbol{\beta}(t) + \boldsymbol{\epsilon}(t),$$

$\mathbf{X}(t)$ is the design matrix where each column corresponds to a functional covariate. Based on this representation, everything in terms of the coefficients estimation and inference proceed the same as in the functional ANOVA model. Here, we will use this model to describe how the relationships between the per capita electric power consumption and per capita GDP growth (as covariates) and CO_2 emissions (as a response) have changed over the years. Following from this, the matrix $\mathbf{X}(t)$ will contain the 2 vectors of functional covariates in addition to the vector that corresponds to the intercept (overall mean) function. For more details, see Ramsay and Silverman (2005).

4 Results and Discussion

In this paper, we examine the trends in CO_2 emissions and its relationship with electricity consumption over the period from 1975 to 2014. As previously mentioned, data from 108 countries across the globe are available. Information on the income group of each country belongs to is also available based on the world bank classification in 2018. Fig.1 displays the raw annual data for both the CO_2 emissions per capita and the electric power consumption per capita on the original scale (panels (a) & (d)).

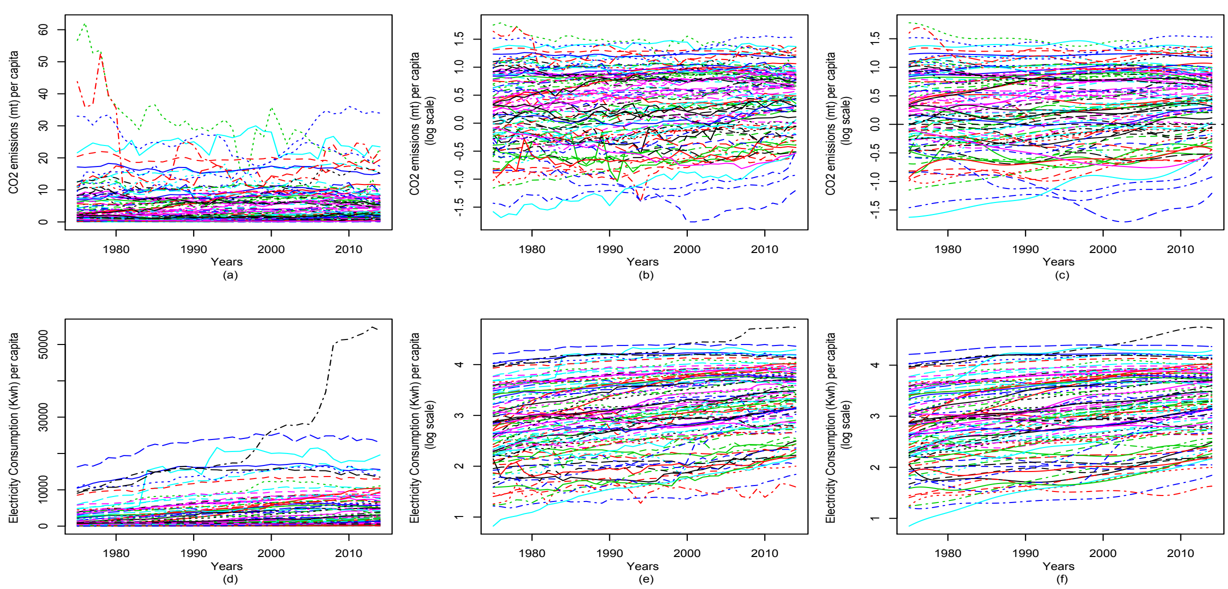

Figure 1: The raw annual data for both the CO_2 emissions (in mt/per capita) and the electric power consumption (in Kwh/per capita) on the original scale (panels (a)&(d)) and the log scale (panels (b)&(e)) as well as the corresponding estimated smooth time trends (panels (c)&(f)).

It is clear from the figure above that there exists a large variability in the data and therefore a log-transformation is needed to adjust for the high-skewness in the data. The middle panels of Fig.1 illustrate the time trends for both the CO_2 emissions and the electric power consumption on the log-scale. The smooth time trends for each of the CO_2 emissions and electricity variate at each country are then obtained using a cubic B-splines basis expansion with 10 terms. Both the degree of the B-splines and the number of basis functions are chosen such that they ensure enough flexibility in the estimated trends without missing important local features; see Fig.1-panels (c) & (f).

Firstly, the functional principal component analysis detailed in Section (3.1) is used to identify the primary modes of variations in the trends of CO_2 emissions and electric power consumption across the different countries. Fig. 2 shows the first 2 functional principal components which account collectively for 99% of the variability in CO_2 emissions across the countries. The figure shows similar results for the electric power consumption. The first FPC which accounts solely for almost 97.5% of the variability, describes the deviations from the average increasing trend in CO_2 emissions over the period 1975 - 2014. A country with a positive score on this first PC has higher level of either CO_2 emissions or electric power consumption than average. It is evident from panels (a) & (c) that the average CO_2 emissions and the average per capita electric power consumption across all countries have been increasing over the years. Whereas, the second FPC which accounts for 2% of the variability describe the contrast between the period 1975-1990 and post 1990 for both variables. A country with a high positive score on the second PC had relatively lower CO_2 emissions and per capita electric power consumption than average before 1990 but considerably higher CO_2 emissions after 1990. This reflects a characteristic of the developing countries and newly industrialized countries. In contrast, a country with a lower score had higher CO_2 emissions pre 1990 relative to post 1990, which mainly characterizes the developed countries with the most advanced technology.

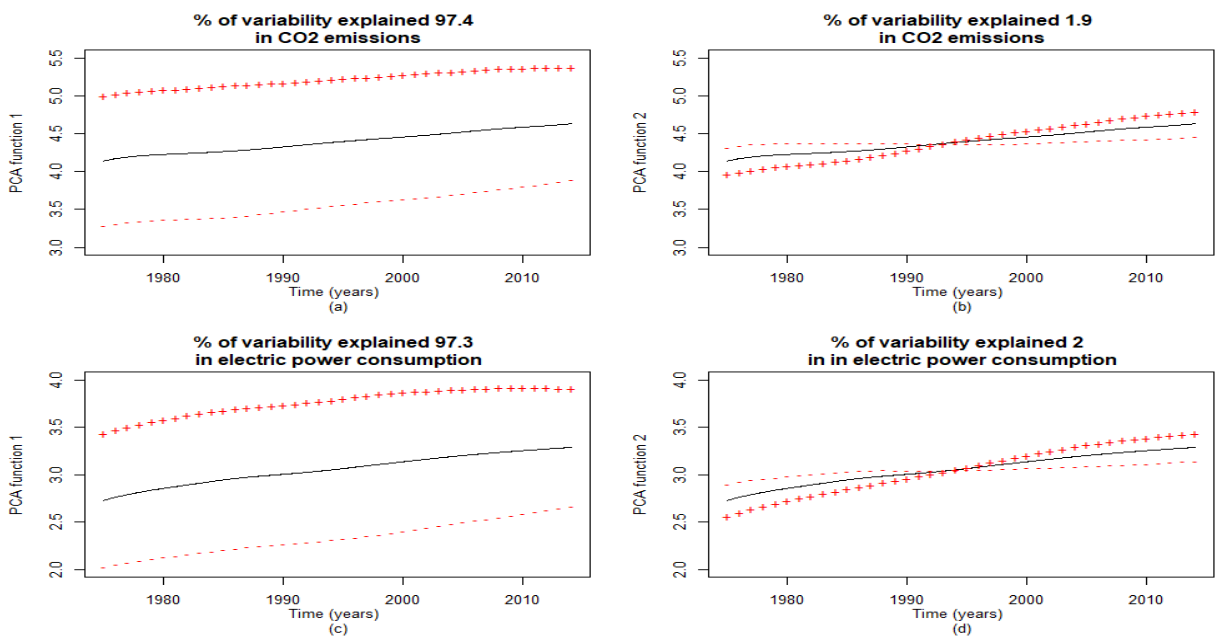

Figure 2: The average trend of CO_2 emissions (top panels) plus and minus a multiple of the corresponding first (a) and second (b) functional principal components and the average trend of per capita electric power consumption (bottom panels) plus and minus a multiple of the corresponding first (c) and second (d) functional principal components.

Fig.3 provides a better explanation and justification of the discrepancies among countries. The right panel of the figure highlights the relatively higher consumption of electricity over the years in the high-income group of countries in contrast to the low-income countries. Despite this high electric power consumption, the highly developed countries including most of the European countries in addition to USA, Canada and Japan have managed to reduce their emissions from the carbon dioxide over the years especially after 1990 (they have negative scores on the second FPC of CO_2 emissions) by reducing their absolute per capita electric power consumption. It should be noted here that this reduction in CO_2 emissions can not only be attributed to the lower absolute electric power consumption but also to the substantial growth of electricity generation from renewable sources, for instance, in Europe from 13% in 1990 to 31% in 2017. On the contrary, in addition to China and India, the major oil producing countries including Kuwait, Saudi Arabia, United Arab Emirates and Bahrain appear to be emitting higher levels of carbon dioxide than global average as they continually inefficiently consume higher volumes of electricity. It is also obvious from Fig.4 that the MENA region countries are emitting CO_2 that relatively exceeds the global average especially after 1990, simultaneously with more per capita electric power consumption post 1990. This result probably highlights the consequences of development, where fossil fuels (the main source of CO_2 emissions) are the most dominant and cheapest form of energy.

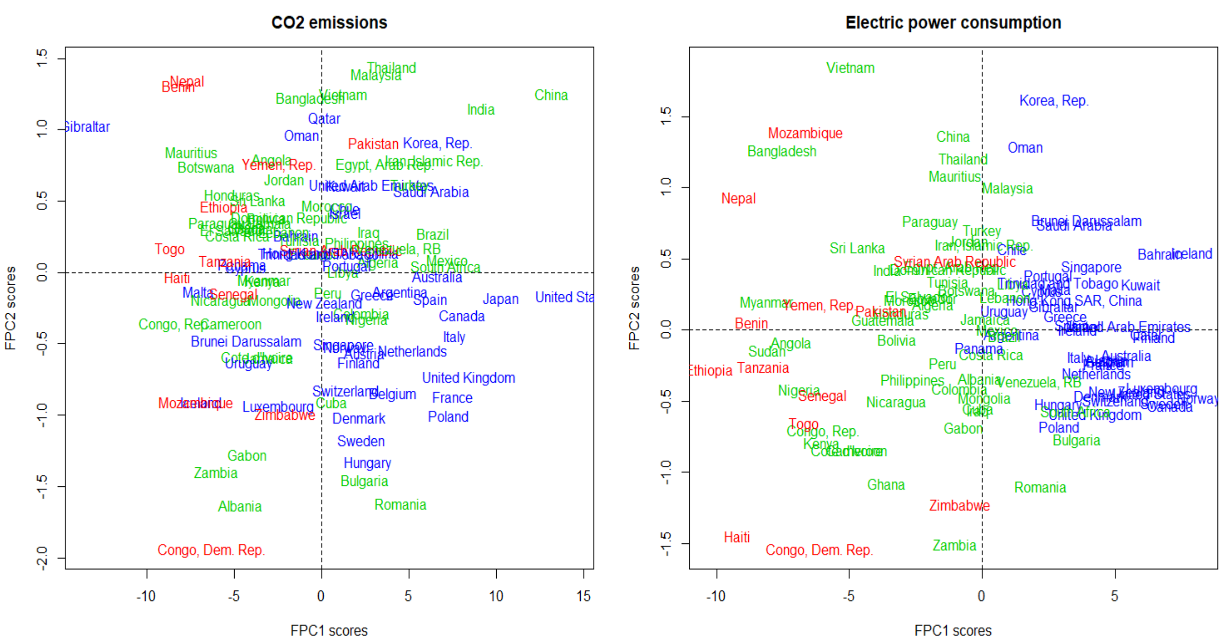

Figure 3: Scatter plots of the scores of the first FPC versus that of the second FPC for the CO_2 emissions (left) and the per capita electric power consumption (right). The red, green and blue colours refer to low, middle and high income groups, respectively.

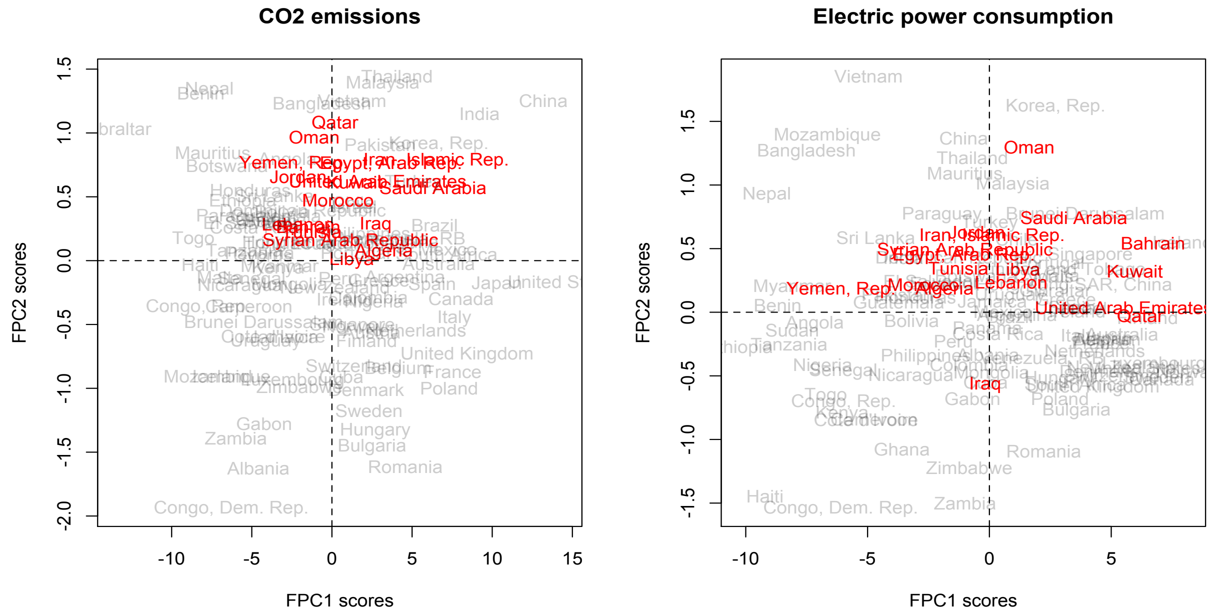

Figure 4: Scatter plots of the scores of the first FPC versus that of the second FPC for the CO_2 emissions (left) and the per capita electric power consumption (right). The red colour refers to the MENA region countries.

Secondly, the functional analysis of variance portrayed in Section (3.2) is employed to study the differences in CO_2 emissions trends across the three income groups. Fig. 5 illustrates the overall mean effect (panel (a)) as well as the three income group specific effects (panels (b-d)) estimated from the data. As identified in the FPCA, the overall average CO_2 emissions has been increasing over the years. It is also clear from the figure that the low-income group countries have consistently lower CO_2 emissions (than the average) over the years (see panel (b) where the red solid curve is below the zero line). On the contrary, the higher income group countries have higher CO_2 emissions that are decreasing over the years, relative to the average CO_2 emissions across all countries. This could be seen as a manifestation of the environmental Kuznets curve model, which is based on the transition that occurs to countries as they move along the different stages of development. However, there is no strong evidence for differences between the mean CO_2 emissions across the 3 income groups.

Finally, a concurrent model, see Section (3.2), is fitted to study the change over time in the relationship between the per capita CO_2 emissions and the per capita electric power consumption and GDP growth. This model is found explaining on average more than 80% of the variability in the CO_2 emissions over the whole study period. The model results indicate that although the CO_2 emissions have been increasing over time, the CO_2 emissions per capita have been significantly dropping since year 2000 (see Fig. 6 - panel (a)). It is also obvious from panels (b) & (c) of the same figure that the influence of both the per capita electric power consumption and the per capita GDP growth on the per capita CO_2 emissions has been varying over the years. Panel (b) indicates that although the CO_2 emissions and electric power consumption are positively related (curve is above the zero-line),

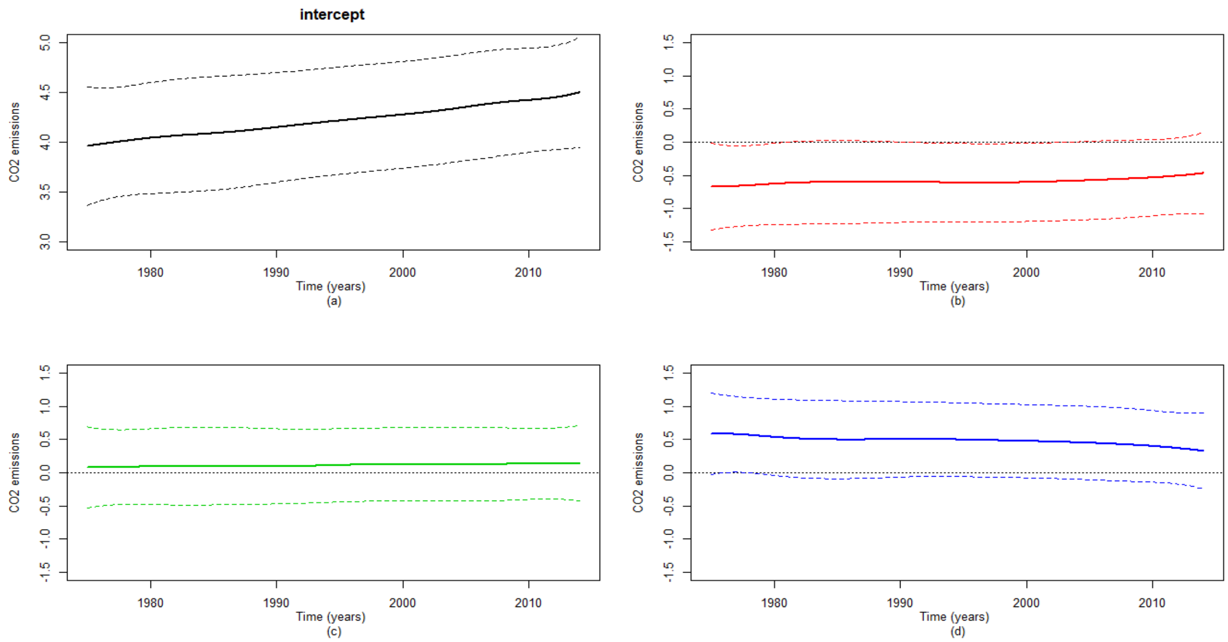

Figure 5: The estimated overall mean effect (a) and the low, middle and high income group specific effects (b-d) along with their corresponding standard error bands (dashed lines).

the influence of electric power consumption on CO_2 emissions has significantly dropped from 1990 to 2006 then slightly increased again between 2006 and 2014. This result may be due to the substantial growth of electricity generation from renewable sources starting the 1990 where renewable energy is not only known to reduce greenhouse gas emissions but also simultaneously create social and economic benefits (Owen, 2006; Pfeiffer and Mulder, 2013). However, it is unable to catch up with increases in energy demand owing to rapid increase in income and population (Devabhaktuni et al., 2013). Leading to filling the gap of energy consumption growth by natural gas driving up the CO_2 emissions post 2006 (BP, 2019). The fitted model shows also a significant positive relationship between CO_2 emissions and GDP growth; see Fig. 6 - panel (c). But, it is noticed that the influence of the per capita GDP growth has been increasing since 1990 up until 2006 where it started to drop slightly. Taking the shape of an inverted U suggesting that, environmental degradation and pollution begin to increase in early stages of economic growth. Then they tend to decrease, due to realizing the importance of environmental quality (Kuznets, 1955).

The same above concurrent model is fitted only to 11 countries of the MENA region, for which data from 1975 to 2014 on per capita GDP growth, electric power consumption and CO_2 emissions are available. These 11 countries are Algeria, Bahrain, Egypt, Iraq, Iran, Jordan, Morocco, Oman, Saudi Arabia, Tunisia and United Arab Emirates. This model enables us to evaluate the differences between the MENA region countries and the rest of the countries. The results of this model are displayed in Fig. 7 which shows that the CO_2 emissions per capita remained almost constant until late 1990's where it started to increase simultaneously with an increase in the effect of GDP growth. This is marking the early stages of EKC where comparing the MENA region growth performance prior and post the 1990s

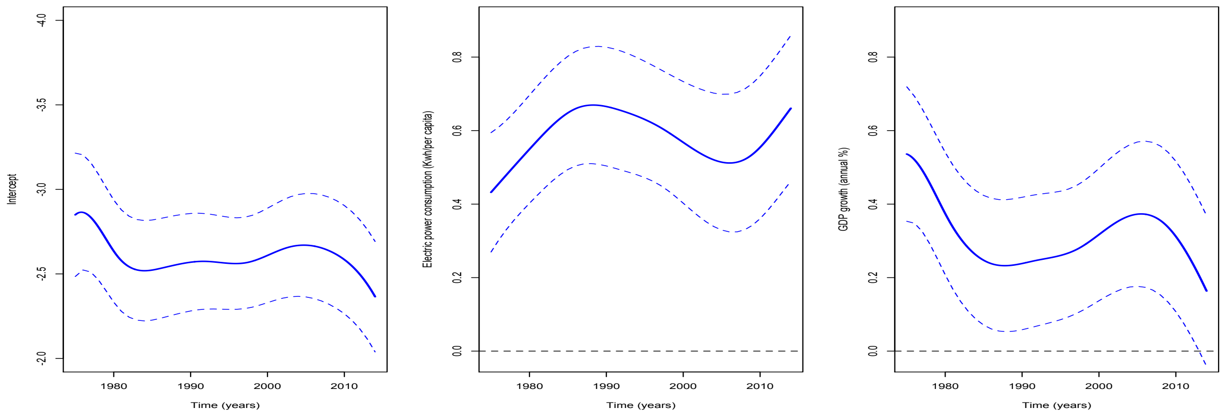

Figure 6: The estimated intercept function (left) and the estimated regression coefficient functions of the concurrent model for the effects of per capita electric power consumption (middle) and per capita GDP growth (right) on per capita CO_2 emissions, along with their standard error bands.

a higher average real GDP growth is witnessed due to undertaken reforms. In Egypt, for example, the 1990s mark a key turning point in Egypt's modern economic history with the initiation of an economic reform and structural adjustment program. However, the influence of electric power consumption on CO_2 emissions remained constant over the years. The same figure also shows the increased variability/gaps between the countries of the same region in the more recent years. This could be attributed to (1) the migration of dirty industries to some of the low and middle income countries of the MENA region; and/or (2) the political economy in the region with the invasion of Iraq and the Arab spring in Egypt and Tunisia. However, further investigation is due in that matter.

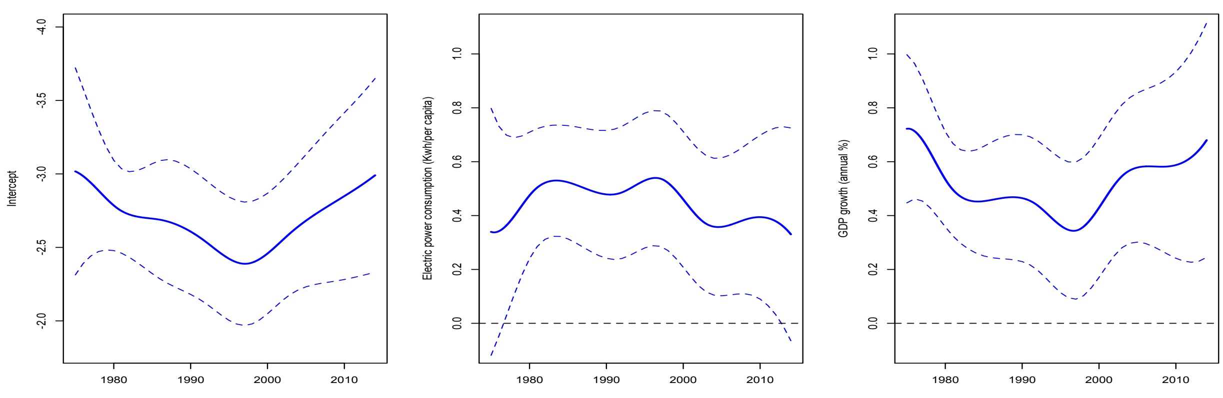

Figure 7: The estimated intercept function (left) and the estimated regression coefficient functions of the concurrent model for the effects of per capita electric power consumption (middle) and per capita GDP growth (right) on per capita CO_2 emissions, along with their standard error bands, for the MENA region countries

5 Conclusion and Policy Implications

Based on the above results, functional data analysis appears to be a powerful exploratory technique for understanding and visualising the differences in CO_2 emissions and electric power consumption trends between countries. It is concluded that the CO_2 emissions is positively related to the country's income level, though there is no enough evidence for differences between the average emissions of the three income groups. It is also found that the global average CO_2 emissions is increasing simultaneously with increases in the per capita electric power consumption and GDP growth. These trends and relationships characterise the MENA region countries including both the developing and the oil producing countries. In contrast, although highly developed countries including USA, Canada, Japan and most of the European countries have CO_2 emissions' levels above average, they managed to reduce their emissions on the global and individual levels over the years starting from sometime during the 1990's. This is likely thanks to both improved energy and technology efficiency, and increases in the capacity of renewables (Du et al., 2017; EEA, 2019). This all, in turn, suggest that the MENA region countries have to undertake serious acts and policies to reduce their carbon dioxide footprints simultaneous with their industrial and economic development. This can be achieved by encouraging the use of more energy efficient technologies and increase the dependence on renewables to generate electric power.

Future work could involve using the functional data analysis approach to predict the electricity demand in the MENA region which may not follow a strictly linear trend. This then helps quantify the gap between electricity demand and supply, as a large gap between the supply and demand in the energy sector may suggest an energy crisis. Therefore, planning and investment in both energy efficient and carbon efficient technologies and resources are necessary to fulfill increased electricity demand while keeping the amount of CO_2 emissions under control.

6 References

1. Aye, G.C. and Edoja, P.E. (2017) Effect of Economic Growth on CO2 Emission in Developing Countries: Evidence from a Dynamic Panel Threshold Model. Cogent Economics & Finance, 5, 1-22.

2. BP (2019) BP Statistical Review of World Energy. London.

3. Choi, C.S. and Abdullah, L. (2016) Prediction of Carbon Dioxide Emissions Using Two Linear Regression-based Models: A Comparative Analysis, Journal of Applied Engineering (JOAE), 4(4), 305-312.

4. De Boor, C. (2001). A Practical Guide to Splines (Revised ed.). Springer.

5. Devabhaktuni, V., Alam, M., Shekara Sreenadh Reddy Depuru, S., Green, R.C., Nims, D. and Near, C. (2013) Solar energy: Trends and enabling technologies. Renewable and Sustainable Energy Reviews, 19, 555-564.

6. Du, K., Lin, B. and Xie, C. (2017) Exploring Change in Chinas Carbon Intensity: A Decomposition Approach. Sustainability, 9(2), 296.

7. EEA (2018) European Environment Agency - Data and maps. www.eea.europa.eu/data-andmaps.

8. EEA (2019) Adaptation challenges and opportunities for the European energy system: Building a climate resilient low carbon energy system, Report No 1/2019.

9. Grossman, G. and Krueger, A. (1991) Environmental impacts of a North American free trade agreement, NBER working paper no. W3914.

10. Grossman, G. and Krueger, A. (1995) Economic growth and the environment, Quarterly Journal of Economics 110, 353-377.

11. Henderson, B. (2006) Exploring between site differences in water quality trends: a functional data analysis approach, Environmetrics, 17, 6580.

12. Hosseini, S.M., Saifoddin, A. and Shirmohammadi, R. and Aslani, A. (2019) Forecasting of CO2 emissions in Iran based on time series and regression analysis, Energy Reports, 5, 619-631.

13. IEA (2016) Energy and Air Pollution: World Energy Outlook Special Report. International Energy Agency (IEA), Paris, France.

14. IPCC (2018) Global Warming of 1.5^{o}C. An IPCC Special Report on the impacts of global warming of 1.5^{o}C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.O. Prtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Pan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. In Press.

15. Khan, J. and Arsalan, M.H. (2016) Solar power technologies for sustainable electricity generation - A review, Renewable and Sustainable Energy Reviews, 55, 414425.

16. Kneip A., Sickles R.C. and Song W. (2004) Functional Data Analysis and Mixed Effect Models. In: Antoch J. (eds) COMPSTAT 2004 Proceedings in Computational Statistics. Physica, Heidelberg.

17. Kuznets, S. (1955) Economic growth and income inequality, American Economic Review 45, 128.

18. Owen, A.D. (2006) Renewable energy: Externality costs as market barriers. Energy Policy, 34(5),632-642.

19. Pachauri, R. K. Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., Church, J. A., Clarke, L., Dahe, Q., Dasgupta, P. et al. (2014) Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change. IPCC.

20. Pal, J. S. and Eltahir, E. A. (2016) Future temperature in southwest Asia projected to exceed a threshold for human adaptability, Nature Climate Change, 6(2), 197.

21. Pfeiffer, B. and Mulder, P. (2013) Explaining the diffusion of renewable energy technology in developing countries. Energy Economics, 40, 285-296.

22. Ramsay J.O. and Silverman BW. (1997) Functional Data Analysis. Springer: New York.

23. Ritchie, H. and Roser, M. (2019) CO_2 and Greenhouse Gas Emissions. Published online at OurWorldInData.org. Retrieved online from:

    https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions

24. Wood, S. N. (2006) Generalized Additive Models - An Introduction with R (1st ed.). Text in Statistical Science Series. Chapman and Hall.