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Research article

Time-varying disaggregation of the income-emissions nexus: New evidence from the United Kingdom

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ABSTRACT

This paper's objective is to investigate the validity of the Environmental Kuznets Curve (EKC) hypothesis utilizing three unique approaches in this era of accelerating climate change and economic volatility. The first step is to introduce and employ a new cointegration test which allows smooth and sharp structural changes through a dummy variable and a Fourier function. Using a time-varying causality approach, the second stage is to assess the EKC hypothesis's validity for each year of a given period, as opposed to the entire period. The third stage is to conduct time-varying analyses not only of the effect of Gross Domestic Product or aggregate income on environmental degradation but also of the effects of the four major economic units' incomes, namely those of the government, non-financial corporations, households, and the rest of the world. This research derives three conclusions using the United Kingdom as a case study from 1830 to 2016. The impacts of aggregate income and the incomes of the three economic units on carbon emissions are consistent with the EKC hypothesis. Second, each of these effects occurs at different times. Thirdly, the EKC hypothesis regarding the association between the nation's trade income and carbon emissions cannot be validated. To provide policymakers with a dynamic, unit-specific, and effective strategy for mitigating environmental degradation, the paper proposes testing the EKC hypothesis for each year over a specific time period, as well as for the effects of both aggregate income and the disaggregate income of four major economic units.

1. Introduction

The EKC hypothesis examines the relationship between changes in income and environmental degradation. In the existing literature, income is predominantly approximated by economic growth or aggregate income (Naveed et al., 2022; Özcan and Öztürk, 2019; Sarkodie and Strezov, 2019). This approach implies that the magnitude and direction of the impact of a change in the income of all economic units on environmental degradation are identical. Consequently, the principal motivation for this paper consists of three components. First, the effect of a change in aggregate income on environmental degradation may differ from the effect of a change in the incomes of individual economic units. Governments, non-financial corporations, households, and the rest of the world comprise these units. Second, the effect of a change in the income of each of these four distinct units on environmental degradation may vary. Third, and most importantly, the impact of a change in aggregate income or individual units' income on environmental degradation may vary over time.

These three components matter for two things. First, unit-specific and time-varying effects could significantly alter the validity of the EKC hypothesis. Second, environmental policy strategies disregarding this fact may be ineffective at preventing environmental degradation because of improper timing or misdirection. Since the Financial Crisis of 2008–2009, the global economy has been subjected to both increased climate change tendencies and financial and economic shocks (IMF, 2022). Furthermore, IMF (2022) forecasts that economic instability will persist between high inflation, high-interest rates, and economic business cycles (expansions or contractions). As a result, unit-specific and time-specific policy strategies are now more important than ever (IPCC, 2022; IMF, 2022). Because environmental change and economic instability can significantly alter the income-environment nexus, requiring time-sensitive strategies.

The paper examines the UK economy for the period 1830–2016 based on three factors that all contribute to testing the time-varying and disaggregated EKC hypothesis for the country. First, the British economy was the first industrialized economy in the nineteenth century, with the

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highest per capita income. Second, since 1830, there have been statistically consistent data for all variables of the British economy. Massive changes in income necessitate structural (technological) modifications to economic models that are realizable in the long-run. Consequently, an exhaustive test of the EKC hypothesis would require observations over a very extended time frame. Third, it was estimated that the United Kingdom was responsible for nearly two-thirds of all pre-1850 carbon emissions due to its massive exports of carbon-intensive goods. Considering the average of its carbon emissions over the past 30 years, the country is currently the sixth-largest economy and the sixth-largest emitter of CO_2 in the world (World Bank, 2023).

To test unit-specific and time-varying EKC hypotheses, this paper employs four methodologies. The first method involves using each economic unit's expenditures as a proxy for its income. A time-varying causality analysis constitutes the second strategy. The third strategy is to propose a new cointegration test which allows for smooth and sharp structural changes. The fourth strategy is to conduct a robust empirical analysis by validating the EKC hypothesis with the suggested test, estimating long-run coefficients by using full-sample and also in a time-varying context, conducting causality analysis, and finally conducting time-varying causality analysis.

The article makes three contributions to the body of knowledge. The first contribution consists of testing the time-varying EKC hypothesis, which describes how the different levels of aggregate and individual unit income influence environmental degradation each year over a specific time period instead of an entire period. The second contribution is to achieve the first contribution by using the time-varying income levels of the four economic units — governments, non-financial firms, households, and the rest of the world — rather than aggregate income. The third contribution is to introduce a new cointegration test, which is an augmentation of the Gregory-Hansen (1996) cointegration test with a Fourier function. The fourth contribution demonstrates why policymakers should adopt time- and unit-specific strategies rather than aggregate and static ones to combat environmental degradation during a time of accelerated climate change and economic instability.

In the second section of the paper, a literature review is conducted. The third section explains analytical and empirical methods. The fourth and fifth sections present and discuss empirical findings, respectively. The final section concludes.

2. Literature review

Table 1 presents a concise overview of the literature study on the Environmental Kuznets Curve (EKC) hypothesis specifically for the United Kingdom. Additionally, a thorough review on the EKC hypothesis for the other countries can be found in Appendix 1. Since the seminal work of Grossman and Krueger (1995), validity of EKC hypothesis has been investigated with wide range of methodologies including OLS (Cheng et al., 2023; Wang et al., 2023; Zeraibi et al., 2023), ARDL and NARDL (Chen et al., 2022; Ehigiamusoe et al., 2023; Frodyma et al., 2022), AMG and PMG (Ali et al., 2023; Aydin et al., 2023; Pirgaip et al., 2023), and GMM (Adedoyin and Zakari, 2020; Danish and Wang, 2019; Zhang et al., 2022) with various causality techniques including Granger (Ehigiamusoe et al., 2023; Rahman and Alam, 2022; Ramzan et al., 2022), Dumitrescu-Hurlin (Bekun et al., 2023; Wang et al., 2023; Zeraibi et al., 2023), and Toda-Yamamoto (Beşe and Kalayci, 2021; Nasreen et al., 2017).

There are few studies examining the validity of the EKC hypothesis in the United Kingdom, though the EKC hypothesis has been the subject of extensive research. Some studies supported the EKC hypothesis for the United Kingdom (Abid et al., 2021; Abid, 2017; Adedoyin and Zakari, 2020; Awaworyi Churchill et al., 2018; Aydin et al., 2023; Ben Amar, 2021; Cheng et al., 2023; Ibrahim and Ajide, 2021; Jaunky, 2011; Nguyen et al., 2020; Pirgaip et al., 2023; Ramzan et al., 2022; Sephton and Mann, 2014; Vanli, 2022), whereas other researches rejected it (Adedoyin and Zakari, 2020; Adewuyi, 2016; Beşe and Kalayci, 2021; Caglar et al., 2021; Isiksal, 2021; Musibau et al., 2021; Robalino-López et al., 2015; Shahbaz et al., 2020). In addition, only five studies employed more than one hundred observations.

There emerge three research gaps in the literature. First, no research has been conducted using a time-varying disaggregated income approach to test the EKC hypothesis. Mikayilov et al. (2018) investigate the emissions-income relationship based on the ratio between growth in emissions relative to growth in GDP, the income elasticity of emissions.[1] We estimate the impact of both aggregate income and the disaggregate income of the four individual economic units on carbon emissions using level data rather than growth rates.[2] Second, only three studies in the existing.

literature use a disaggregated expenditure approach to test the EKC hypothesis. The theoretical basis for how the expenditure approach can explain the relationship between income and the environment is not explained in these works. Importantly, they do not examine the EKC hypothesis

through a time-varying causality analysis. Third, a disaggregated income approach has not been used to test the EKC hypothesis for the United Kingdom.

This paper fills in these three research gaps by achieving four points. First, this study adopts a time-varying causality approach to test the EKC hypothesis for each component of gross domestic product (GDP). Second, the study applies a time-varying and disaggregate approach to testing the

validity of the EKC hypothesis for the UK economy. Third, the study takes the expenditures of economic units as a proxy for the part of their income that directly influences environmental degradation.

3. Empirical methodology

3.1. Analytic methodology

3.1.1. Expenditures as a surrogate for income

The International Monetary Fund, the World Bank, the United Nations, and the European Union all use the System of National Accounts (SNA), a macroeconomic accounting technique, to benchmark the primary economic activities and the economic units that conduct these activities. In the SNA approach, governments, non-financial corporations, households, and the rest of the world are the primary economic units (Daniele, 2017). GDP is the sum of government purchases, private investment expenditures, private consumption expenditures, and net exports (exports minus imports) according to the expenditure approach. The conventional method for testing the EKC hypothesis involves calculating per capita income by dividing the gross domestic product by population, followed by a regression of per capita income on carbon emissions. This approach assumes that a change in the income of each of the four economic units will have the same effect on environmental degradation simultaneously, in the same magnitude, and in the same direction.

Governments, non-financial corporations, households, and the rest of the world use their income to finance investment and consumption expenses. Taxes collected by governments include sales, production, and income taxes. Non-financial corporations generate various types of income, including profit, dividend, interest, royalties, and income from

[1] They aim to demonstrate if there is a relative or absolute decoupling between aggregate income (GDP) and emissions, which occur when emissions grow less rapidly than GDP and when emissions decrease relative to the pace of economic growth, respectively.

[2] It may not be optimal to estimate the long-term or cointegration relationships between income and emissions based on their short-term or annual growth rates. In economics, short-run refers to a period of one year or less, whereas long-run typically refers to a period of five years or more (for example, development plans are made for a five-year period).

Table 1
Literature review of EKC hypothesis in the UK.

Author & Year	Period	Variables	Methodology	Results
Pirgaip et al. (2023)	1971–2020	GDP, government spending, renewable energy consumption, CO_2 emissions	AMG	EKC only validated for UK, US, and Canada
Cheng et al. (2023)	2005–2015	Co2 emissions, GDP per capita, population, labor force, population aged 15–64, renewable energy consumption	OLS, STIRPAT	EKC validated only on G7 Countries
Aydin et al. (2023)	1990–2018	GDP, renewable energy, ecological footprint, multifactor productivity, research and development expenditure	AMG, Emirmahmutoğlu & Köse causality	EKC validated
Ramzan et al. (2022)	1995–2020	Ecological footprint per capita, renewable energy consumption, number of reported patents on environmental technologies, KOF financial Globalization Index, Revenue generated from environmental taxes, GDP per capita	Granger causality, Residual-based bootstrap modified likelihood ratio	Inverted U-shaped
Vanli (2022)	1948–2018	GDP per capita, energy consumption, CO_2 emissions per capita, imports of goods per capita	ARDL, VECM	EKC validated
Beşe and Kalayci (2021)	1960–2014	GDP, squared GDP, CO_2 consumption, energy consumption	Toda Yamamoto causality, Var Granger causality	EKC not validated
Abid et al. (2021)	1990–2019	CO_2 emissions, technological innovation, financial development, FDI, trade openness, GDP, urban population, energy consumption	FMOLS, DOLS, Dumitrescu-Hurlin causality	EKC validated
Fatai Adedoyin et al. (2021)	1995–2018	CO_2 emissions, GDP per capita, primary energy consumption, international tourist arrivals, economic complexity index, degree of global financial crisis, dummy variables for post-Brexit countries	Pooled, Random, and Fixed OLS, GMM	EKC validated
Isiksal (2021)	1993–2017	CO_2 emissions, real GDP, renewable energy consumption, military expenses	CCEMG, Dynamic CCEMG, CS-ARDL	EKC not validated
Musibau et al. (2021)	1980–2018	CO_2 emissions, GDP per capita, squared GDP per capita, renewable energy, Non-renewable energy, energy innovation, energy efficiency	Quantile on Quantile Regression	U Shaped
Ibrahim and Ajide (2021)	1990–2019	CO_2 emissions, non-renewable energy, renewable energy, trade openness, research and development expenditure, eco-innovation, GDP per capita, squared of GDP per capita, FDI, gross fixed capital formation, services value added	MG, PMG	EKC validated
Caglar et al. (2021)	1982–2014	Environmental footprint, GDP per capita, renewable energy consumption, non-renewable energy consumption, financial development, domestic credit to the private sector, information and communication technologies	PMG, Granger causality	EKC not validated
Nguyen et al. (2020)	2000–2014	CO_2 emissions, FDI, trade, GDP per capita, imported ICT goods, exported ICT goods, innovation, spot oil price, energy intensity level of primary energy, credit offered by bank to private sector, stock-market capitalization, liquid liabilities	FMOLS, Quantile Regression	Inverted U-shaped
Shahbaz et al. (2020)	1870–2017	R&D expenditures per capita, GDP per capita, CO_2 emissions per capita, energy consumption per capita, broad money per capita, financial development per capita	Bootstrapped ARDL	U-shaped
Adedoyin and Zakari (2020)	1985–2017	CO_2 emissions per capita, real GDP, energy use, economic policy uncertainty	ARDL, ECM, Granger causality	EKC not validated
Ben Amar (2021)	1751–2016	CO_2 emissions, economic growth, population	Dynamic correlation, Cross-wavelet coherency	Inverted U-shaped with turning point mid-20th century
Awaworyi Churchill et al. (2018)	1870–2014	CO_2 emissions, GDP, squared GDP, trade, population, financial development	MG, CCEMG, AMG, PMG	Inverted U-shaped
Abid (2017)	1990–2011	CO_2 emissions, GDP per capita, inflation, education, gross fixed capital formation, public expenditure, financial development, FDI, trade openness, official development assistance, political stability and absence of violence, government effectiveness, quality of regulation, control of corruption	GMM	EKC validated
Sephton and Mann (2014)	1830–2003	CO_2 emissions, SO_2 emissions, GDP per capita	OLS, MARS	Inverted U-shaped with turning point 1966 and 1967
Fosten et al. (2012)	1830–2003	CO_2 per capita, real GDP per capita, gas prices, SO_2 per capita	ECM	Inverted U-shaped with turnint point 1954
Jaunky (2011)	1980–2005	CO_2 emissions, GDP	VECM, DOLS, Granger causality	EKC validated

partnerships. It is possible for households to earn wages, salaries, self-employment income, social security benefits, pensions, investment income (interest, dividends, etc.), and welfare payments. The rest of the world refers to all countries besides a particular country. According to our analysis, a home country's trade relationship with the rest of the world makes sense due to the trade income it will generate. If a nation's export income exceeds or falls short of its import payments, its trade income will be positive or negative, respectively.

The source of a change in the expenditures of economic units is an increase or decrease in their income. Because economic units can primarily use their income for savings and expenditures. Expenditures are the portion of income that is not saved. Thus, proxying the income of economic units by their expenditures is relevant for investigating the effect of changing income levels on carbon emissions for three main reasons.

First, total expenditures influence the quantity of carbon emissions caused by energy consumption during the production of goods and services. Because the total sum of these expenditures constitutes aggregate demand, which determines the quantity of aggregate supply of goods and services, aggregate energy demand for production, and consequently, the level of carbon emissions, in other words, expenditures represent a portion of income that supports the activities of economic units that result in carbon emissions (Blanchard and Sheen, 2013). Consequently, using expenditures as a proxy for income may be a more direct and efficient method for investigating the relationship between income and carbon emissions.

Second, the effect of a change in net wealth (assets minus liabilities) of economic units on carbon emissions is controlled by consumption and

Table 2
Data description.

Variable	Definition	Measurement	Source
CO_2	Carbon Emissions	Million Tones	National Infrastructure Commission (2022)
ENGY	Energy Use	Megawatt Hours	National Infrastructure Commission (2022)
GDP	Gross Domestic Product	Million Pound	Millennium of UK's Macroeconomic Data (Bank of England, 2022)
GINC	Government Income	Million Pound	Millennium of UK's Macroeconomic Data (Bank of England, 2022)
HINC	Household Income	Million Pound	Millennium of UK's Macroeconomic Data (Bank of England, 2022)
CINC	Corporate Income	Million Pound	Millennium of UK's Macroeconomic Data (Bank of England, 2022)
POP	Population	Individual (1000)	Millennium of UK's Macroeconomic Data (Bank of England, 2022)
TINC	Trade Income	Million Pound	Millennium of UK's Macroeconomic Data (Bank of England, 2022)

investment expenditures as proxies for income. As a proxy for total income, the GDP does not include changes in net wealth. The GDP by income approach includes the aggregate income initially earned by non-financial firms through the sale of goods and services on the market for goods and services, which is then allocated to the factors of production. Nevertheless, according to the life-cycle hypothesis, consumption expenditures are determined not only by non-financial income earned through production activities but also by financial income earned through financial investment (Ando and Modigliani, 1963; Modigliani and Brumberg, 1954).

In roughly the last four decades, the process of financialization has demonstrated that financial income is also a significant determinant of investment expenditures. Financialization refers to the increasing use of savings for financial investment instead of non-financial investment. This process transforms the finance sector into a growth sector itself, decelerating overall and industrial economic expansion. Because greater profitability of financial investment relative to non-financial investment could reduce the propensity of non-financial firms to make non-financial investments, thereby reducing their energy demand and carbon emissions (Dore, 2008; Krippner, 2005; Palley and Palley, 2013). This is especially significant for the British economy, where financial assets and liabilities are a primary source of income due to the rising trend of financialization.

Third, the EKC hypothesis necessitates both a disaggregate and historical analysis, especially for today's developed economies, such as the United Kingdom, the first industrialized nation in the 18th century. As a proxy for income, expenditures permit the disaggregation of the effects of each economic unit on carbon emissions. This disaggregation may not be possible when attempting to calculate the income of each economic unit based on their financial and non-financial balances due to the scarcity of data for these balances, especially historical data. For example, financial wealth data for UK households are available as of 1920, whereas disposable income data is available as of 1855 (See Sheet A57 in Bank of England (2022)). Flow of funds regarding the UK's private sector is available only as of 1952 (Sheet A58 in Bank of England (2022)). Instead of losing a substantial number of observations, which may significantly reduce the robustness of time-varying causality, we take expenditures as a surrogate for each of the four economic units that are available in a statistically consistent manner beginning with 1830. Furthermore, this surrogate might be more required for those nations that do not have systematic historical data regarding the financial balances of economic units.

3.1.2. Models, hypotheses, and data

The contribution of governments, non-financial corporations,

Table 4
Unit root test results.

Variable	Opt. Frequency	F Test	FADF Test Stat.	ADF Test Stat.
CO2	2	5.062	–	−1.151 (0.916) [5]
ENGY	4	2.621	–	−1.508 (0.824) [7]
GDP	2	3.654	–	0.56 (0.988) [8]
GDP2	2	3.729	–	1.5 (0.999) [8]
GINC	5	0.701	–	−1.067 (0.729) [4]
GINC2	5	0.758	–	−0.95 (0.77) [4]
HINC	2	3.968	–	1.346 (0.999) [6]
HINC2	2	2.109	–	2.035 (1) [6]
CINC	1	3.698	–	−0.412 (0.903) [13]
CINC2	1	3.656	–	0.016 (0.958) [13]
POP	3	8.523	−2.468 [3]	–
TINC	2	3.152	–	−1.833 (0.364) [6]
TINC2	5	2.773	–	−2.164 (0.22) [4]

Note: Numbers in the parentheses show the p-values, and numbers in the brackets indicate the optimal lag length.

Table 5
Test results of FSB-GH cointegration test.

Model	Test Equation	Test Statistics	Optimal Frequency	Break Data
$\ln CO_{2t} = f(\ln GDP_t,$	FC	−8.962*	3	1861
$\ln GDP_t^2, \ln ENGY_t,$	FC/T	−10.091*	3	1861
$\ln POP_t)$	FC/S	−10.112*	2	1967
$\ln CO_{2t} = f(\ln GINC_t,$	FC	−8.533*	3	1863
$\ln GINC_t^2, \ln ENGY_t,$	FC/T	−9.131*	3	1863
$\ln POP_t)$	FC/S	−9.498*	3	1871
$\ln CO_{2t} = f(\ln HINC_t,$	FC	−9.501*	3	1926
$\ln HINC_t^2, \ln ENGY_t,$	FC/T	−10.970*	3	1859
$\ln POP_t)$	FC/S	−10.391	2	1967
$\ln CO_{2t} = f(\ln CINC_t,$	FC	−9.530*	2	1970
$\ln CINC_t^2, \ln ENGY_t,$	FC/T	−9.577*	2	1973
$\ln POP_t)$	FC/S	−9.698*	2	1972
$\ln CO_{2t} = f(\ln TINC_t,$	FC	−7.827*	1	1866
$\ln TINC_t^2, \ln ENGY_t,$	FC/T	−8.313*	2	1961
$\ln POP_t)$	FC/S	−9.157*	2	1914

Note:* denotes the significance at the 1% level. The critical values are tabulated in Appendix 3.

Table 3
Descriptive statistics.

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
CO2	5.832	6.109	6.493	4.179	0.642	−1.275	3.435	52.159	0.000
ENGY	7.006	7.174	7.921	5.242	0.736	−0.700	2.543	16.917	0.000
GDP	12.474	12.354	14.439	10.590	1.094	0.151	1.963	9.081	0.011
GINC	10.836	10.765	12.837	8.602	1.390	−0.107	1.519	17.440	0.000
HINC	12.071	11.940	14.017	10.415	1.010	0.278	2.141	8.156	0.017
CINC	9.928	9.391	12.654	7.084	1.679	0.302	1.698	16.044	0.000
POP	10.662	10.738	11.091	10.092	0.284	−0.461	1.909	15.882	0.000
TINC	3.063	8.370	10.760	−11.560	8.672	−0.809	1.740	32.785	0.000

Table 6
The estimations of Long-Run Coefficients.

Model 1	Coefficients	t-statistics
Constant	−14.590*	−6.192
GDP	2.511*	5.016
GDP2	−0.106*	−6.059
ENGY	1.056*	14.199
POP	−0.160	−1.205
Model 2	**Coefficients**	**t-statistics**
Constant	−6.299*	−4.324
GINC	2.729*	15.046
GINC2	−0.123*	−16.113
ENGY	0.958*	17.716
POP	−0.893*	−5.285
Model 3	**Coefficients**	**t-statistics**
Constant	−0.928	−1.023
CINC	0.823*	9.139
CINC2	−0.046*	−11.536
ENGY	1.198*	27.290
POP	−0.486*	−4.654
Model 4	**Coefficients**	**t-statistics**
Constant	−22.869*	−8.811
HINC	4.673*	8.625
HINC2	−0.187*	−9.480
ENGY	0.839*	12.308
POP	−0.572*	−4.172
Model 5	**Coefficients**	**t-statistics**
Constant	9.679*	4.847
TINC	0.002	1.046
TINC2	−0.002*	−2.816
ENGY	1.342*	14.564
POP	−1.229*	−5.009

Note: * shows the significance at the 1% level.

Table 7
The results of the Causality Test.

Ho:	Test Statistics	Bootstrap Critical Values		
		90%	95%	99%
$GDP \nrightarrow CO_2$	36.432*	9.58	12.408	18.802
$GDP2 \nrightarrow CO_2$	66.457*	9.316	11.783	17.728
$GINC \nrightarrow CO_2$	33.514*	9.099	11.657	17.174
$GINC2 \nrightarrow CO_2$	33.518*	8.934	11.439	17.753
$HINC \nrightarrow CO_2$	45.66*	9.748	12.428	18.203
$HINC2 \nrightarrow CO_2$	49.246*	9.304	11.892	17.773
$CINC \nrightarrow CO_2$	91.078*	9.062	11.529	17.375
$CINC2 \nrightarrow CO_2$	88.573*	8.938	11.409	16.900
$TINC \nrightarrow CO_2$	356.676*	8.514	10.974	16.665
$TINC2 \nrightarrow CO_2$	179.87*	10.151	12.827	19.523

Note: * shows the significance at the 1% level. The critical values are obtained using 10,000 bootstrap simulations.

households, and the rest of the world to the rate of economic growth in the United Kingdom from 1830 to 2016 is depicted in Fig. 1. Apparently, the rate of change of GDP and the rate of change of its components differ over time. As a consequence, this study hypothesizes that time-varying changes in GDP and its components could substantially alter the relationships between income and environmental degradation, thereby impacting the validity of the EKC hypothesis. To test this hypothesis, the following four empirical hypotheses are developed. The purpose of the first two hypotheses is to test the validity of the EKC hypothesis in terms of the effects of the GDP and its components on carbon emissions. The second and third hypotheses test, respectively, whether the income-environment nexus should be investigated in a time-varying manner.

H0 1. EKC hypothesis does not hold for the effect of GDP on carbon emissions.

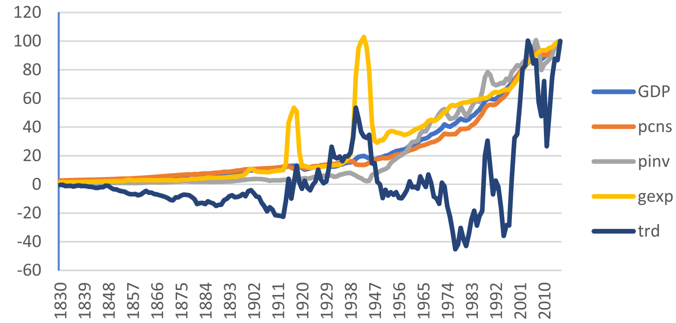


Fig. 1. The rate of change in GDP and the contributions of its components, 1830–2016 (2016 = 100).
Notes: GDP, Pcns, Pinv, Gexp, and Trd are abbreviations for gross domestic product, private consumption, private investment, government expenditures, and international trade, respectively.
Source: Bank of England (2023).

H0 2. EKC hypothesis does not hold for the effects of GDP's components on carbon emissions.

H0 3. The effect of a change in aggregate income on carbon emissions does not occur at different times than a change in the incomes of individual economic units.

H0 4. The effects of the changes in each economic unit's income on carbon emissions do not occur at different times.

We develop the five models listed below to test these four hypotheses. We consider government expenditures, private investment expenditures, private consumption expenditures, and net exports as government income, non-financial corporate income, household income, and trade income, respectively. In the models, we include nonrenewable energy consumption (engy) and population (pop) as control variables. First, as stated by Arminen and Menegaki (2019), energy consumption is a significant determinant of carbon emissions, and its exclusion from a model in which carbon emissions are the dependent variable would result in an omitted variable bias. As a result, energy consumption was utilized as a regressor in a large number of studies examining the determinants of carbon emissions (See Appendix 2 for detailed explanations).

Secondly, the exclusion of population could lead to the same issue, the omitted variable bias, as the effects of population on consumption and production determine the level of carbon emissions. An increase or decrease in population can produce a corresponding rise or fall in household consumption. An increase or decrease in consumption indicates an increase or decrease in the demand for private goods and services, which will increase private investment expenditures or international trade, or in the demand for public goods and services, which will increase government expenditures. However, as people's income increases, their propensity to consume decreases, and their consumption patterns may become greener, which explains the time-varying effects of the population (Bongaarts, 1992; Casey and Galor, 2016; Cheng et al., 2023).

Consequently, in the early phases of economic development, a population increase or decrease can produce a corresponding increase or decrease in carbon emissions. In the later phases of economic development, a population increase or decrease may result in a lesser or greater reduction in carbon emissions due to the income effect, even despite an increase in life expectancy. In the vast majority of research on the EKC hypothesis, proxies for income, carbon emissions, and energy consumption are used in proportion to population, specifically carbon emissions per capita, Gross Domestic Product per capita, and energy consumption per capita, respectively (Mikayilov et al., 2018). This study utilizes aggregate data on carbon emissions, Gross Domestic Product (GDP) and its components, and energy consumption without adjusting by population. Because it is not feasible to evaluate each component of

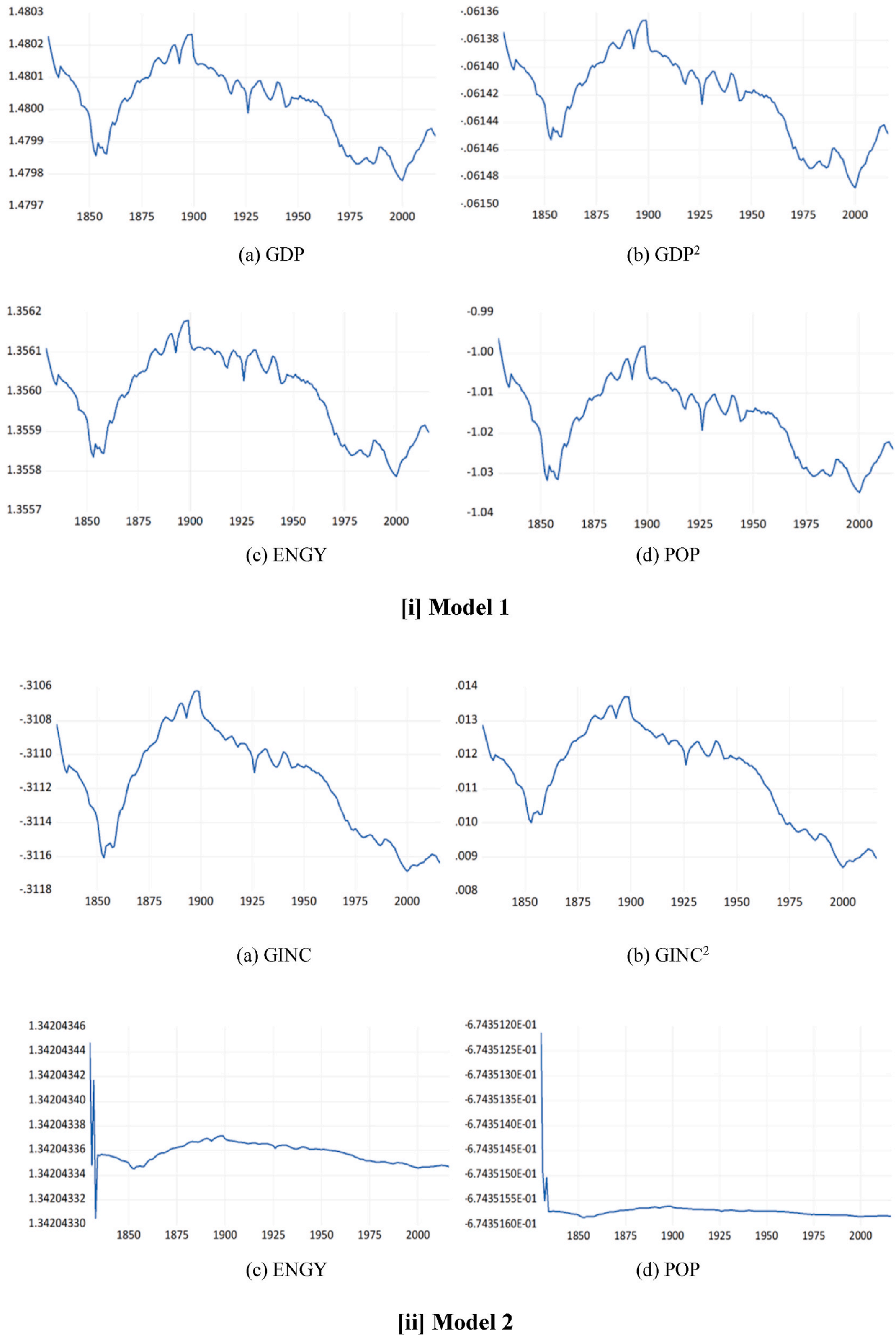
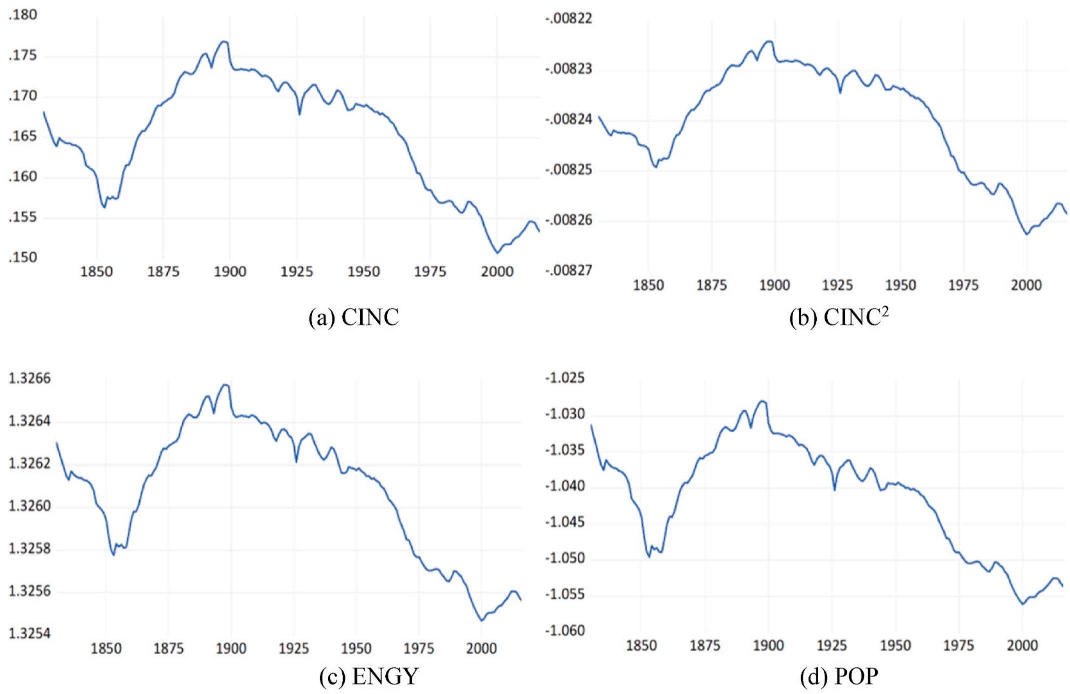


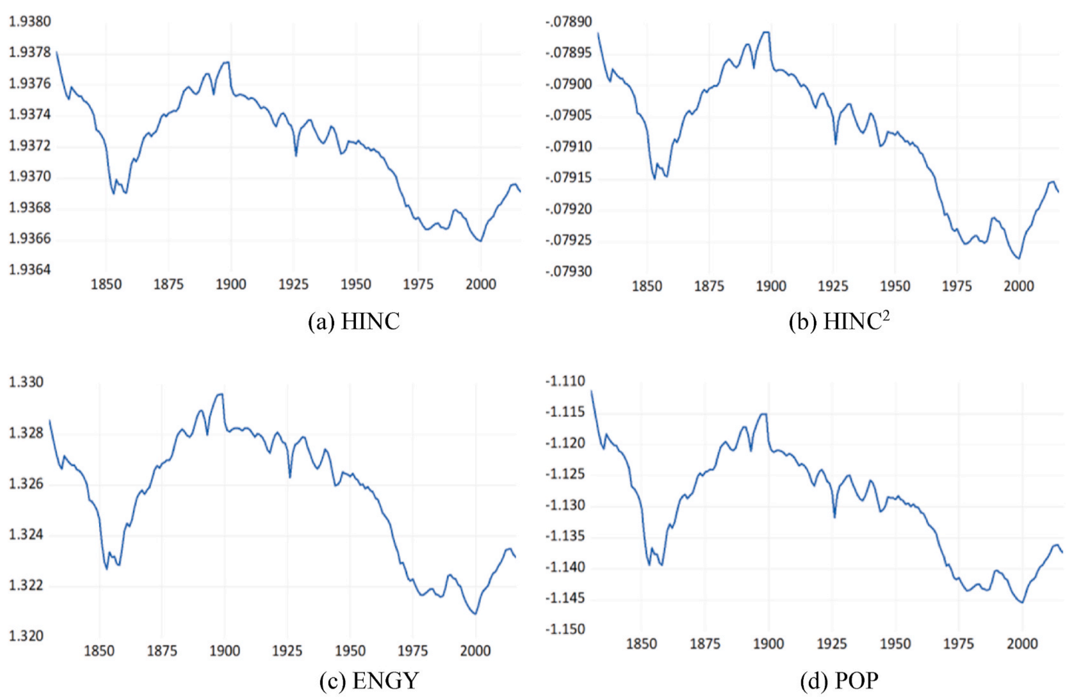
Fig. 2. Time-Varying Coefficients.

GDP on a per capita basis. That the use of population in a model where these variables are divided by population can cause a correlation problem (Sinha et al., 2019). Thus, we use population as a separate variable to account for the effect of a change in population on carbon emissions.

1. $\text{InCO}_2 = \text{f} (\text{InGDP} + \text{InGDP}^2 + \text{InEngy} + \text{InPop})$
2. $\text{InCO}_2 = \text{f} (\text{InGinc} + \text{InGinc}^2 + \text{InEngy} + \text{InPop})$



[iii] Model 3



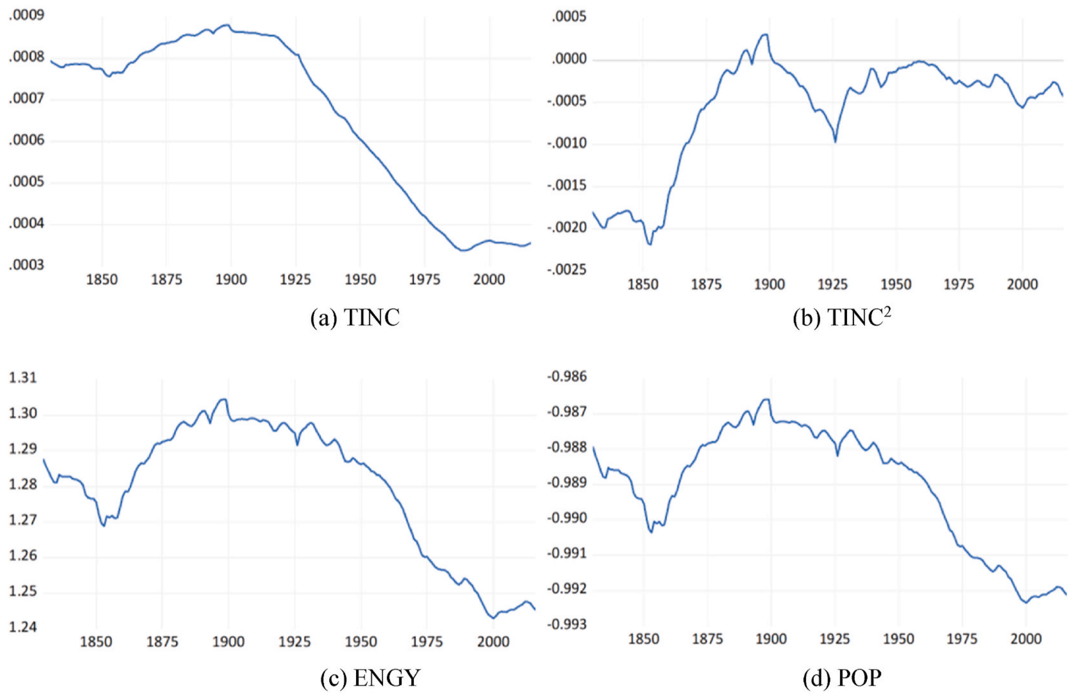
[iv] Model 4

Fig. 2. (*continued*).

3. $InCO_2 = f\ (InCinc + InCinc^2 + InEngy + InPop)$
4. $InCO_2 = f\ (InHinc + InHinc^2 + InEngy + InPop)$
5. $InCO_2 = f\ (InTinc + InTinc^2 + InEngy + InPop)$

where *InCO*$_2$, *InGDP*, *InGDP*^{2}, *InGinc*, *InCinc*, *InHinc, InTinc*, *InEngy*, and *InPop* are the natural logarithms of carbon emissions, GDP, the square of GDP, government income, corporate income, household income, trade income, energy use, and population, respectively.

The data used in this study spans from 1830 to 2016 on an annual frequency basis. The definition, measurement units, and sources of the variables are presented in Table 2.



[v] Model 5

Fig. 2. (*continued*).

3.2. Econometric methodology

We have a two-step empirical methodology. Cointegration estimation is the first stage. Estimating causality is the second step. In order to obtain the highest level of robustness for our results, we evaluate the robustness of both the first and second phases individually, too.

The estimation of cointegration consists of three stages. First, the cointegration (long-run) relationships between the variables are estimated. Cointegration coefficient estimation is the second step. The third step is to estimate whether these coefficients vary over time. This three-step estimation is designed to accomplish two goals. The initial step is to verify the robustness of the cointegration estimates. Second is the estimation of causality relationships against this backdrop of robust long-term estimates between variables.

Two stages are involved in causality estimation. The estimation of non-time-varying causality relationships between variables is the first step. The estimation of time-varying causal relationships between variables is the second step. The first estimation functions as the basis for the second estimation as well as a robustness test.

3.2.1. Unit root test

To consider the effects of the structural changes on the unit root test results, we employ the recently introduced unit root test of Enders and Lee (2012). Enders and Lee (2012) suggest augmenting the traditional augmented Dickey-Fuller unit root test with a Fourier function to capture the effects of multiple structural breaks. One can estimate the following model to apply the Fourier function augmented Dickey-Fuller (FADF) unit root test:

$$\Delta Y_t = \beta_1 + \beta_2 Y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \alpha_1 \sin(2\pi kt/T) + \alpha_2 \cos(2\pi kt/T) + u_t \quad (1)$$

where Y_t is the series to be tested, sin and cos constitutes a Fourier function, k is a particular frequency, t is the trend term, and T shows the sample size. The value of k is not known a priori and should be determined endogenously. By following the suggestion of Enders and Lee (2012), we estimate Eq. (1) for each value of k in the interval [1, 2, …,5] and select the value that minimizes the sum of squared residuals. We add the lags of the dependent variable as regressors to remedy the autocorrelation problem and determine the optimal lag length using Akaike information criteria. As can be seen from Eq. (1), in the case of the absence of the Fourier function, Eq (1) becomes the test regression of the augmented Dickey-Fuller unit root test. So, we first test the null of $H_0 : \alpha_1 = \alpha_2 = 0$ using a traditional F test. The critical values of this test are tabulated in Enders and Lee (2012). After determining the significance of the Fourier function, we can test the stationarity of the series using the FADF unit root test by examining the null hypothesis of $H_0 : \beta_2 = 0$ using a t-test. The critical values of this t-test are also tabulated in Enders and Lee (2012). If we find the trigonometric terms as non-significant, we can apply the ADF unit root test.

3.2.2. Cointegration test

Following Perron's milestone study in 1989, numerous unit root and cointegration tests have been introduced to the literature, which account for structural breaks. Cointegration tests that consider structural changes can be classified into two distinct groups. The first group involves tests that only consider sharp breaks. For instance, the cointegration tests developed by Gregory and Hansen (1996), Carrion-i-Silvestre and Sansó (2006), Hatemi-j (2008), and Maki (2012) incorporate dummy variables to capture abrupt breaks. In contrast, the second group of tests accounts for smooth breaks. For example, Tsong et al. (2016), Banerjee & Carrion-i-Silvestre (2017), and Yilanci (2023) have proposed new cointegration tests that employ a Fourier function to allow for gradual changes. Therefore, it can be stated that cointegration tests generally consider either sudden or gradual changes.

In this paper, we suggest a new cointegration test that captures both smooth and sharp breaks. For this purpose, we consider the model specification of Gregory and Hansen (1996) (GH). GH mainly use three model specifications; Model C, Model C/T, and Model C/S. Model C allows us to analyze the influence of the change in the intercept, while

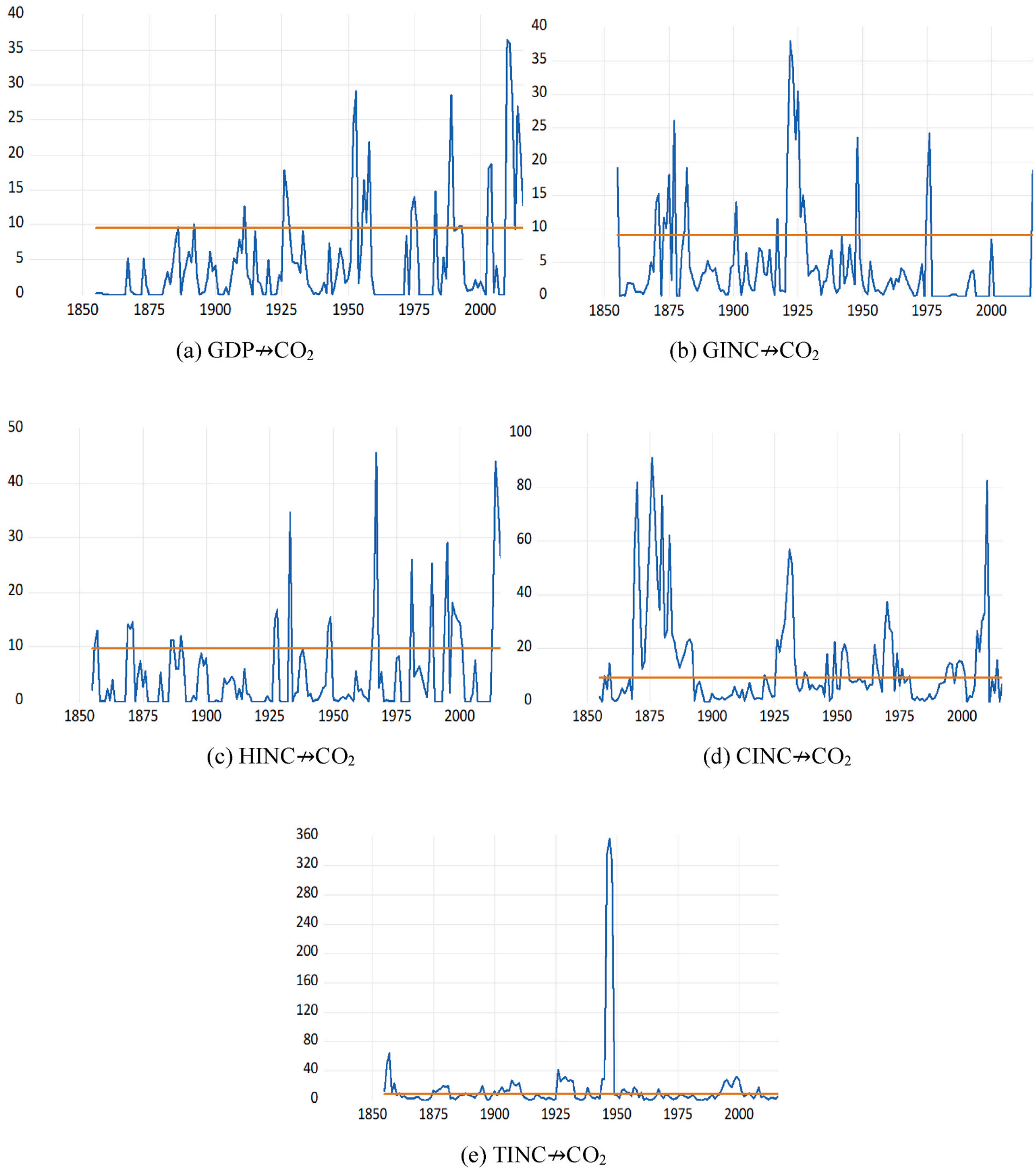


Fig. 3. Time-Varying Causality Test Results..
(Note: The red line shows the critical value obtained using 10,000 simulations.).

Model C/S Model allows us to examine the impact of a shift in both the intercept and slope. Finally, Model C/T represents a test equation that incorporates a trend component into Model C.

We modified the Model C by incorporating a Fourier function as follows:

$$Y_t = \mu_1 + \mu_2 D_t + \varphi f_t + \alpha_1 X_t + u_t \ (\text{Model FC})$$

where Y_t and X_t show the dependent and independent variables, respectively. μ_1 is the constant and μ_2 contains the effect of structural change on the constant. f_t is the Fourier function that is employed to capture the influence of smooth breaks. By following Ludlow and Enders (2000) we use single frequency and define the Fourier function as below:

$$f_t = \theta_1 \sin(2\pi kt / T) + \theta_2 \cos(2\pi kt / T)$$

where k, t, and T are a specific frequency, trend term, and sample size, respectively. D_t in Model FC denotes the dummy variable which is used for capturing the effect of structural change on the long-run relationship and is defined as below:

$$D_t = \begin{cases} 0 & if\ t \leq TB \\ 1 & if\ t > TB \end{cases}$$

where t and TB indicate time and time of structural break, respectively. The Fourier augmented Model C/T can be presented as follows:

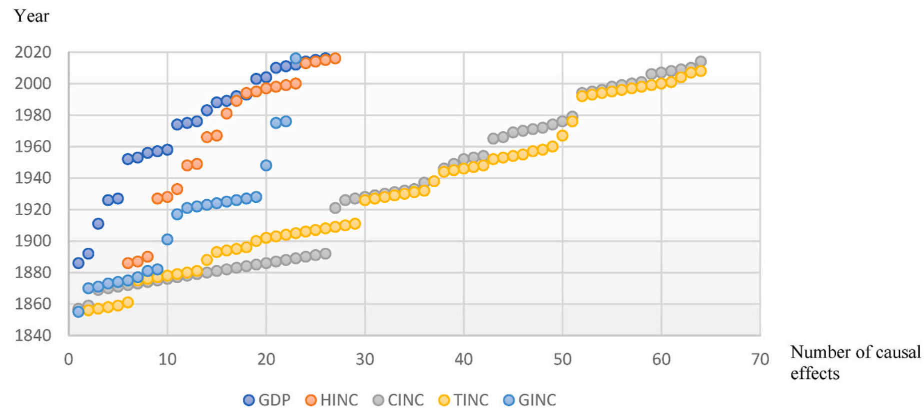


Fig. 4. Causal effects of GDP and its components on carbon emissions by year and number of causal effects.

$$Y_t = \mu_1 + \mu_2 D_t + \gamma trend + \varphi f_t + \alpha_1 X_t + u_t \ (\text{Model FC/T})$$

and, finally the regime-switching model, that is, modified Model C/S can be denoted as follows:

$$Y_t = \mu_1 + \mu_2 D_t + \varphi f_t + \alpha_1 X_t + \alpha_2 X_t D_t + u_t \ (\text{Model FC/S})$$

where α_1 denotes the slope coefficient before the structural break date and $\alpha_1 + \alpha_2$ is the slope coefficient after the break.

After estimating the cointegration test equation, we obtain the residuals of the equation and apply the augmented Dickey-Fuller unit root test to the residuals. To determine the structural change date and optimal frequency value, we estimate the test equation for each break date (TB) and frequency (k) pair and select the TB and k, which produce minimum test statistics. The minimum test statistic is also used to test the null of no cointegration. We present the asymptotic critical values in Appendix 3 using the sample size as 1000 by running 10,000 simulations by considering a different number of regressors (n = 1, 2, 3, 4) and frequency values (k = 1, 2, 3, 4, 5) and small sample properties in Appendix 4.

3.2.3. Time-varying parameter estimation

The rejection of the null hypothesis of no cointegration enables us to estimate the long-run coefficients using the ordinary least squares or any other long-run estimation techniques such as FMOLS or DOLS. However, the magnitudes or significance of the estimated coefficients may change over time. To consider such a movement and to reveal the periods when the EKC hypothesis is valid or invalid, we can estimate the coefficients using flexible least squares proposed by (Kalaba and Tesfatsion, 1989). Consider the following linear regression model:

$$y_t = x_t' \beta_t + \varepsilon_t \quad (5)$$

where y_t and ε_t are scalars, x_t is $(K \times 1)$ and β_t is $(1 \times K)$ vectors. To estimate Eq. (5) the following weighted cost function must be minimized:

$$C(\beta_1, ..., \beta_1, \lambda, T) = ssr + \lambda ssd$$

where *ssr* shows the sum of squared residuals of Eq. (5), *ssd* is the sum of squared changes in the coefficient vector between t and $t+1$. λ is a positive weighting factor which controls the level of smoothness imposed on the time-varying coefficients. If $\lambda \to \infty$, the cost function gives the *ssd* the highest priority, so FLS yields the OLS solution. However, if $\lambda \to 0$ the model perfectly fits the dependent variable (See, (Soybilgen and Eroğlu, 2019)). So, it can be easily seen that the selection of λ is a highly critical part of the FLS procedure. By following the studies of Soybilgen and Eroğlu (2019) we consider three values for λ 1, 10, and 100. The results show that the selection of the weighting parameter does not change the magnitude of coefficients much. So, we only present the results for $\lambda = 100$.

3.2.4. Lag-augmented granger causality in a time-varying context

To test the causality relationship between the variables, we employ a lag-augmented causality test suggested by Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). The multivariate test regression can be written in a compact form as follows:

$$Y_t = \tau \Gamma' + X\Phi' + Z\Psi' + \xi$$

where $Y = (y_1, y_2, ..., y_t)'_{T\times n}$, $\tau = (\tau_1, ..., \tau_T)'_{T\times 2}$ with $\tau_t = (1, t)'_{2\times 1}$ and $\Gamma = (\beta_0, \beta_1)_{n\times(q+1)}$, $X = (x_1, ..., x_T)'_{T\times nk}$ with $x_t = (y'_{t-1}, ..., y'_{t-k})'_{nk\times 1}$, $\Phi = (\delta_1, ..., \delta_k)_{n\times nk}$, $Z = (z_1, ..., z_T)'_{T\times nd}$ with $z_t = (y'_{t-k-1}, ..., y'_{t-k-d})'_{nd\times 1}$, $\Psi = (\delta_{k+1}, ..., \delta_{k+d})_{n\times nd}$ and $\xi = (\xi_1, ..., \xi_T)'_{T\times n}$. d shows the additional lag that is determined using the maximum integration levels of the variables. By assuming $Q_\tau = I_T - \tau(\tau'\tau)^{-1}\tau'$ and $Q = Q_\tau - Q_\tau Z(Z'Q_\tau Z)^{-1} Z' Q_\tau$, we can obtain the ordinary least squares estimator as follows:

$$\widehat{\Phi} = Y' QX(X'QX)^{-1}$$

To test the null hypothesis of no-causality, $H_0: R\varphi = 0$ where R is a matrix of restrictions whose dimension is $m \times n^2 k$ and $\varphi = vec(\Phi)$ by ignoring augmented lags, we can compute the following Wald test statistic:

$$\mathscr{W} = (R\widehat{\varphi})' \left[R\{\widehat{\Sigma}_\xi \otimes (X'QX)^{-1}\}R'\right]^{-1} R\widehat{\varphi}$$

where $\widehat{\varphi} = vec(\widehat{\Phi})$, $\widehat{\Sigma}_\xi = \frac{1}{T}\widehat{\xi}'\widehat{\xi}$, and $\otimes$ shows the Kronecker product. $\mathscr{W}$ has a χ^2_m distribution with m degree of freedom.

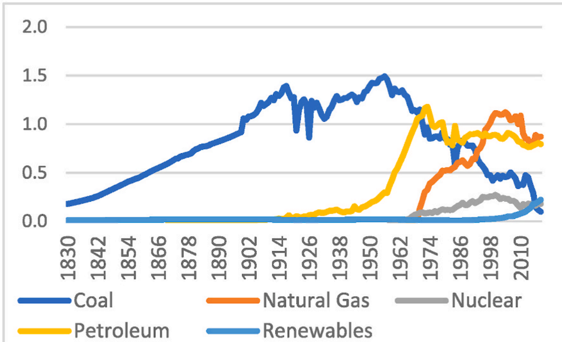
To detect the instabilities in the causality relationship, we follow the suggestions of Shi et al. (2020, 2018) and employ the time-varying causality test that was introduced initially by Swanson (1998). We first determine the sub-sample size by using the following formula Phillips et al. (2015):

$$ss = \left\{T\left(0.01 + 1.8 \Big/ \sqrt{T}\right)\right\}$$

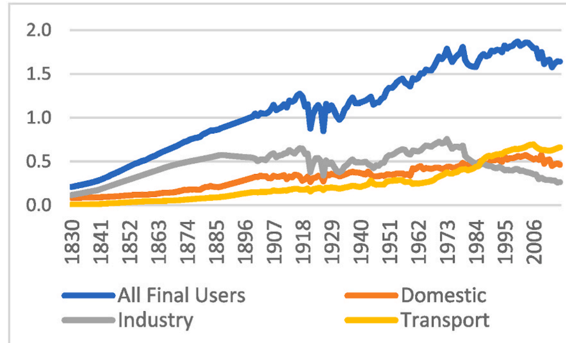
The beginning point of the first sub-sample is $\tau_1 = T - ss + 1$, and the last point is $\tau_2 = \tau_1 - ss - 1$. By keeping the sample size constant, the last point of the regression runs from ss to the last observation of the sample (T), while the first observation runs from the first observation of the sample to the $T - ss$ th observation. By examining the computed test statistics over the sub-samples, one can reveal the sub-samples when the causality relationship changes.

4. Empirical findings

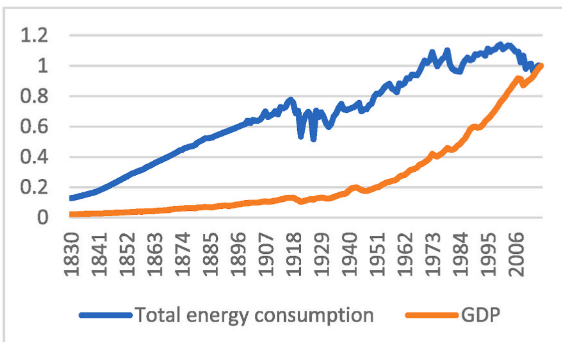
To get insight into data, we first compute the descriptive statistics



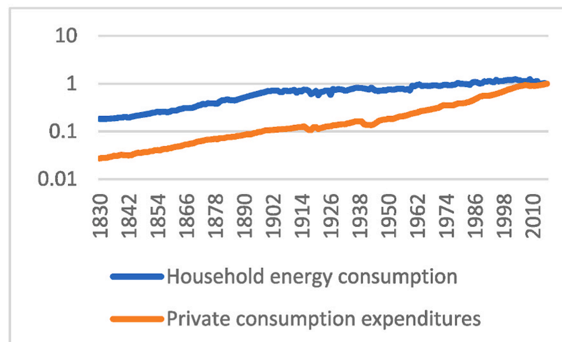
a. Energy mix



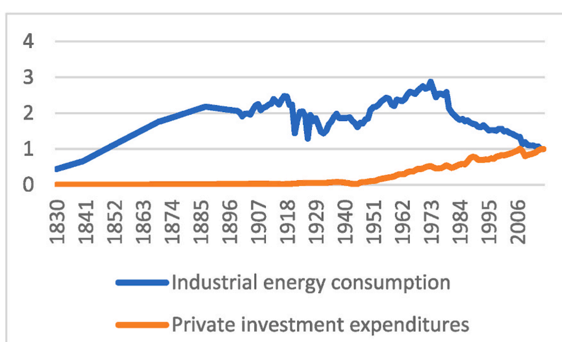
b. Energy consumption by final user



c. GDP and total energy consumption, 2016=1



d. Private investment expenditures and industrial energy consumption, 2016=1



e. Private consumption and domestic energy consumption 2016=1

Fig. 5. Energy consumption trends in the UK, 1830–2016.
Source: National Infrastructure Commission (2023)

and present the outcomes in Table 3tbl3.

The descriptive statistics in Table 3 show that HINC has the maximum mean value while TINC has the minimum. The results also show that the values of POP clustered more closely around its mean according to the other series since the POP has the minimum standard deviation. Also, GDP has the maximum standard deviation among the series with a high mean, which shows that the values of the GDP are spread out over a wide range, and there is a lot of variability among the observations. The values of skewness show that only the values of three series (GDP, HINC, CINC) are skewed to the right, with a long tail of high values. The remaining series are negatively skewed, and the values of CO2 seem to be highly negatively skewed. The values of kurtosis show that CO2 has a leptokurtic distribution; that is, the tails of the series' distribution are fatter than the normal distribution since the coefficient of kurtosis is higher than 3. The p-values of the Jarque-Bera test statistics support the evidence of non-normality for all series.

To proceed with implementing the newly suggested cointegration test, we first must determine the integration levels of the variables since the cointegration test necessities that all the variables are integrated at one. Thus, we apply the ADF and FADF unit root test and present the results in Table 4tbl4.

The findings in Table 4 support the evidence of the significance of the Fourier function for only the POP series. The optimal frequency is found as 3 for this series, which indicates three smooth changes are affecting the POP series over time. The FADF test statistic is lower than the critical values at the traditional significance levels, which indicates that the POP series has a unit root. For the remaining series, we found the Fourier function as non-significant. Thus, we applied the traditional unit root test, ADF, and found them as non-stationary, which satisfies the necessary condition to apply the cointegration test. We apply the suggested cointegration test, which allows for smooth and sharp breaks, and tabulate the findings in Table 5tbl5[3].

We reject the null hypothesis of no cointegration for each test equation because FSB-GH test statistics are higher than the critical values. Thus, we can conclude that there is a long-run relationship between the considered variables in each equation. Optimal frequencies generally show two and three smooth breaks affecting the long-run relationship. Besides, structural change dates are observed around the 1860s, 1960s and early 1970s. Upon analyzing these dates, it is evident that the introduction of the Alkali Act in 1863, which aimed to reduce hydrogen chloride emissions during alkali production, served as a catalyst. In addition, in the same year, "On Radiation Through the Earth's Atmosphere" presented to the British Royal Society, John Tyndall provided the first substantiation and elaboration of Joseph Fourier's concept of the 'greenhouse effect' which posited that the absence of Earth's atmosphere would result in a much colder planet. Our findings are consistent with those of Hendry (2020), who estimated the break dates to be 1912, 1925, and 1969; with Sephton and Mann (2014), who predicted the break dates to be 1966–1967; and with Fosten et al. (2012), who predicted the break dates to be 1859 and 1970.

Next, we estimate the long-run coefficients and report the results in Table 6tbl6. The findings in Table 6 show that we find all coefficients as significant except the constant term in Model 3 and the slope coefficient of TINC in Model 5. According to the overall findings, the EC is found as positive and statistically significant, while POP is found as negative and significant in each model. These results show that EC deteriorates the environment while an increase in POP has a healing effect on the environment. Besides, we can conclude that the EKC is valid according to all models except Model 5 since we found the GDP and components as positive and significant while the square of it as negative and significant.[4]

The coefficients may change over time due to factors such as climate agreements signed and changes in government policies during the analysis period. As a result, we also estimate the time-varying coefficients using the FGLS method and present the results in Fig. 2fig2.

The results in Fig. 2 show that the coefficients change over time, but this change does not influence the validity of the EKC since the change is quite small. Overall findings show that, especially in the late 1800s, the harmful impact of regressors on the environment increased; however, after the beginning of the 1900s, this effect decreased.[5]

Next, we test the causality relationship between the variables, using model specifications from Eqs. (1)–(5) and presenting the causality results in Table 7tbl7.

The results in Table 7 support the evidence of causality running from all considered determiners to the CO2 in the entire sample since test statistics are higher than the bootstrap critical values at the 1% significance level. Next, we test the causality in a time-varying framework. We determined the sub-sample size as 26 by considering the suggestion of Phillips et al. (2015) and used 10,000 simulations to obtain critical values. Fig. 3fig3 illustrates the findings.

Fig. 3 demonstrates that the existing causality relationship varies over time. In Fig. 4fig4, the horizontal and vertical axes represent, respectively, the years and the number of the causal effects. During the period 1850–2016, the GDP (LGDP), household income (LHINC), corporate income (LCINC), trade income (LTINC), and government income (LGINC) had causal effects on carbon emissions in 26, 27, 64, 64, and 23 years, respectively. Therefore, it is erroneous to infer results from the effects of the GDP on carbon emissions for the same effects of the GDP's components. In a given year, the causal effects of GDP on carbon emissions may coincide with the effect of any growth component. In 1866, 1927, and 1989, for instance, both GDP and household income had causal effects on carbon emissions. In 1927, 1952, and 1976, the GDP and corporate income had causal effects on carbon emissions. However, it would be erroneous to presume that the effects of GDP on carbon emissions during these years stem solely from household income or corporate income. Because there are numerous years in which the GDP has no effect on carbon emissions, while its components do. Thus, a component-based analysis of the impact of consumption and investment activities on carbon emissions will be more accurate, precise, and explanatory. To illustrate this, we present two distinct accounts of the effects of GDP and its components on carbon emissions.

4.1. The explanation of empirical findings based on GDP's effects

Prior to the 1900s, there is only a two-year causality between GDP (LGDP) and carbon emissions (LCO2); however, after the 1900s, there is an episodic causality in many years (Fig. 3a). This is the result of two factors. First, during the period 1826–1908, the average amplitudes of economic contractions and expansions were −2.5 and 10.0 percent, while during the periods 1908–1947 and 1947–2009, they were −12.0 and 32.0 percent and −2.8 and 61.8 percent, respectively. Second, the average number of years of contraction and expansion during the period 1826–1908 was 1.4 and 4.5, whereas the corresponding numbers for the periods 1908–1947 and 1947–2009 were 2.5 and 7.3 and 1.8 and 13.8, respectively (Dimsdale and Thomas, 2019). As previously discussed, economic contractions and expansions may result in a massive decline or increase in energy consumption and carbon emissions, respectively.

In particular, a post-World War II economic prosperity and concomitant increase in energy consumption (Fig. 5cfig5) explains why the GDP had more frequent effects on carbon emissions between 1952 and 1958. As Hendry (2020) noted, rising economic growth caused carbon emissions to increase in the 1950s and 60s, after oscillating dramatically from the end of World War I, the General Strike of 1926, and the Great Depression of 1929 until the end of World War II. However, as Sephton and Mann (2014) noted, the Clean Air Act of 1956 initiated the transition from 90% coal to 75% coal, the highest carbon-emitting energy source, to nuclear power, which explains the breakdown of the GDP's causal effect on carbon emissions during the late 1950s and early 1960s. In the 1960s and early 1970s, this transition mitigated the impact of GDP on carbon emissions. The economic contraction during the Stagflation Crisis of the 1970s and concomitant significant decline in energy consumption (Fig. 5c) explain the effects of the GDP on carbon emissions from 1974 to 1976 (Fig. 3a). Between the early 1990s and the Global Financial Crisis of 2008, there was also an economic prosperity. However, rising energy efficiency and renewable energy consumption (Fig. 5a), structural transformation, the rise of greener private consumption habits, and the United Kingdom's signing of the Montreal Protocol of 1987 and the Kyoto Protocol of 1997 to reduce greenhouse gas emissions limited the effects of GDP on carbon emissions to 1992 and 1993.

Fig. 5 c illustrates the system-wide effects of these developments by comparing the declining rate of carbon emissions and energy consumption to the increasing rate of economic growth during this period. Following the 2008 financial crisis, there was a prolonged economic contraction and a concomitant drop in energy consumption. In addition, as the first legally binding national emissions reduction target in the world, the Climate Change Act of 2008 was enacted following the Global

[3] We also employ several cointegration tests to check the robustness of the findings and present the results in Appendix 5. Most of the results support the evidence of cointegration for each equations except equation (5), for which we use TINC as dependent variable. The primary reason for this outcome is that these tests fail to consider both sharp and gradual changes.

[4] To check the robustness of the findings, we also estimate the long-run relationship using the FMOLS method, which produces similar results to the OLS. The results are available upon reasonable request.

[5] To test the significance of the coefficients over time, we also computed confidence bands which show that TINC2 is insignificant in the analysis period and indicate the robustness of the full-time results.

Financial Crisis (Gransaull et al., 2023; Laes et al., 2014). These factors resulted in a colossal decrease in energy consumption (Fig. 5c), which explains the unbroken effect of GDP on carbon emissions from 2010 to 2016 (Fig. 3a and Fig. 4).

4.2. The explanation of empirical findings based on the effects of GDP components

As a result of the decline in the adolescent population and the decline in fertility, household income did not play a significant role in growth cycles in the Victorian economy between 1830 and 1910. There were thus only eight sporadic years in which household income had a causal effect on carbon emissions during this time period (Fig. 3e). In the 1920s and 1930s, there were high unemployment rates above equilibrium due to inadequate demand, which may account for the effects of private consumption on carbon emissions as a result of declining household income in 1927, 1928, and 1933 (Berg and Louw, 2005).

Industrialization and corporate investment expenditures were the primary drivers of growth cycles in the Victorian economy. The causal effects of corporate income on carbon emissions occurred in 26 of the 35 years between 1857 and 1892 (Fig. 3g and Fig. 4). This is due to the fact that industrial energy consumption was significantly higher than domestic (household) energy consumption until the mid-1910s (Fig. 5d and Fig. 5e). During the three decades preceding the 1920s, however, the causal effects of corporate income on carbon emissions ceased to exist due to a decline in private investment expenditures and consumption of energy (Fig. 5d). The Great Strike of 1926 and the Great Depression of 1929 accelerated this trend. Between 1926 and 1946, the contribution of private investment expenditures to GDP fell as low as 0.09%, which may explain the causal effects of corporate income on carbon emissions in ten of the twelve years between 1926 and 1938 (Broadberry, 2009; Bruland, 2004).

In the 1870s and 1920s, government income had causal effects on carbon emissions. The period between the mid-19th century and World War II was characterized by the transition of the British government from a small, laissez-faire government to a mature, modern state that made substantial investments in urban infrastructure, public health and social order, education, and social transfers in response to the rapid growth of urbanization and industrialization (Middleton, 2004). During the 1870s and 1920s, government expenditures grew at a faster-than-average rate, which may have contributed to increased energy consumption and carbon emissions.

In the post-WWII period, the causal effects of household income in 1948, 1949, 1966, and 1967 (Fig. 3e) could be attributed to rising household income as a result of low unemployment rates and generous welfare state expenditures until the 1970s (Fig. 5e). The reason why there were only four years of causal effects from household income is because domestic (residential) energy use was stagnant until the 1960s and increased slowly until the 1980s (Fig. 5e), and industrial and transportation sectors drove energy consumption during this period (Fig. 5b). Following World War II, industrial energy consumption increased dramatically between the 1950s and the mid-1970s due to high rates of productivity growth (Fig. 5d).

However, industrial energy consumption slowed in the mid-1970s due to the Stagflation Crisis, which explains the causal effects of corporate income on carbon emissions in five years between 1946 and 1954 and six years between 1965 and 1972 (Fig. 3g). The cessation of these causal effects between the middle of the 1950s and the middle of the 1960s may be attributed to the Clean Air Act of 1956.

Until the early 2000s, both private consumption expenditures and energy consumption increased consistently (Fig. 5e), which explains the causal effects of corporate income on carbon emissions between 1994 and 2000 (Fig. 3e and Fig. 4). During the 1980s, however, the rate of private investment expenditures weakened dramatically, and industrial energy consumption fell precipitously (Fig. 5d) due to a decline in this sector's total value-added and an increase in energy efficiency (Griffin et al., 2016). The average contribution of private investment expenditures to GDP decreased from 0.97 during the 1950-80 period to 0.42 during the 1980–2007 period and to −0.01 during the 2008–2016 period (Bank of England, 2023). Between 1980 and 1993, corporate income had no causal relationship with carbon emissions. The increasing frequency of the impact of corporate income on carbon emissions between 1994 and 2001 may be attributable to the rapidly decelerating rate of investment expenditures and energy consumption, as well as a cleaner energy mix with the increased use of renewables and natural gas (Fig. 3g and Fig. 5 d). Similarly, the causal effects of corporate income on carbon emissions between 2007 and 2010 could be attributed to the discernible decline in these expenditures and the decline in industrial energy consumption.

In the latter half of the 1850s, between the 1870s and 1911, between 1926 and 1926–1960, 1992–2001, and 2007–2008, trade income had causal relationships with carbon emissions (Fig. 3 i and Fig. 4). The contribution of net trade to the nation's gross domestic product was 0.65 percentage points between 1870 and 1913, -0.46 percentage points between 1926 and 1945, 1.19 percentage points between 1946 and 1958, 1.49 percentage points between 1992 and 2001, and -0.07 percentage points between 2007 and 2008 (Harley, 2004). This trend could be explained by the fact that exporting industries consumed more energy and increased their carbon emissions during periods of positive net trade but consumed less energy and decreased their carbon emissions during periods of negative net trade. The increasing energy consumption between the 1870s and World War I, the declining energy consumption between the mid-1920s and World War II, the increasing energy consumption between 1946 and the late 1950s, and the steady decline in energy consumption between 1992 and 2001 support this explanation (Fig. 5d).

5. Discussion

Table 8 summarizes the rejection and acceptance of all six hypotheses based on the paper's empirical findings. According to the cointegration estimates, the EKC hypothesis is supported by all models except the fifth. The analysis of causality also confirms these results. There are causal relationships between trade income or trade income squared and carbon emissions. However, causality alone is insufficient to reject the null of the second hypothesis, as appropriate coefficient values for the effect of trade income on carbon emissions could not be determined using coefficient estimates.

As described in depth in the preceding section, the effects of the gross domestic product and its components on carbon emissions occur at different times. We, therefore, reject the third and fourth hypotheses for all models. The rejection of these hypotheses does not imply that the EKC hypothesis holds true for Model 5, as time-varying causality is not a test of the EKC hypothesis. The confirmation of the EKC hypothesis indicates that the effect of a change in income on carbon emissions varies over time. The rejection of Hypotheses 3 and 4 demonstrates, however, that the effects of the variation in each economic unit's income either exacerbate or mitigate environmental degradation at different times. Analysis of time-varying causality pinpoints when these effects occur.

These results indicate three things. First, the EKC hypothesis should be tested separately for each component of GDP or aggregate income to establish its unit-specific viability. Because the EKC hypothesis may be viable for the impact of a change in aggregate income on environmental degradation even if it is not viable for the effect of a change in the income of the government, corporations, households, or the rest of the world. For instance, the EKC hypothesis holds for the effect of a change in aggregate income on environmental degradation in the UK but not for the effect of a change in trade income or the income of the rest of the world. Consequently, the policymaking implication of this result is that the United Kingdom's environmental policy strategies should be determined based on the specific effects of each component of aggregate income on environmental degradation. Due to the disparity between the

Table 8
Hypotheses testing.

Hypotheses	Model 1		Model 2		Model 3		Model 4		Model 5	
	GDP	GDP^2	GINC	$GINC^2$	CINC	$CINC^2$	HINC	$HINC^2$	TINC	$TINC^2$
H0 1:	$\Rightarrow$									
H0 2:			$\Rightarrow$		$\Rightarrow$		$\Rightarrow$		$\nRightarrow$	
H0 3:	$\Rightarrow$	$\Rightarrow$								
H0 4:			$\Rightarrow$	$\Rightarrow$	$\Rightarrow$	$\Rightarrow$	$\Rightarrow$	$\Rightarrow$	$\Rightarrow$	$\Rightarrow$

effects of aggregate income and the effects of each component of aggregate income, a policy strategy based on aggregate income is likely to have an adverse effect on environmental sustainability. The paper intended to further concretize this argument by explicating the EKC hypothesis for the United Kingdom based on the effects of aggregate income and its components on environmental degradation through two distinct narratives in the previous section. The first option may sound reasonable, but it would be utterly deceptive. The latter is more accurate and precise, which is essential for attaining environmental sustainability.

Second, it may be assumed that the effect of a change in aggregate income will occur simultaneously with the effects of changes in the incomes of governments, corporations, households, and the rest of the world. This may cause policymakers to overlook the significance of adopting time-varying environmental policies despite adopting these strategies in a unit-specific manner. However, these strategies should also be dynamic in accordance with the diverse effects of a change in the income of each economic unit over time. This point was clarified by the distinct time-varying narratives of the effects of GDP and its components on carbon emissions, which demonstrated conclusively that the two categories of effects occur in different years and for different durations.

Third, it is assumed that the effect of a change in the incomes of governments, corporations, households, and the rest of the world will occur simultaneously. This may also cause policymakers to implement ineffective environmental policy strategies. Because the preceding section's analysis of the effects of each form of income on carbon emissions revealed that these effects also vary in terms of years and durations.

6. Conclusion

The purpose of this paper was to examine the validity of the EKC hypothesis with regard to the effects of not only GDP or aggregate income but also its individual components on carbon emissions in each year of a given period, as opposed to the entire period. In order to accomplish this, the paper suggested a new cointegration test that allows for smooth and sharp breaks. Using the instance of the United Kingdom between 1830 and 2016, this paper reaches three conclusions. The impacts of aggregate income and the incomes of the three but not all four economic units on carbon emissions are consistent with the EKC hypothesis. Second, each of these effects is time-varying. The effects of aggregate income and each economic unit's income (governments', households', corporations', and the rest of the world's) on carbon emissions occur at distinct times. Additionally, the effects of each of these four economic entities occur at distinct times. Thirdly, the EKC hypothesis regarding the relationship between trade income and carbon emissions cannot be validated. The paper confirms the literature's findings (Abid et al., 2021; Adedoyin and Zakari, 2020; Awaworyi Churchill et al., 2018; Aydin et al., 2023; Ben Amar, 2021; Fosten et al., 2012; Ibrahim and Ajide, 2021; Jaunky, 2011; Nguyen et al., 2020; Pirgaip et al., 2023; Ramzan et al., 2022; Sephton and Mann, 2014) that validate the EKC hypothesis in terms of the effects of aggregate income on carbon emissions.

This paper is the first to make the systematic disaggregation of the income-emissions nexus. The term 'systematic disaggregation' refers to estimating the impact of each economic unit's income on carbon emissions as opposed to the impact of the aggregate growth on carbon emissions. Given the findings of this paper, future research should investigate the income-emissions nexus by focusing predominantly on the effects of each economic unit's income on carbon emissions. Because the effect of aggregate growth on carbon emissions may shed light on the income-emissions nexus in general. Nonetheless, given the paper's above-noted second finding, accurate, precise and specific policy solutions can be derived from a disaggregate rather than an aggregate approach.

The paper demonstrates how to implement a time-varying and systematic disaggregation of the income-emissions nexus using universally applicable empirical models and universally accessible data sets. A sufficient quantity of data on government, corporate, household, and the rest of the world's incomes are available for the overwhelming majority of countries due to the expenditures approach used to calculate the GDP as a benchmark across the world (For example, see World Development Indicators). Consequently, researchers and policymakers can use these data on their own countries to conduct a time-varying disaggregated analysis of the income-emissions nexus utilizing the empirical methodologies presented in this paper. To promote this scientific and policy-making advancement, prominent academic journals of environmental sustainability may publish special volumes on whether, why, and how to disaggregate the income-emissions nexus.

In addition, the United Nations Development Program can employ a time-varying disaggregate analysis of the income-emissions nexus in order to implement Sustainable Development Goals 7, 13, 12, and 17, which, respectively, are Affordable and Clean Energy, Responsible Production and Consumption, Climate Action, and Partnership for the Goals. The fact that a global climate action strategy requires mitigating the impact of income on carbon emissions in all nations connects these four objectives to the topic of this study. Basing environmental policy strategies on the distinct and time-varying (yearly) impact of each of the four growth components on carbon emissions is the most fundamental prerequisite both for individual nations and the UNDP to specify accurate, precise, specific, and dynamic policy strategies to combat environmental degradation in light of the three findings of this paper.

The primary limitation of the paper is its focus on a single developed economy, the United Kingdom. However, due to income disparities, the causal effects of GDP and its components on carbon emissions in developing economies may exhibit a distinct trend than in developed nations. Future research can apply the same analytic and empirical methodology developed in this paper to test the time-varying and disaggregated income-emissions nexus in the other developed and developing countries.

Author contributions

Veli Yilanci: Conceptualization, Methodology (empirical), Software, Formal analysis, Data curation, Writing – original draft, Visualization. Taner Akan: Conceptualization, Methodology (analytical), Investigation, Writing – original draft, Writing – review & editing, Visualization. Ali Haydar Işık: Validation, Investigation, Writing – original draft, Writing – review & editing.

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.

Data availability

Data will be made available on request.

Appendix 1

Table A1
Literature Review of EKC Hypothesis

Author & Year	Period	Country	Variables	Methodology	Results
Wang et al. (2023)	1995–2018	36 OECD Countries	Ecological footprint, economic efficiency, financial development, renewable energy consumption, industrialization	FMOLS, Dumitrescu-Hurlin Causality	Inverted U-shaped
Bekun et al. (2023)	1990–2016	E7 Countries	Real GDP, investment in energy sector, financial development, trade openness, institutional quality, ecological footprint, square of real GDP	AMG, CCEMG, Dumitrescu-Hurlin Causality	EKC validated
Ehigiamusoe et al. (2023)	1980–2018	Malaysia	Environmental degradation, ecological footprint, GDP, squared GDP, energy consumption, agricultural value added, industry value added, bank-based financial sector, market-based financial sector, urban population, FDI, trade openness	ARDL, Granger Causality	EKC validated
Ali et al. (2023)	1975–2020	India, China, Bangladesh, Japan, Singapore, South Korea	GDP, renewable energy, CO_2, non-renewable energy, labor, capital	AMG, Dumitrescu-Hurlin Causality	N Shaped EKC
Zeraibi et al. (2023)	1990–2020	22 Developing Countries	CO_2 emissions, GDP per capita, public debt, renewable in electricity production	DOLS, FMOLS, AMG, Dumitrescu-Hurlin Causality	Inverted N-shaped
Pata and Yurtkuran (2022)	1970–2018	Switzerland, The Netherlands, Sweden, Austria, Denmark	Environmental footprint, economic growth, globalization	FMOLS, CCR, Fourier Toda Yamamoto Causality	EKC validated
Fakher et al. (2023)	1994–2019	OPEC Countries	Ecological footprints index, adjusted net savings, pressures on nature, environmental vulnerability, environmental performances, environmental sustainability, GDP per capita, squared GDP per capita, cubic GDP per capita, non-renewable energy, renewable energy, financial development, population density, composite trade share	Panel DSURE	Inverted N-shaped
Khan et al. (2022)	1985–2019	34 Developing Countries	co2 emissions, GDP, squared GDP, financial development, FDI, trade, economic instability	DOLS, Granger Causality	EKC validated
Gyamfi et al. (2022)	1990–2016	14 Mediterranean Countries	CO_2 emissions, GDP, squared GDP, total natural resources rents, square of total natural resources rents, energy use, aging population, economic globalization	QR, OLS, Dumitrescu-Hurlin Causality	Inverted U-shaped
Caglar (2022)	1974–2020	UK	CO_2 emissions, real GDP, trade openness, financial development, nuclear energy technology research and development budget	NARDL	EKC validated
Frodyma et al. (2022)	1970–2017	28 EU Countries	Real GDP per capita, production-based CO_2 emissions per capita, consumption-based CO_2 emissions per capita	ARDL Bounds Cointegration	EKC not validated on most of the countries
Chen et al. (2022)	1990–2019	Newly Industrialized Countries	CO_2 emissions, natural resource rent, green technology innovation, economic growth	CS-ARDL, AMG & CCEMG	EKC validated
Shahbaz et al. (2022)	1995–2019	40 Developing Countries	Consumption-based CO_2 emissions, production-based CO_2 emissions, population, energy intensity level of primary energy, renewable energy consumption. per capita income, squared per capita income	AMG, MMQR, Dumitrescu-Hurlin Causality	U-shaped only when CO_2 emissions calculated based on production pattern
Hao et al. (2022)	1985–2020	BRICS Countries	CO_2 emissions, economic growth, nuclear energy consumption, renewable energy consumption, population density, urbanization, economic globalization	Granger Causality, FMOLS, DOLS	Inverted U-shaped
Rahman and Alam (2022)	1960–2020	60 Most Open Countries	CO_2 emissions per capita, trade openness, renewable energy use, total number of patent applications, per capita GDP, squared per capita GDP	Driscoll Kraay FE, PCSE, Granger causality	EKC validated
Balogh (2022)	2000–2018	152 Non-EU Countries	CO_2 per capita, GDP per capita, squared GDP per capita, agricultural machinery, agriculture forestry and fishing value added per worker, agricultural raw materials exports, WTO membership, participation of Kyoto protocol or Paris agreement, EFTA membership, NAFTA membership, MERCOSUR membership, ASEAN membership	FMOLS, DOLS, Dumitrescu-Hurlin Causality	U-Shaped
Zhang et al. (2022)	2000–2020	G-7 Countries	ecological sustainability, financial development, digital trade, economic growth, renewable energy	Dumitrescu-Hurlin Causality, Cup-FM, Cup-BG, System GMM	EKC validated

(continued on next page)

Table A1 (*continued*)

Author & Year	Period	Country	Variables	Methodology	Results
Ben Amar (2021)	1751–2016	UK	Real GDP, CO_2 emissions, population	Dynamic Correlation, Cross-wavelet coherency	Inverted U-shaped with turning point mid-20th century
Anwar et al. (2021)	1991–2018	ASEAN Countries	CO_2 emissions, GDP, squared GDP, renewable energy consumption, non-renewable energy consumption	FMOLS, DOLS, FE-OLS	Inverted U-Shaped
Htike et al. (2021)	1990–2015	86 Developed and Developing Countries	Total CO_2 emissions, CO_2 emissions of electricity and heat production, manufacturing industries and construction, residential, transport, agriculture/ forestry/fishing, commercial and public services, other energy industry own use, GDP per capita, total final energy consumption, renewable energy share in total, total natural resource rent, trade openness	PMG-ARDL	EKC holds on minority of the selected sectors
Dogan et al. (2020)	1980–2014	BRICST Countries (Russia excluded)	Ecological footprint per capita, GDP per capita, squared GDP per capita, energy structure, energy intensity, population growth	FMOLS, DOLS, AMG	EKC not validated
Kacprzyk and Kuchta (2020)	1992–2012	161 Countries	CO_2 emissions, real GDP per capita	Fixed and Random OLS	Inverted U-shaped
Destek and Sinha (2020)	1980–2014	24 OECD Countries	Per capita ecological footprint, per capita real GDP, per capita renewable energy consumption, per capita real non-renewable energy consumption, trade openness	PMG, CCE, FMOLS	EKC not validated
Danish and Wang (2019)	1992–2013	BRICS Countries	CO_2 emissions per capita, GDP per capita, trade ratio, biomass energy, foreign direct investment, urbanization, Kyoto Protocol	GMM, Fixed-Effect OLS, PMG	N-Shaped
Destek et al. (2018)	1980–2013	15 EU Countries	Ecological footprint per capita, real GDP per capita, renewable energy consumption per capita, non-renewable energy consumption per capita, trade openness	PMG, FMOLS, DOLS	U-Shaped
Nasreen et al. (2017)	1980–2012	South Asian Countries	CO_2 emissions, aggregate financial stability index, economic growth, energy consumption, population density	ARDL, Toda Yamamoto Causality	Inverted U-Shaped
Shahbaz et al. (2017)	1980–2015 (Italy: 1860–2015; Japan, 1950–2015)	G7 Countries	CO_2 emissions, real GDP per capita	Hiemstra & Jones and Discks Panchenko Causality	Inverted U SHAPED (with only exception of JAPAN)
Dong et al. (2016)	1990–2012	189 Countries	Consumption-based CO_2 emissions, production based CO_2 emissions, GDP per capita, squared GDP, cubic GDP	Fixed, Random and Dynamic OLS	EKC not validated
Ben Jebli et al. (2016)	1980–2010	25 OECD Countries	Renewable and non-renewable energy, CO_2 emissions, real GDP, real exports and imports	Granger causality, FMOLS, DOLS	Inverted U-shaped
Sephton and Mann (2014)	1980–2003	UK	CO_2 emissions, SO_2 emissions, GDP	OLS, MARS	Inverted U-shaped with turning point 1966 and 1967

Table A2
Literature Review of EKC Hypothesis with Expenditure Approach

Author & Year	Period	Country	Variables	Methodology	Results
Adewuyi (2016)	1990–2015	40 Countries (Top 10 countries of America, EU, Asia and Africa)	Per capita carbon emissions, per capita carbon emissions from transport sector, per capita carbon emissions from manufacturing sector, per capita income, share of household consumption expenditure in GDP, share of investment expenditure in GDP, share of government expenditure in GDP, trade openness, secondary school enrollment, compliance with law and order index, population growth, per capita energy consumption	PMG, MG, DFE	EKC not validated
Robalino-López et al. (2015)	1980–2025	Venezuela	CO_2 emissions, total GDP, GDP generated by the productive sectors, energy consumption in the industrial sectors, consumption of fuel in the industrial sectors, total consumed energy, share of sectors in the total GDP, energy intensity of sectors, the energy matrix, final consumption expenditure, gross domestic capital formation, general final government expenditures, exports, imports	DOLS	EKC not validated
Robalino-López et al. (2014)	1980–2025	Ecuador	CO_2 emissions, total GDP, GDP generated by the productive sectors, energy consumption in the industrial sectors, consumption of fuel in the industrial sectors, total consumed energy, share of sectors in the total GDP, energy intensity of sectors, the energy matrix, final consumption expenditure, gross domestic capital formation, general final government expenditures, exports, imports	DOLS	EKC not validated

Appendix 2

Itkonen (2012) and Jaforullah and King (2017) highlight the potential inefficiencies associated with using energy consumption as a predictor of carbon emissions. Energy consumption is utilized as a regressor in this research for five reasons.

First, as noted by Jaforullah and King (2017: 86), a positive correlation exists between energy consumption and carbon emissions "unless an economy's energy mix changes dramatically from one period to another." During the time period between 1830 and 2016, all energy resources used in the United Kingdom exhibited significant variation, as depicted in Fig. 5 a.

Second, as Arminen and Menegaki (2019) emphasized, the exclusion of energy consumption would result in an omitted variable bias because energy consumption is the most significant factor influencing carbon emissions. The omission of required variables in EKC analysis restricts its width and depth (Stern, 2004). This is why energy consumption is used as a regressor in the models where carbon emissions is a dependent variable by the students of energy economics in leading energy journals, including Energy and Energy Economics journals where Itkonen's and Jaforullah and King's papers were published, respectively (Akan, 2023; Arminen and Menegaki, 2019; Inglesi-Lotz and Dogan, 2018; Shahbaz et al., 2018; Tajudeen et al., 2018). In particular, the 'Manual' for the EKC hypothesis cites energy consumption as a basic regressor as it is a key determinant of both production and consumption (Inglesi-Lotz, 2019).

Thirdly, in accordance with Bildirici and Ersin (2023), we have utilized only nonrenewable energy and not total energy consumption in order to mitigate a potential endogeneity issue.

Fourth, we first test for a redundant variable problem. The following LM test statistics show that ENGY should be included in the relevant models.

Model	LM Test Stat.	p-value
$\ln CO_{2t} = f(\ln GDP_t, \ln GDP_t^2, \ln ENGY_t, \ln POP_t)$	201.598	0.000
$\ln CO_{2t} = f(\ln GINC_t, \ln GINC_t^2, \ln EC_t, \ln POP_t)$	313.873	0.000
$\ln CO_{2t} = f(\ln HINC_t, \ln HINC_t^2, \ln EC_t, \ln POP_t)$	151.482	0.000
$\ln CO_{2t} = f(\ln CINC_t, \ln CINC_t^2, \ln EC_t, \ln POP_t)$	744.737	0.000
$\ln CO_{2t} = f(\ln TINC_t, \ln TINC_t^2, \ln EC_t, \ln POP_t)$	212.121	0.000

We also compute information criteria for two models (with and without ENGY) and provide the results as follows.

Income Proxy	Model with ENGY			Model Without ENGY		
	AIC	SIC	HQ	AIC	SIC	HQ
GDP	−2.497	−2.410	−2.462	−1.762	−1.693	−1.734
GINC	−1.789	−1.703	−1.754	−0.798	−0.729	−0.770
HINC	−2.332	−2.245	−2.297	−1.737	−1.668	−1.709
CINC	−2.339	−2.253	−2.304	−0.722	−0.653	−0.694
TINC	−0.773	−0.686	−0.738	−0.011	0.058	0.017

The results of three information criteria denote that we should include the ENGY variable in the relevant models as additional regressors. These results confirm Arminen and Menegaki's above-cited hypothesis (2019).

Fifth, Jaforullah and King (2017: 85) observe that the strength of the link between energy consumption data and CO_2 emissions data implies that "evidence of cointegration could be found despite the absence of a pertinent nonstationary determinant." To test whether Jaforullah and King's claim is applicable to our research, we re-test the cointegration relationship between the variables, excluding the ENGY variable, and present the results below.

Model	Test Equation	Test Statistics	Optimal Frequency	Break Point
$\ln CO_{2t} = f(\ln GDP_t, \ln GDP_t^2, \ln POP_t)$	FC	−9.144*	2	1975
	FC/T	−9.995*	5	1858
	FC/S	−10.067*	2	1920
$\ln CO_{2t} = f(\ln GINC_t, \ln GINC_t^2, \ln POP_t)$	FC	−8.944*	2	1863
	FC/T	−8.410*	2	1865
	FC/S	−5.597	2	1981
$\ln CO_{2t} = f(\ln HINC_t, \ln HINC_t^2, \ln POP_t)$	FC	−5.775**	4	1919
	FC/T	−5.914***	4	1892
	FC/S	−5.748	4	1917
$\ln CO_{2t} = f(\ln CINC_t, \ln CINC_t^2, \ln POP_t)$	FC	−4.620	3	1925
	FC/T	−5.812	1	1920
	FC/S	−7.420*	1	1935
$\ln CO_{2t} = f(\ln TINC_t, \ln TINC_t^2, \ln POP_t)$	FC	−4.628	3	1975
	FC/T	−4.517	3	1975
	FC/S	−5.284	3	1970

Note: *, **, and *** show the significance at the 1%, 5%, and 10% levels, respectively.

According to these findings, we could not find any long-run relationship for the last equation, and find a cointegration relationship for only Model FC/S when we consider CINC as the income proxy. Thus, we estimate the long-run coefficients considering the first four equations and present the findings as follows.

Model 1	Coefficients	t-statistics
Constant	−46.570*	−46.467
GDP	8.786*	25.836
GDP2	−0.324*	−27.220
POP	−0.594*	−3.175
Model 2	**Coefficients**	**t-statistics**
Constant	−28.028*	−21.662
GINC	3.899*	14.025
GINC2	−0.174*	−14.973
POP	1.156*	5.702
Model 3	**Coefficients**	**t-statistics**
Constant	−22.114*	−20.944
CINC	2.071*	11.872
CINC2	−0.100*	−12.951
POP	1.640*	10.492
Model 4	**Coefficients**	**t-statistics**
Constant	−52.929*	−44.637
HINC	10.216*	25.127
HINC2	−0.389*	−26.259
POP	−0.695*	−3.766

Note: * denotes the statistical significance at the 1% level.

We establish a cointegration relationship for four out of five models. Second, we establish statistically significant long-run effects from all variables included in the four models to the dependent variable. As a result, we can conclude that Jaforullah and King's abovecited hypothesis does not hold, at least for our research, given these two important findings, in addition to the fact that LM and information criteria tests indicate the inclusion of energy as a regressor in our models.

Overall, the results of the Akaike, Schwarz, and Hannan Quinn information criteria as well as the LM test indicate that energy consumption, ENGY, should be included in our models as an additional regressor.

Appendix 3

Table A3
Asymptotical Critical Values.

Model FC					
n=1	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−5.85672	−5.77639	−5.62399	−5.51738	−5.43646
5%	−5.34897	−5.28665	−5.11151	−4.96154	−4.86628
10%	−5.07087	−5.02206	−4.84064	−4.70259	−4.58992
n=2	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−6.13783	−6.1412	−6.08422	−5.89782	−5.80735
5%	−5.64486	−5.64767	−5.52644	−5.37693	−5.26881
10%	−5.38897	−5.39999	−5.26827	−5.10484	−4.98615
n=3	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−6.43569	−6.36538	−6.31984	−6.21791	−6.17085
5%	−5.91357	−5.90962	−5.8441	−5.70925	−5.66796
10%	−5.66191	−5.66293	−5.59614	−5.45281	−5.38083
n=4	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−6.65114	−6.62791	−6.62349	−6.49854	−6.50351
5%	−6.12794	−6.17097	−6.13758	−6.03403	−5.98419
10%	−5.88718	−5.92381	−5.86771	−5.7842	−5.7066
Model FC/T					
n=1	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−6.20507	−6.11816	−6.05662	−5.9171	−5.90026
5%	−5.66047	−5.63657	−5.542	−5.42764	−5.32116
10%	−5.41237	−5.39584	−5.27918	−5.17398	−5.05526
n=2	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−6.43566	−6.40394	−6.33968	−6.27353	−6.16754
5%	−5.91344	−5.92089	−5.84021	−5.76332	−5.65473
10%	−5.66786	−5.67829	−5.60746	−5.49194	−5.41424
n=3	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−6.6628	−6.61709	−6.5882	−6.56524	−6.46057
5%	−6.18246	−6.15236	−6.1268	−6.07861	−5.98039
10%	−5.93258	−5.91633	−5.88363	−5.80551	−5.71575
n=4	k = 1	k = 2	k = 3	k = 4	k = 5

(*continued on next page*)

Table A3 (*continued*)

Model FC					
1%	−6.85236	−6.85357	−6.906	−6.77244	−6.76644
5%	−6.39068	−6.39111	−6.40007	−6.32394	−6.26533
10%	−6.14824	−6.16356	−6.13602	−6.07844	−6.01332
Model FC/S					
n=1	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−6.23095	−6.14135	−6.0069	−5.88364	−5.79638
5%	−5.74295	−5.61206	−5.44733	−5.35808	−5.2321
10%	−5.45998	−5.37583	−5.19573	−5.04823	−4.95468
n=2	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−6.74669	−6.72509	−6.59739	−6.50955	−6.41591
5%	−6.26155	−6.20732	−6.11208	−5.98461	−5.89448
10%	−5.99724	−5.9549	−5.84497	−5.70034	−5.60504
n=3	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−7.20659	−7.20187	−7.07941	−7.02467	−6.93311
5%	−6.69446	−6.64736	−6.59952	−6.52987	−6.43971
10%	−6.42566	−6.39743	−6.34947	−6.26238	−6.18907
n=4	k = 1	k = 2	k = 3	k = 4	k = 5
1%	−7.56425	−7.54028	−7.56776	−7.4818	−7.44667
5%	−7.06883	−7.04749	−7.06392	−6.99503	−6.93924
10%	−6.81002	−6.78991	−6.78619	−6.7436	−6.66438

Note: n shows the number of regressors. K denotes the frequency value. The critical values are obtained 100,000 simulations by considering 1000 observations.

Appendix 4

Size and power properties

To analyze and compare the small sample properties of the proposed cointegration test (FGH) with the Gregory-Hansen (GH) cointegration test, we employ the following data generation process which was used by Banerjee et al. (1986), Zivot (2000) and Lee et al. (2015) before:

$$\Delta y_t = \alpha_0 + \delta_1 (y_{t-1} - \beta x_t) + \varphi_1 \Delta x_t + e_{1t}$$

$$\Delta x_t = \psi' \Delta x_{t-1} + \zeta DU_t + a_1 \sin(2\pi kT / t) + a_2 \sin(2\pi kT / t) + e_{2t}$$

$$\Omega = E(e_t e_t') = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}.$$

where y_t and x_t are I(1), $e_t = (e_{1t}, e_{2t})$, $\sigma_1^2 = \sigma_{\Delta y_{1t}}^2$ and $\sigma_2^2 = \sigma_{\Delta y_{2t}}^2$. The assumptions $\beta = 1$, and $\zeta = a_1 = a_2 = 1$, and $\sigma_{12} = \sigma_{21} = \theta$ are made before investigating the properties. The size and power performance of the suggested test are examined by employing 10,000 replications with the 5% significance level, considering structural breaks only in intercept (Model FC). The following scenarios are considered:

- Δx_t is allowed to follow an autoregressive process with the persistence parameter $\psi = \{0.0, 0.6, 0.9\}$.
- - By letting $\sigma_1^2 = 1$ we set σ_2^2 vary along with $\{1, 6, 16\}$; and,
- - By considering different sample sizes as n = 100 and n = 500.

We report the size properties in Table A4.

Table A4
Size Comparison of the Tests

ψ	σ_2^2	FGH	GH
0.5	1	0.0524	0.0477
0.5	6	0.0533	0.0465
0.5	16	0.048	0.0453
0.6	1	0.0557	0.046
0.6	6	0.0512	0.051
0.6	16	0.0532	0.0437
0.9	1	0.0664	0.0576
0.9	6	0.0614	0.057
0.9	16	0.0624	0.0509

Note: The size properties are computed using a sample size of 100 by running 10,000 simulations.

The results in Table A4 show that the size distortions of both tests are negligibly small; that is the size of the test is very close to the considered significance level.

Next, we compute and compare the power properties of FGH and GH cointegration test and provide the findings in Table A5.

Table A5
Power Comparison of the Tests

ψ	σ_2^2	n = 100		n = 200		n = 500	
		FGH	GH	FGH	GH	FGH	GH
0.5	1	0.124	0.108	0.308	0.275	0.976	0.978
0.5	6	0.121	0.113	0.302	0.273	0.980	0.978
0.5	16	0.117	0.115	0.301	0.277	0.978	0.975
0.6	1	0.122	0.107	0.305	0.272	0.977	0.979
0.6	6	0.119	0.104	0.307	0.275	0.978	0.979
0.6	16	0.124	0.106	0.304	0.282	0.975	0.976
0.9	1	0.143	0.128	0.340	0.292	0.982	0.981
0.9	6	0.137	0.124	0.337	0.305	0.982	0.979
0.9	16	0.146	0.124	0.331	0.294	0.979	0.979

Note: The power properties are computed running 10,000 simulations.

The findings in Table A5 indicate that the power of the FGH test increases as there is an increase in the persistence parameter. On the other hand, when the sample size is 500, we see that the power of the test becomes very high, as expected. Upon comparing the power properties of both the GH and FGH tests, it becomes evident that the FGH test exhibits superior power in every scenario when n equals 100 and 200. However, when n increases to 500, the difference in power between the two tests becomes negligible.

Appendix 5

To check the robustness of the suggested cointegration test, we employ several cointegration tests: Traditional cointegration tests (Engle-Granger and Phillips-Ouliaris), cointegration tests that allow sudden breaks (Gregory-Hansen and Hatemi-J), and cointegration test that consider smooth breaks (2017). The findings reveal a long-run relationship for most of the equations.

Table A6
Robustness of the FGH Cointegration Test

Model	Engle-Granger	Phillips-Ouliaris	Gregory-Hansen	Hatemi-J	Banerjee et al.
			Model CS	Model CS	Test Stat
Eq. 1	−2.123 (0.921)	−5.038 (0.011)**	−8.411 [0.193]*	−10.049 [0.342,-1.622]*	−1.622 {4}
Eq. 2	−2.962 (0.613)	−4.202 (0.097)***	−7.825 [0.198]*	−9.218 [0.299,1.344]*	1.344 {4}
Eq. 3	−2.566 (0.794)	−4.696 (0.03)**	−7.263 [0.198]*	−8.969 [0.332,1.02]*	1.020 {4}
Eq. 4	−1.857 (0.96)	−4.745 (0.026)**	−8.942 [0.738]*	−9.706 [0.695,-1.139]*	−1.139 {4}
Eq. 5	−1.562 (0.982)	−1.369 (0.99)	−4.522 [0.508]	−9.259 [0.62,0.531]*	0.531 {1}

Note: *, ** and *** denote the significance at the 1, 5 and 10% levels, respectively. Number in the parentheses, brackets and curly brackets show the p-values, breakpoints, and optimal frequencies, respectively.

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