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CO_2 behavior amidst the COVID-19 pandemic in the United Kingdom: The role of renewable and non-renewable energy development

Tomiwa Sunday Adebayo [a], Hauwah K.K. AbdulKareem [b], Bilal [c, *], Dervis Kirikkaleli [d], Muhammad Ibrahim Shah [e, f], Shujaat Abbas [g]

[a] Department of Business Administration, Faculty of Economics and Administrative Sciences, Cyprus International University, Nicosia, North Cyprus, Via Mersin 10, Turkey
[b] Department of Economics and Development Studies, Kwara State University, Malete, Nigeria
[c] Accounting School, Hubei University of Economics, Wuhan, PR China
[d] Department of Banking and Finance, European University of Lefke, Turkey
[e] Department of Resource Economics and Environmental Sociology (REES), University of Alberta, Edmonton, Canada
[f] Alma Mater Department of Economics, University of Dhaka, Bangladesh
[g] Graduate School of Economics and Management, Ural Federal University, Ekaterinburg, Russia

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ABSTRACT

The spread of the COVID-19 pandemic since the end of 2019 has forced an unprecedented lockdown worldwide, and environmental quality was significantly affected by the pandemic and its induced lockdown. The objective of this study is to examine the role of renewable energy, non-renewable energy and COVID-19 case on CO_2 emission in the context of United Kingdom. Several non-linear techniques such as Fourier ADL cointegration test, Non-Linear ARDL, Markov switching regression, and Breitung and Candelon (BC) causality test are employed to attain this objective. The result reveals that there is long run cointegration among the variables in this study. The results demonstrate that positive (negative) shift in renewable energy development decrease (increase) CO_2 emissions while positive (negative) shocks in fossil fuel energy increase CO_2 emissions. Moreover, negative (positive) variation in COVID case leads to a decrease (increase) in CO_2 emissions. Moreover, an uni-directional causal impact was found to run from all the variables – renewable energy, fossil fuel, and COVID-19 case to CO_2 emissions. Finally, several policy recommendations are provided.

1. Introduction

Environmental degradation occupies a priority position amidst the myriad of challenges the world has to grapple with. In fact, it is considered the leading global problem in the 21st century [1]. The deterioration in the environment has been linked to pressure from human's productive and consumptive activities, particularly exploitation of natural resources, which have accelerated climate, ecological and developmental distortions. Carbon emission (CO_2), which is generally used to account for environmental quality [2], has risen rapidly in the last 13 decades by 45% [3]. However, with the spread of the COVID-19 pandemic in the first quarter of 2020, which forced an unprecedented global lockdown, the world experienced a sharp decline in CO_2 emissions in 2020 by 6.4% which amounts to 2.3 billion tonnes [4]. Daily emissions in the world got reduced by 17%, with countries experiencing an average reduction rate of 26% in April 2019 [5]. Ironically, the reduction in emissions is not only less than anticipated by experts but also short-lived. CO_2 emission soon reverted to its previous upward trend as a result of the resumption of economic activities once the virus was brought under control. A larger environmental threat however looms as emissions are rising faster than human activities even though data shows that daily activities are yet to return to the pre-COVID-19 state [6]).

The United Kingdom (UK) is one of the countries that was greatly hit by the pandemic. From an initial 2 COVID-19 cases in January to a jump of almost 10,000 cases on March 25, 2020, a skyrocketed figure of about 50,000 and 100,000 cases were

* Corresponding author.
E-mail addresses: twaikline@gmail.com (T.S. Adebayo), abdulkareem.hauwah@gmail.com (H.K.K. AbdulKareem), bilal@hbue.edu.cn (Bilal), dkirikkaleli@eul.edu (D. Kirikkaleli), ibrahimecondu@gmail.com, mshah3@ualberta.ca (M.I. Shah), Shujaat.abbass@gmail.com (S. Abbas).

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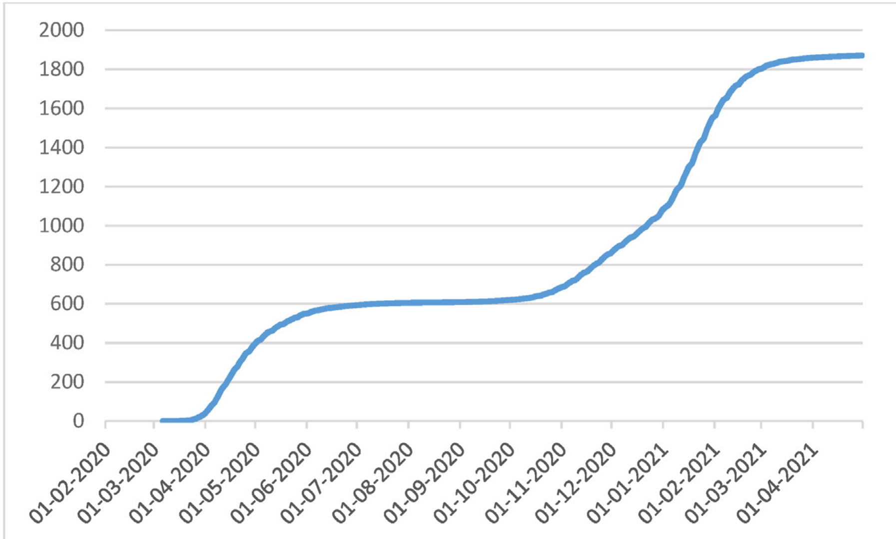

Fig. 1. Total Coronavirus Cases per million in the United Kingdom.
Source: Center for Systems Science and Engineering (CSSE) at Johns Hopkins University

recorded in an average of 10 days each – 25th April and 16th April 2020 respectively [7]. The disastrous situation has been largely attributed to the slow reaction of the UK government in imposing a total lockdown as a swift response to the pandemic in order to nip it in the bud. Inadequate testing and insufficient Personal Protective Equipment (PPE) are other contributory factors. As of July 2021, over 5.6 million COVID-19 cases were recorded in the UK, with a total death of about 130, 000. The graphs below in Figs. 1 and 2 depict the upward trend in COVID-19 cases and deaths per million, respectively, in the UK.

However, rather than looking at the cases and deaths alone, it is useful to look at excess mortality, which gives a comprehensive picture of the effects of the pandemic. In Fig. 3, if we now look at the excess mortality data, we see an increasing trend from April 2020. This figure refers to the cumulative difference between the death number from COVID and the forecasted number of deaths for a similar period of the previous year.

The high incidence of COVID-19, among other factors, was positively impactful for the environment in terms of reduced CO2 emission. UK's CO_2 emission was 354 million tonnes as of 2019, indicating a 41% reduction in its 1990 levels. These recent developments in CO_2 emission reduction are not unconnected to the progress made in its energy intensity as well as the rise in the adoption of renewable energy. Despite the significant strides made, however, the per-capita emissions of the UK in 2019 was 5.3 tonnes exceeding the average world emission of 4.8 tonnes but lower than that of the European Union (EU) of 7.0 tonnes [8]. Consequently, the UK takes the fourth position in global historical CO_2 emissions. In its effort to further reduce emissions, 42% of the UK's electricity in 2020 is from renewable energy sources compared to 41% of fossil fuels [9]. The country has also adopted several schemes such as the Renewable Obligation and Feed-in Tariff, which support large and small scale installations (respectively) of electricity from renewable sources [10]. In 2020 and for the first time in the UK, renewable electricity outstripped electricity from fossil fuel which indicate that investments in renewables are yielding remarkable results [9].

Setting the most ambitious CO_2 emission reduction goals in April 2021, the UK intends to lower emissions by a whopping 78% by 2035 [11]). Additionally, the climate Change Act amended in 2019 aimed for net-zero emissions for the UK in 2050. This is equivalent to a 100% less emissions target. To this end, the UK Government, as highlighted by the Energy and Climate Intelligence Unit, formulated various policies to drive the target, including the Emission Trading Scheme, Contracts for Difference, Energy Company Obligation, and Climate Change Levy. As expressed by the [12]; The UK energy policy has consistently focused on the objectives of security, affordability, and decarbonization with power generation from renewable sources expected to surpass 50% by 2030 [13]. COVID-19 has, however, been reported by the Energy and Economic Growth (EEG) to hamper renewable technologies and generation as the capacity of renewables is estimated to decline by 13% in 2020 [14]).

It is against this background that this study aims to investigate the effect of renewable energy on CO_2 emissions in the UK while accounting for COVID-19. This study contributes to empirical literature in two strategic areas. Its first significance lies in the spatial scope of the paper. The UK is specifically selected for this study given the relatively high projected 13% decrease in emissions in connection with widespread lockdown and restrictions in human activities occasioned by the second and third waves. This estimate is lower than that of the US (12%), China (1.7%), India (9%), and the rest of the world (7%) [15]. By 2030, the UK'S CO2 emission is considered to be declined by 31% starting with the year 2019 but the estimates suggest that it will only be lower by 10%, which is a major hindrance towards achieving carbon neutrality and SDG agenda of this country [16]. By looking at the role of renewable and non-renewable energy, we seek to provide a policy perspective on how the carbon neutrality dream can be achieved through the help of energy in the UK. Moreover, tackling CO2 emission through renewable energy development is essential for achieving several SDGs such as affordable and clean energy (SDG7), sustainable cities and communities (SDG11), responsible consumption and production (SDG12) and climate action (SDG13). This country has to urgently replace its fossil fuel technology with the renewable ones because as outlined in the climate change act (2008), the country intends to decrease greenhouse gas emissions by at least 80% by 2030 compared to its 1990 baseline. But one of the major problems faced by the government is that currently, the country heavily relies on imported energy which exacerbates its energy security problem [17]. Therefore, the solution lies in how fast the country can

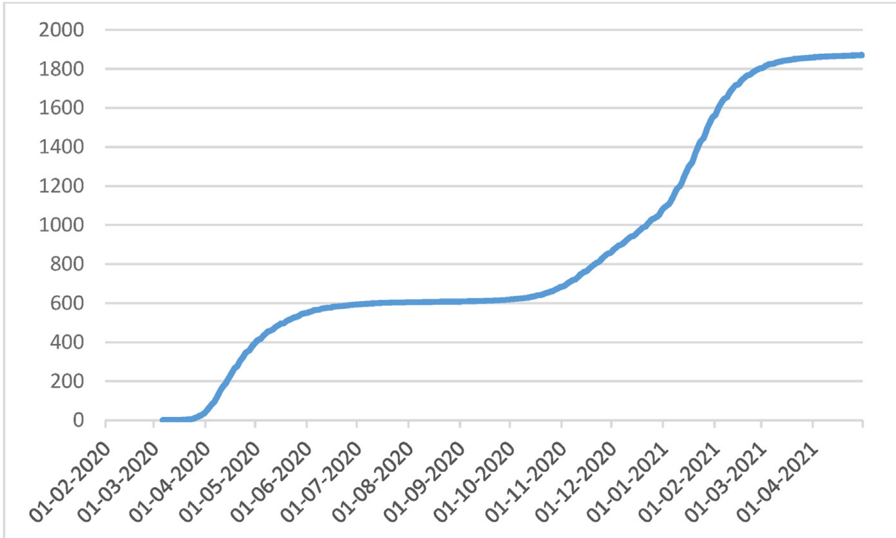

Fig. 2. Total Coronavirus Deaths per million in the United Kingdom.
Source: Center for Systems Science and Engineering (CSSE) at Johns Hopkins University

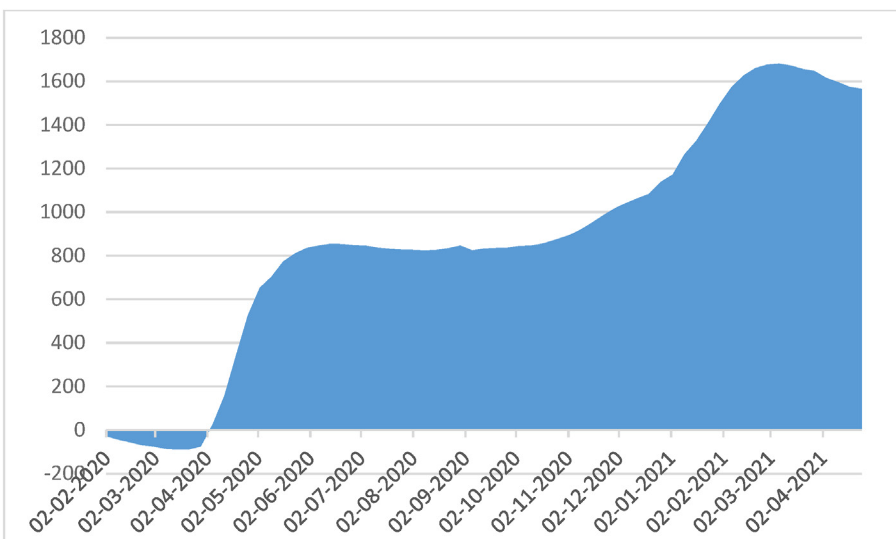

Fig. 3. Cumulative excess mortality per million in the United Kingdom.
Source: Human Mortality Database (2021)

transition itself to a low carbon economy. Needless to say, the low carbon economy transition requires the massive deployment of renewable energy technologies. Moreover, the power generation in this country has been historically associated with fossil fuels technology, and as of today, the majority of power comes from the fossil fuel such as oil and coal. These two major sources have contributed to about 53% in the electricity generation in 2016 [18]. However, in 2020, according to a climate think tank called Ember, fossil fuel electricity was outpaced by renewable energy in UK's electricity for the first time ever, mainly because of wind power [9]. This demonstrates the country's commitment towards achieving carbon neutrality by emphasizing more on renewables and away from fossil fuel technology.

The aim of this paper is to provide an empirical basis for the aforementioned postulations by taking COVID-19 into account to investigate its effect (if any) on CO_2 emission in the UK. This study is therefore among the few in mainstream journals to devote attention to this. The second area where this study is unique is in its methodological contributions. We are adopting superior nonlinear models such as Fourier ARDL cointegration test [19], Nonlinear ARDL, Markov switching regression [20]) and Breitung and Candelon (BC) causality test [21]). The reason for choosing non-linear models is outlined in Ref. [22]; who also used non-linear methods to understand the COVID-19 pandemic impacts on renewable generation in Denmark. The authors mentioned that the restrictions imposed due to COVID-19 and its nature has irregular and sudden jumps and if one utilizes linear models for capturing those jumps, they won't be able to do so. Another difficulty with linear dynamic is that they are not able to capture the complex and asymmetric dynamics in the variables, especially when we deal with high-frequency data. So if we use linear frameworks for analysing the relationship among the high -frequency series, we might end up with poorly behaved estimates. As such, it is necessary to apply non-linear dynamics in our case. Specifically, we apply nonlinear ARDL and Markov Switching regression. The use of the nonlinear ARDL (NARDL) technique allows modelling both short run and long run estimates and detecting associated asymmetric effects [23], and also discovering hidden cointegration [24]. The uniqueness of the Markov switching regression model is in being able to typify different structures in a time series into different regimes in order to capture the dynamic patterns that exist within the series [25]. For the cointegration test, the Fourier ADL cointegration approach is employed, given its ability to capture nonlinearity without losing degrees of freedom when the model contains many dummy variables [22]. These attributes make it a suitable choice for the analysis in view. Furthermore, the use of the BC test disaggregates causality into short, medium and long term and thus, allows for time frequency forecasting [22,26]. Employing these varied advanced estimation techniques push the boundary of existing literature in this subject area.

The next section, which is Section 2 presents the literature review and a research gap and third section presents the detailed methods of analysis. In Section 4, the results of the empirical study are presented and discussed and conclusions and policy implications are given in Section 5.

2. Literature review

2.1. COVID-19 and CO2 emissions

In examining the link between COVID-19 and CO2 emissions, there appears to be a consensus in the literature as various studies such as Aktar et al. [27] have alluded to the decremental impact of COVID-19 pandemic on CO2 emissions. Aktar et al. [27] documented that the lockdown occasioned by the pandemic had an unprecedented impact on the pattern of energy consumption which led to a global decline in CO2 emissions. Similarly [28], assessed the effect of COVID-19 on CO2 emissions in 23 European countries and ten economic sectors during the initial six months period of 2020. The study indicated that Europe experienced a decline in CO2 emissions by over 195,600 tons between January and June 2020. Comparing the CO2 emission for the year with that of 2019, the author documented a 12.1% reduction in CO2 emissions, with the highest decline recorded in the Accommodation and Food Service, Manufacturing, Retail and Wholesale, and Transportation sectors. This result aligns with [29,30]. The former found that the pandemic prompted an unparalleled significant daily decline in global CO2 emissions, while the latter estimates a 7.8% decrease in fossil CO2 emissions between January and April 2020.

[31] examined the direct and indirect effects of COVID-19's demand shocks on CO2 emissions in Asia-pacific countries. Using the input-output and hypothetical extraction methods, the study gathered data from the records of the Asian Development Bank on COVID-19 economic impact scenarios. Findings show that COVID-19-induced demand shocks had a 1–2% decremental effect on CO2 emissions. The study further revealed that while direct demand shocks accounted for an 85-63% reduction in CO2 emissions, indirect demand shocks had a lesser impact of a 15–37% decline in CO2 emissions. Exploring both the short and long-run effect of COVID-19 on CO2 emissions in the United States [32], indicate that COVID-19 induced a 50%, 30%, and less than 10% reduction in jet fuel, gasoline and electricity demand leading ultimately to a 15% reduction in CO2 emissions.

2.2. Energy and CO2 emissions

[33] analyzed the impact of economic growth and energy consumption – both renewable and nonrenewable - on CO2 emissions in China using provincial panel data from 1995 to 2012. Findings revealed that although nonrenewable energy exert a positive influence on CO2 emissions, the level of influence differed across regions. Renewable energy consumption, on the other hand, indicated no significant effect on the Environmental Kuznet Curve (EKC) Hypothesis in all three regions. In terms of causality, the results were mixed. Nonetheless, a bidirectional link was ascertained between renewable energy consumption, CO2 emissions, and economic growth in the long run for all regions. Also [34], examined the dynamic relationship that exist among economic growth, CO2 emissions, and energy consumption in 116 countries from 1994 to 2014. Results from the panel vector autoregression (PVAR) and system-generalized method of moment (System-GMM) exhibit a positive unidirectional causal relationship from energy consumption to CO2 emissions in Middle East and North African (MENA) countries but a negative relationship was found for Sub-Saharan Africa (SSA) and Caribbean-Latin America countries. CO2 emissions were, however not found to have a causal effect on energy consumption globally except for MENA countries.

In a similar vein [35], examined the effect of renewable and nonrenewable energy alongside income and trade openness on CO2 emissions for ten countries in SSA from 1980 to 2011. Using panel estimations, a longrun relationship was revealed among the variables. Nonrenewable energy was found to wield a positive effect on CO2 emissions while renewable energy reduces CO2 emissions. The study further revealed a unidirectional causal link from CO2 emissions to renewable energy and from nonrenewable energy to emissions. Furthermore [36], employed an autoregressive distributed lag (ARDL) bounds testing approach and vector error correction model (VECM) and Granger causality approach to analyze the CO2 emissions, GDP, energy production, and foreign trade link in China. The data utilized time series data ranging from 1980 to 2014. Of the numerous findings, findings that agree with [35] include the confirmation of a long-run association among the variables, the incremental and decremental impact of nonrenewable and renewable energy, respectively, on CO2 emissions. Further review of the study showed that a shortrun bidirectional causality was established between CO2 emissions and to renewable energy.

2.3. Research gap

From the gaps observed in the previous review, this study fills a cavity in the literature by contributing in three strategic areas. First, it can be observed that none of the studies examining the COVID-19-CO2 emissions-energy nexus focused on the UK. Most of these studies focused on the globe (e.g., Ref. [27], Asia (e.g., Ref. [31], and the US (e.g., Ref. [32], with the closest to the UK being that conducted for Europe by Ref. [28]. However, it is pertinent to dwell on the UK specifically given the relatively high projected 13% decrease in emissions in connection with widespread lockdown and restrictions in human activities occasioned by the second and third waves. This estimate is lower than that of the US (12%), China (1.7%), India (9%), and the rest of the world (7%) [15]. This study is therefore among the few to devote attention to the UK and lend empirical credence to the projection on COVID-19 induced decline in CO2 emissions. An additional research gap lies in the studies of CO2 emissions and energy. Most studies such as [33,34,36]; and [35] did not include COVID-19 in their analysis of CO2 emissions and energy. Rather, the attention is on economic growth, as evident in most studies reviewed in this context. Therefore, this study will consider COVID-19, CO2 emissions and energy in the same study context to obtain a holistic perspective on the subject matter.

Lastly, a methodological gap has been observed from the existing literatures. Although several methodologies such as GMM, Granger causality, and ARDL have been employed in literature to analyze the variables in focus, nonlinear models are quite uncommon. Nonlinear models are critical in estimating the restrictions and nature of COVID-19 which are irregular and characterized by sudden jumps that linear models would not capture [22]. Also, linear models do not have the ability to accommodate complex and asymmetric high-frequency data dynamics - the type associated with COVID-19 data. We are, therefore, adopting superior nonlinear models such as the Fourier ARDL cointegration test [19], nonlinear ARDL, Markov switching regression [37]), and Breitung and Candelon (BC) causality test [38]).

3. Data and methodology

3.1. Data

The study's motive is to assess the affluence of renewable energy (REC), COVID-19 cases (CASES) and FOS on carbon emissions (C02) in United Kingdom. The study utilized daily dataset from February 1, 2020 to April 2021 to investigate these interconnections. The dependent variable is CO2 whilst the independent variables are FOS, CASES, and REN. The data for carbon emission, the dependent variable of this paper, comes from the carbon monitor website (https://carbonmonitor.org/), which is an international initiative that tracks near real time CO_2 emission worldwide. The independent variables are REN, which is renewable energy production (measured in MW) and FOS, which denotes fossil fuel energy production (measured in MW), come from ENTSO-E Transparency Platform. Finally, CASES is measured as number of daily COVID-19 cases which is obtained from John Hopkins University database. The natural logs of the variables of investigators are taken to reduce heteroskedascity. The study model is illustrated by Equation (1) as follows:

$$lnCO_{2t} = \vartheta_0 + \vartheta_1 lnFOS_t + \vartheta_2 lnREN_t + \vartheta_3 lnCASES_t + \varepsilon_t \tag{1}$$

In the above Equation, CO_2, FOS, REN and CASES demonstrate CO_2 emissions, renewable energy and cases of daily COVID-19 and ln refers to natural logarithms. Furthermore, t and ε represent time and error term, respectively. It is vital to present summary of variables of investigation. Table 1 lists summary of variables in their raw form. The mean of FOS (11992.11) is highest accompanied by REN (10369.75), CASES (9747.93) and CO_2 (888.7644). The skewness value unveiled that all the series are positively skewed. Furthermore, the kurtosis value disclosed that CO_2, REN, FOS, and CASES are platykurtic (value less than 3). Moreover, the Jarque-Bera value disclosed that the variables of interest do not conform to normality.

Table 1
Descriptive statistics.

	CO_2	REN	FOS	CASES
Mean	888.7644	10369.75	11992.11	9747.93
Median	874.6741	9974.25	11362.74	3726.5
Maximum	1353.55	19373.58	23849.23	68192
Minimum	448.4915	3101	3884.25	−4787
Std. Dev.	184.2633	3088.99	4515.791	13330.17
Skewness	0.177195	0.325745	0.379114	1.983317
Kurtosis	2.52776	2.542885	2.282638	6.795962
Jarque-Bera	6.594399	11.98168	20.61007	570.2147
Jarque-Bera Probability	0.036987	0.002502	0.000033	0
Sum	403499.1	4707869	5444416	4425560
Sum Sq. Dev.	15380697	4.32E+09	9.24E+09	8.05E+10
Observations	454	454	454	454

3.2. Methodology

3.2.1. Stationarity test

We utilized the Fourier ADF and Augmented Dicky Fuller (ADF) unit root tests to catch stationarity features of series. The ADF specification is depicted as follows:

$$\Delta y_t = \theta y_{t-1} + x_t\gamma + \theta_1 \Delta y_{t-1} + \theta_2 \Delta y_{t-2} \ldots\ldots\ldots\ldots\ldots + \theta_p \Delta y_{t-p} + \nu_t \tag{2}$$

where $\theta = \rho$-1 and ρ is the coefficient of the AR (θ), variable of study is depicted by y_t, Δ is difference and the error term is illustrated by ν_t. To address the issue of autocorrelation, the lagged term has been introduced. Conventional unit root tests such as ADF, on the other hand, are unable to detect structural breakdowns. The series of interest may have experienced certain structural changes, resulting in various types of nonlinearity. Enders and Lee (2012) employed the Fourier function composed of various frequencies to enhance the ADF test for a nonlinear framework. A Fourier function is defined by the equation below:

$$Y(t) = \theta_0 + \theta_1 t + \sum_{j=1}^{m} T_j sin\left(\frac{2\pi jt}{N}\right) + \sum_{j=1}^{m} \rho_j \, cos\left(\frac{2\pi jt}{N}\right); m \le \frac{N}{2}; t = 1, 2 \tag{3}$$

In Equation (3), trend coefficients and intercept are depicted by θ_1 and θ_0 respectively. Moreover, ρj and τj represents dynamics displacement of the function of Fourier and amplitude respectively. In the following equation, j and j are two nonlinear parameters, and if one of them is significant, then there is nonlinearity. If these values are zero, nevertheless, the process will become linear.

3.2.2. Cointegration

In order to catch the variables of study longrun association, we applied cointegration test. Cointegration necessitates the integration of all series in the same sequence. We use Banerjee et al. [19]'s Fourier ADL cointegration analysis. Unlike the traditional cointegation tests such as [39,40]; Banerjee et al. [19]'s Fourier ADL cointegration can capture series nonlinear longrun association. This test eliminates the need to define the length of the breaks and avoids power loss when overusing dummies. The following is the formula for this test:

$$\Delta y_{1t} = d(t) + \Delta_1 y_{1,t-1} + \pi y_{2,t-1} + \tau \Delta y_{2,t-1} + \varepsilon_t \tag{4}$$

The Banerjee et al. [19]'s Fourier ADL cointegration null and alternative hypotheses are “no cointegration” and “cointegration exist” respectively.

3.2.3. Markov Switching Regression

Given the nonlinearity attribute of the variables and a rapid shift in the variation in variables of study, applied the Markov Switching Regression(SWR) proposed by Ref. [41]; which is a better option relative to other statistical techniques. This approach is a nonlinear alternative. The concepts of this method are extremely adaptable and may alter in response to regime transitions. This approach is suitable when series are nonstationary. As [20] stated, nonlinearity occur when a process undergoes discrete changes in regimes, i.e., events in which the dynamic behavior of a given series differs. The Markov Switching regression with two regimes can be expressed as follows:

$$X_t = \theta_1 + \sum_{i=1}^{p} \gamma_{1,i} X_{t-1} + \theta_{1,t} \ if \ S_t = 1 \quad (5)$$

$$X_t = \theta_2 + \sum_{i=1}^{p} \gamma_{2,i} X_{t-1} + \theta_{2,t} \ if \ S_t = 2 \quad (6)$$

where $\theta_{i,t}$ denote identically and independently distributed with variance σ^2_i and mean 0. Moreover, s_t stand for state variable and it is controlled by Markov chain first-order. The following matrix format can be used to display the variable probabilities transition.

$$P = \begin{matrix} \rho 11 & \rho 12 \\ \rho 21 & \rho 22 \end{matrix} \quad (7)$$

Here, the framework will remain longer in state i if the ρ_{ij} value is small. The state duration is anticipated to be $\frac{1}{\rho_{ij}}$. The numbers of regime can be $r \geq 2$.

3.2.4. Non-linear ARDL method

The NARDL was used in this study to catch the relationship between CO_2 and the regressors. When the series are 1(0), or 1 (1), or both 1(0) and 1 (1), the asymmetric ARDL method can be used. The NARDL necessitates an effective lag selection, and endogeneity concerns may be addressed by selecting an adequate lag period. Appropriate lag is also useful in resolving the difficulties of potential multicollinearity in the NARDL [23]. Variables are separated using the NARDL premised on their negative and positive shifts. As a result, renewable energy use, fossil fuel and CASES are dissolved into negative and positive motions in our fundamental model. We converted series into shocks. ($lnREN^+$, $lnREN^-$, $lnFOS^+$, $lnFOS^-$, $lnCASE^+$, $lnCASE^-$). In addition, the partial total of FOS, REN, and CASE movements are shown below.

$$lnREN^+ = \sum_{i=1}^{t} \Delta lnREN^+ + \sum_{i=1}^{t} max(REN_i, O) \quad [3a]$$

$$lnREN^- = \sum_{i=1}^{t} \Delta lnREN^- + \sum_{i=1}^{t} min(lnREN_i, O) \quad [4a]$$

$$lnFOS^+ = \sum_{i=1}^{t} \Delta lnFOS^+ + \sum_{i=1}^{t} max(lnFOS_i, O) \quad [5a]$$

$$lnFOS^- = \sum_{i=1}^{t} \Delta lnFOS^- + \sum_{i=1}^{t} min(lnFOS_i, O) \quad [6a]$$

$$lnCASE^+ = \sum_{i=1}^{t} \Delta lnCASE^+ + \sum_{i=1}^{t} max(lnCASE_i, O) \quad [7a]$$

$$lnCASE^- = \sum_{i=1}^{t} \Delta lnCASE^- + \sum_{i=1}^{t} min(lnCASE_i, O) \quad [8]$$

In a NARDL setting, the following equation can be utilized to incorporate both short run and long run dynamics.

$$\begin{aligned} \Delta lnCO_{2t} = {} & \vartheta_0 + \sum_{i=1}^{t} \vartheta_1 \Delta lnCO_{2t-i} + \sum_{i=1}^{t} \vartheta_2 \Delta ln\mathrm{REN}^+_{t-i} \\ & + \sum_{i=1}^{t} \vartheta_3 \Delta ln\mathrm{REN}^-_{t-i} + \sum_{i=1}^{t} \vartheta_4 \Delta ln\mathrm{FOS}^+_{t-i} + \sum_{i=1}^{t} \vartheta_5 \Delta ln\mathrm{FOS}^-_{t-i} \\ & + \sum_{i=1}^{t} \vartheta_6 \Delta ln\mathrm{CASE}^+_{t-i} + \sum_{i=1}^{t} \vartheta_7 \Delta ln\mathrm{CASE}^-_{t-i} + \beta_1 lnCO_{2t-i} \\ & + \beta_2 ln\mathrm{REN}^+_{t-i} + \beta_3 ln\mathrm{REN}^-_{t-i} + \beta_4 ln\mathrm{FOS}^+_{t-i} + \beta_5 ln\mathrm{FOS}^-_{t-i} \\ & + \beta_6 ln\mathrm{CASE}^+_{t-i} + \beta_7 ln\mathrm{CASE}^-_{t-i} + \varepsilon_t \end{aligned} \quad [9]$$

The previous equation may easily be transformed into an error correction model by adding an error correction term (ECT).

$$\begin{aligned} \Delta lnCO_{2t} = {} & \vartheta_0 + \sum_{i=1}^{t} \vartheta_1 \Delta lnCO_{2t-i} + \sum_{i=1}^{t} \vartheta_2 \Delta ln\mathrm{REN}^+_{t-i} \\ & + \sum_{i=1}^{t} \vartheta_3 \Delta ln\mathrm{REN}^-_{t-i} + \sum_{i=1}^{t} \vartheta_4 \Delta ln\mathrm{FOS}^+_{t-i} + \sum_{i=1}^{t} \vartheta_5 \Delta ln\mathrm{FOS}^-_{t-i} \\ & + \sum_{i=1}^{t} \vartheta_6 \Delta ln\mathrm{CASE}^+_{t-i} + \sum_{i=1}^{t} \vartheta_7 \Delta ln\mathrm{CASE}^-_{t-i} + \beta_1 lnCO_{2t-i} \\ & + \beta_2 ln\mathrm{REN}^+_{t-i} + \beta_3 ln\mathrm{REN}^-_{t-i} + \beta_4 ln\mathrm{FOS}^+_{t-i} + \beta_5 ln\mathrm{FOS}^-_{t-i} \\ & + \beta_6 ln\mathrm{CASE}^+_{t-i} + \beta_7 ln\mathrm{CASE}^-_{t-i} + \rho ECT_{t-1} + \varepsilon_t \end{aligned} \quad [10]$$

To identify the long-run connection between CO2 and the regressors, the NARDL bounds test is utilized. If the F-statistic is larger than the lower and upper critical values, the null hypothesis is rejected.

3.2.5. Causality test

The present takes a further step by assessing the causal interrelationship between CO_2 and the regressors. In doing so, we applied the novel frequency domain causality test proposed by Ref. [21] which has the capability of capturing causal interrelationship between series at different frequencies-short, medium and long-term respectively. Unlike the conventional causality tests (Granger and Todo-Yamamoto), this test has the capacity to identify causal interrelation at different frequencies. This causality test is better than other standard causality tests since it enables causal interconnection between variables in short and long-term. This will enable us to understand the shifts that can be addressed by policy interventions, whether short or long-term [42].

4. Discussion of findings

This section of the paper presents the outcomes of the methodologies applied. The study proceeds by assessing the stationarity features of the series of investigation. In doing so, we applied both ADF and Fourier ADF unit root tests. The outcomes of the ADF test are presented in Table 2. The outcomes unveiled that at level, CO_2, FOS, and CASE are stationary; however, at first difference, all the series are stationary. Furthermore, we applied the Fourier ADF test, which is an advancement over conventional ADF test. The advantage of the Fourier ADF test is that it can identify series stationarity characteristics if the series are nonlinear. The outcomes of the Fourier ADF are disclosed in Table 2 and the outcomes unveiled that at level, CASE and CO_2 are stationary; nonetheless, at first difference, all the variables of study are stationary.

Table 2
ADF and Fourier ADF unit root test.

	Fourier ADF Test Statistic	F-Statistic	Frequency	Fourier ADF Test Statistic	F-Statistic	Frequency
	At Level			At First Difference		
ln CASE	−3.579756*	3.849105	1.000000	−4.897121***	2.323677	5.000000
ln CO2	−4.279162**	4.434370	1.000000	−7.842221***	0.522582	4.000000
ln FOS	−5.667878	6.086178	3.000000	−9.036363***	0.858848	3.000000
ln REN	−2.836861	3.959732	5.000000	−20.24805***	3.581879	5.000000
	Fourier ADF Test CV					
Frequency	1%		5%			10%
1	−4.42		−3.81			−3.49
2	−3.97		−3.27			−2.91
3	−3.77		−3.07			−2.71
4	−3.64		−2.97			−2.64
5	−3.58		−2.93			−2.60
	CV					
	10.35		7.58			6.35
ADF						
	At Level			At First Difference		
	t-Statistic		Prob.	t-Statistic		Prob.
ln CASE	−2.1259		***0.5294***	−5.2268***		***0.0001***
ln CO2	−4.3061***		***0.0033***	−9.7160***		***0.0000***
ln FOS	−5.0940***		***0.0002***	−17.3703***		***0.0000***
ln REN	−9.1538***		***0.0000***	−16.6109***		***0.0000***

Note: *, ** and *** represents 1%, 5% and 10% level of significance.

Subsequently, we proceed to assess the long-run connection between CO_2 and FOS, REN and CASE. Unlike prior studies, we applied the Fourier ADL cointegration test to identify the long-run connection between CO2 and FOS, REN and CASE. The benefit of the Fourier ADL cointegration test is that it can capture long-run association between series, the series are nonlinear and also take into account unknown structural breaks in series. The outcome of the Fourier ADL cointegration is presented in Table 3. The Test Statistic outcome is −5.837 which is greater than the critical value at significance level of 1%, 5% and 10% respectively. Since the T-statistics is greater than the %, 5% and 10%, the null hypothesis “No Cointegration” is rejected at all the significance level. This demonstrates that CO_2 and FOS, REN, and CASE move together in the long-run.

After the long-run association between CO_2 and the regressors is established, we applied both Markow Switching Regression and Nonlinear ARDL to capture the influence of REN, FOS and CASE on CO_2 emissions. The outcomes of the Nonlinear ARDL are unveiled in Table 4. The results unveil that positive (negative) shift in renewable energy usage decrease (increase) CO_2 emissions in the United Kingdom. This result complies with the finding of [43] for Chile who established that a positive shift in renewable energy contributes to environmental sustainability in the United Kingdom. Similarly, the study of [44] in the United States established that positive (negative) in renewable energy leads to decrease (increase) in CO_2 emissions in the United Kingdom. Contrarily, our study contradicts the research of [45] who established positive interrelation between renewable energy utilization and CO_2. The study of [46] also validates the positive linkage between CO_2 and renewable energy use. The negative connection is most likely due to the fact that renewable technology uses pure and cleaner energy sources that are committed to meeting current and future needs, as well as being a source of pollution mitigation. In the United Kingdom's perspective, this result is realistic because the nation has implemented a number of strategies to increase renewable energy utilization and mitigate pollutant fossil fuel utilization, such as enacting the carbon tax, shifting electricity production to renewables, and decreasing consumption of coal-based electricity.

Table 3
Fourier ADL outcomes.

	T-Statistics	Frequency	Min AIC
Model	−5.837	1	16.612
	CV		
	1%	5%	10%
	−5.54	−4.89	−4.55

Note: CV stands for critical value.

As expected, positive (negative) shocks in fossil fuel (FOS) increase CO_2 emissions in the United Kingdom. The study of [47] for Mexico complies with this finding by establishing that an upsurge in FOS leads to degradation of the environment. The study of [22] for highly decentralized economies and [48] for Malaysia who established that increase in nonrenewable energy triggers CO_2 emissions. The probable reason for this association is that combustion of fossil fuels such as coal and oil has raised the concentration of CO2 in the United Kingdom and the rest of the globe during the last century. Since coal or oil burning creates CO2 by mixing carbon in the air with oxygen, this happens. In addition, negative (positive) variation in CASE leads to decrease (increase) in CO2 emissions. This outcome is as anticipated given that the increase in COVID-19 cases has led to shut down of several production sectors in the United Kingdom which utilizes nonrenewable energy consumption.

As a robustness check, we applied the MSR. The MSR outcomes are depicted in Table 4. In the first and second regimes, decrease in CO_2 emissions by −0.007808% and −0.007808% is attributed to 1% upsurge in renewable energy utilization. Furthermore, in the first and second regimes, 1% increase in fossil fuel increase CO_2 emissions by 0.006910% and 0.012126% respectively. This outcome is similar with the outcomes of the nonlinear ARDL estimate. Lastly, in the first regime, 1% upsurge in CASE decrease CO_2 emissions in United Kingdom by −0.000570% when other indicators are held constant. Contrarily, in the second regime, 1% upsurge in CASE contributes to CO_2 emissions in the United Kingdom by 0.000009765% when other factors are held constant.

The present research proceeds by assessing the causality between CO_2 and FOS, REN and CASE by utilizing frequency-domain causality test in Table 5. The benefit of this approach is that the causal interrelationship between CO_2 emissions and the variables of investigation can be captured at dissimilar frequencies. The outcomes unveil that at all frequencies, CASE Granger cause CO_2. This implies that CASE is a good predictor of CO_2 in United

Table 4
Nonlinear ARDL and Markow switching regression.

Nonlinear ARDL				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
lnREN_POS	−0.018160	0.005500	−3.302120	0.0010
lnREN _NEG	0.019816	0.004635	4.275817	0.0000
lnFOS_POS	0.038121	0.003569	10.68102	0.0000
lnFOS_NEG	0.037298	0.004067	9.171859	0.0000
lnCASE_POS	−0.008250	0.000912	−9.046052	0.0000
lnCASE_NEG	0.000001	0.000883	0.019018	0.9848
C	749.3386	36.42778	20.57053	0.0000
CointEq(-1)*	−0.236326	0.035634	−6.632100	0.0000
F-Bounds Test	Null Hypothesis: No levels relationship			
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	5.45579	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99
Markow Switching Regression				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
lnFOS	0.006910	0.000486	14.23314	0.0000
lnCASE	−0.000570	0.000117	−4.853666	0.0000
lnREN	−0.007808	0.000643	−12.14008	0.0000
C	143.3397	11.65890	12.29445	0.0000
		Regime 2		
lnFOS	0.012126	0.001365	8.883434	0.0000
lnCASE	0.000009765	0.000399	0.244459	0.8069
lnREN	−0.010478	0.001658	−6.319882	0.0000
C	−30.67693	27.93687	−1.098080	0.2722

Table 5
BC causality test.

	Long-term		Medium-term		Short-term	
Direction of causality	$w_i = 0.01$	$w_i = 0.05$	$w_i = 1.00$	$w_i = 1.50$	$w_i = 2.00$	$w_i = 2.50$
$lnCASE \rightarrow lnCO_2$	11.202*** (0.003)	11.050*** (0.004)	6.769** (0.033)	5.137* (0.076)	3.851 (0.145)	5.188* (0.074)
$lnFOS \rightarrow lnCO_2$	15.018*** (0.000)	15.028*** (0.000)	1.327 (0.514)	0.235 (0.888)	1.512 (0.4695)	2.020 (0.364)
$lnREN \rightarrow lnCO_2$	22.338*** (0.000)	22.125*** (0.000)	12.480*** (0.001)	4.459 (0.107)	14.224*** (0.000)	17.468*** (0.000)

Note: <> and () represents Wald test stat and Prob-value. *, ** and *** represents 1%, 5% and 10% level of significance. CV stands for critical value.

Kingdom. Also, renewable energy use can predict CO_2 in all frequencies; however, fossil fuel can only predict CO_2 in the long-term. These outcomes have strong policy suggestions on policy suggestions.

5. Conclusions and policy implications

With the significant progress made in the adoption of renewable energy in the UK alongside a considerable decline in CO_2 emissions experienced in 2020 which was majorly plagued by the ravaging COVID-19 pandemic, it became pertinent to examine the effect of renewable energy on CO_2 emissions in the UK while accounting for COVID-19. The Fourier ARDL cointegration test, the Markov switching regression, Nonlinear ARDL and the BC causality test, which are advanced econometric analysis, were employed in the empirical investigation to achieve this objective. The results demonstrate that positive (negative) shift in renewable energy usage decrease (increase) CO2 emissions while positive (negative) shocks in fossil fuel (FOS) increase CO2 emissions. Moreover, negative (positive) variation in COVID case leads to decrease (increase) in CO2 emissions. The findings of the regime switching regression reveal that in the presence of COVID-19, renewable energy lessens emissions while fossil fuel upsurges it in both regimes. However, COVID-19 was found exhibit mixed effects, reducing emissions in the first regime but worsening it in the second regime. Furthermore, an uni-directional causal impact was found to run from all the variables — renewable energy, fossil fuel and COVID-19 - to CO_2 emissions. These findings lend empirical support to the practical experiences of the UK who has made giant strides in lowering its CO_2 emissions by increasing adoption of renewables and reducing energy from fossil fuel sources. Also, reductions in emissions were experienced in the first wave of the pandemic while they are rising again with the second and third waves.

These findings bear several policy implications for the UK especially in the face of the pandemic. It is crucial for palliatives and support programs to incorporate measures for accelerating the development and deployment of renewable energy capacities and technologies. The UK government needs to increase its investment in the renewable energy sector not only to sustain the progress made so far, but also to boost employment and activities in the sector. These investments could take the form on installing additional solar and wind plants, raising taxes on fossil fuel energy sources and prioritizing the maintenance of nuclear and hydro power facilities to increase effectiveness, efficiency and sustainability. Innovative systems should also be explored through research and development on how to improve energy systems.

More stringent measures are also needed to be undertaken to mitigate the attendant ills of the pandemic on both human and the environment. Selective partial lockdown can be introduced rather than total shutdown of the economy with strict enforcement of both pharmaceutical and pharmaceutical COVID-19 protocols. This has a trifold benefit of ensuring a reduction in the number of positive cases and deaths, keeping the essential sectors of the economy active while also limiting CO_2 emissions. These measures will not only assist the UK in meeting its 50% energy target from renewables in 2030 and place it on track to achieve its zero net emissions by 2050, but also speed up efforts to attain the sustainable development goal (SDG) 7 of affordable and clean energy by 2030. The UK government should further encourage its citizens to use more energy and carbon efficient technologies so as tackle CO_2 emissions. Moreover, sufficient funding should be dedicated to achieving sustainable development goals such as SDG13 and SDG7. The individuals should also adopt sustainable lifestyles to promote environment friendly behavior across the country [16].

This study employed aggregated COVID-19 and CO_2 data to achieve the stated objective of investigating the effect of renewable energy on CO_2 emissions in the UK while accounting for COVID-19. Future studies can focus on utilizing disaggregated data of the UK to analyze the COVID-CO_2 nexus in Wales, Scotland, England and Northern Ireland. More so, given that this study focuses on the UK only, future research can extend the scope of this research to cover other countries, regions as well as conduct a comparative analysis between and among countries. The COVID-induced impact on CO_2 emissions can be compared among high COVID incidence countries such as the UK and the United States, or between the UK and low COVID incidence countries such as New Zealand.

Data availability

Data are available upon request from the corresponding author.

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CRediT authorship contribution statement

Tomiwa Sunday Adebayo: Formal analysis, Investigation, Resources, Writing – original draft. **Hauwah K.K. AbdulKareem:** Resources, Writing – original draft, Writing – review & editing. **Bilal:** Resources, Writing – original draft, Supervision, Writing – review & editing. **Dervis Kirikkaleli:** Software, Supervision. **Muhammad Ibrahim Shah:** Conceptualization, Formal analysis, Investigation, Resources, Data curation, Software, Writing – original draft, Supervision, Writing – review & editing. **Shujaat Abbas:** Writing – review & editing, Visualization, Resources, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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