Sectoral Energy Consumption and Environmental Degradation in Pakistan: An Empirical Evidence from Correlated Component Regression

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Abstract

This study has investigated the sectoral energy consumption influences on CO2 emissions in Pakistan while analyzing data from 1992 to 2022. The correlated component regression method has been adopted in this research because it works effectively to address multicollinearity challenges, manage high-dimensional datasets with limited sample size and numerous independent variables and also produce reliable results. Moreover, as a relatively new methodological approach, the correlated component regression provides a novel contribution to analyzing complex data structures. Our findings show that oil consumption in five sectors including household, industrial, transport, power and government produce increased CO2 emissions which enhances environmental pollution. According to the estimated results, increasing oil consumption by 1 percent in the households, industries, transport, power, and government sectors leads to an increase in CO2 emissions by 0.010 percent, 0.025 percent, 0.118 percent, 0.010 percent and 0.016 percent, respectively. In contrast, oil consumption in the agricultural sector indicates a negative effect on CO2 emissions, implying a 0.024 percent decrease in environmental pollution following a 1 percent increase in agricultural oil consumption. Moreover, gas consumption in the household, commercial, fertilizer, power, industrial and transport sectors is found to have a positive relationship with CO2 emissions. A 1 percent increase in gas consumption in the household, commercial, fertilizer, power, industrial and transport (CNG) sectors leads to an increase in environmental pollution by 0.047 percent, 0.061 percent, 0.223 percent, 0.093 percent, 0.055 percent and 0.010 percent, respectively. Conversely, gas consumption in the cement sector demonstrates a negative influence on CO2 emissions, suggesting that environmental degradation decreases by 0.014 percent following a 1 percent increase in cement sector gas consumption. Additionally, coal consumption in the power and brick kiln sectors, both have positive effects on CO2 emissions, showing that a 1 percent increase in coal consumption in the power and brick kiln sectors leads to a 0.014 and 0.039 percent corresponding increase in CO2 emissions. Based on the study's findings following are the key recommendations. Energy-saving technologies should be promoted in high emissions-intensive industries and renewable energy-based technologies including solar and wind along with public and electric transportation should also be encouraged. The gas-using sectors need to adopt hydrogen and biogas as cleaner alternatives for their operations. The power and brick kiln sectors need to transition their coal usage with renewable power generation technologies while the fertilizer sector requires low-emissions-intensive solutions.

Keywords: Correlated component regression, CO2 emissions, Oil consumption, Gas consumption, Coal consumption, Sectoral analysis, Pakistan

JEL Classification: C19, Q40, Q50

Introduction

Climate change is regarded as one of the most significant and challenging global issues, acting as a threat multiplier that affects the most vulnerable populations and exacerbates existing inequalities. Climate change affects developing countries more than developed countries, where resources are inadequate to tackle climate-change issues. Pakistan, although contributing approximately 0.9% to global greenhouse gas emissions, is among the most negatively affected countries by climate change and air pollution. According to the long-run Climate Risk Index, Pakistan was identified as the 8th most adversely affected nation due to climate change from 2000 to 2019. During the period from 1999 to 2018, its position was even worse, placing it as the 5th most adversely affected country (Eckstein et al., 2021).

Energy has crucial importance both in the development and functioning of the global economy. Researchers such as Stern (1997), Cleveland et al. (2000) and Murphy and Hall (2011) have identified energy as an important factor of production. Being an indispensable component for agricultural production, industry, transportation, commerce and the home, demand for energy will increase as the global population grows and living standards improve through economic development. The increasing trend of mobility, urbanization and a more integrated world economy will exacerbate energy consumption and dependence. Historical evidence demonstrates that rising energy usage and mechanization have their own set of consequences for environmental sustainability, public health, safety standards, living conditions, and community well-being (Connors, 1998). Thus, climate change and global warming triggered by fossil fuels have been two global environmental challenges since the middle of the 20th century. From an economic perspective, the energy sector has been a significant source of environmental degradation triggered by energy usage and its transmission. The rising trend of CO2 emissions has been a significant reason for environmental degradation.

In Pakistan, CO2 emissions from energy consumption, including oil, gas and coal, have increased more than two times over the past twenty years. Coal is the highest growth achiever, showing more than five times an increase over the previous twenty years, followed by gas indicating a more than two-times rising trend and oil contributing approximately 50% more in CO2 emissions as compared to the last twenty years (Butt et al., 2021).

Economic development holds crucial significance for all nations across the world including developing, developed and emerging economies. Furthermore, many development goals can be achieved with the help of sustainable economic growth. Tang et al. (2016) indicated that energy holds cornerstone importance in determining economic progress and achieving long-term development. Krueger and Grossman (1991) empirically examined and found that per capita GDP growth enhanced environmental pollution at low levels of income while it mitigated pollution at high levels of income. Stern (2004) argued that economic development, without technological or structural change, directly enhanced environmental pollution and numerous other environmental challenges. Yi et al. (2023) and Ramlogan and Nelson (2024) have emphasized that an increase in production or manufacturing-related activities leads to an acceleration in environmental pollution. Xue et al. (2021) concluded that environmental sustainability can be attained by enhancing economic development, reducing fossil fuels and discouraging foreign direct investment. Some researchers show that carbon taxes serve as a tool to reduce the harmful effects of global warming. For instance, Gaspar et al. (2019) demonstrate that climate change has now become a clear and current threat to the world economy. Its harmful effects can be controlled through establishing carbon taxation on coal burning and other fossil fuel emissions. These actions would encourage countries to transition to clean and environmentally conscious energy sources. The authors further suggested that a carbon price of $75 per ton of carbon emissions should be levied on large pollution-emitting countries to limit global warming to under 2°C by 2030.

Some other studies evaluated the effect of aggregated oil, gas, electricity and coal consumption on CO2 emissions. For instance, Amer et al. (2024) demonstrated that energy use of oil, gas and coal together with population and economic growth have positive effects on CO2 emissions. Ahmad et al. (2022) studied and concluded that an increase in coal, gas, oil and electricity consumption enhanced CO2 emissions, while a decrease in these energy sources mitigated the environmental pollution in India, Pakistan and Bangladesh. Sharif et al. (2023) explored that coal and oil consumption directly affected carbon emissions, while gas consumption inversely impacted CO2 emissions in the top eleven pollution-emitting countries. Shah et al. (2022) empirically analyzed and demonstrated that depreciation in exchange rate and surge in energy consumption enhanced the environmental pollution in Pakistan.

The escalation of CO2 emissions and environmental damage in many countries has prompted academicians to determine various contributing factors, with a specific emphasis on the role of energy consumption. Various previous studies (Abbas et al., 2021; Ahmad et al., 2016; Aftab et al., 2021; Fatima et al., 2018; Hu et al., 2021; Khan et al., 2020; & Yavuz et al., 2023) have investigated aggregated and disaggregated energy consumption effects on carbon emissions. However, the literature review shows a lack of research focusing on sectoral energy consumption influence on CO2 emissions in Pakistan. The sectoral analysis is important both for designing and implementing environment-concerning policies because it can help to identify which sectors increased CO2 emissions and where resources are required to deal with CO2 emissions for achieving environmental sustainability. The present research bridges this gap by exploring an in-depth analysis across various sectors of oil, gas and coal usage and their influences on CO2 emissions in Pakistan. Following this research gap, this study has the following primary objectives:

- **i.** To investigate the impact of sectoral energy consumption of oil, gas and coal on CO2 emissions in Pakistan.
- **ii.** To determine the relative contributions of various sectors in oil, gas and coal consumption to CO2 emissions in Pakistan.

Specifically, this research uses disaggregated oil use in the household, industry, agriculture, transport, power, and other government sectors. Gas consumption is disaggregated into seven sub-sectors including household, commercial, cement, fertilizer, power, industrial, and transport sectors. Finally, coal consumption is evaluated specifically in the power and brick kilns sectors. This comprehensive analysis of energy consumption across various sectors and their influence on CO2 emissions would help the policymakers in Pakistan to identify sectors with high emissions levels to prioritize resource allocation for environmental sustainability and economic development. To achieve the aforementioned objectives, this research adopts the correlated component regression (CCR) methodology because this technique provides more robust estimate results especially when the explanatory variables exhibit multicollinearity issues. Moreover, the CCR technique performs well when proceeding with high-dimensional datasets with small sample sizes and numerous independent variables as investigated in this research. Traditional regression methods produce inaccurate and indefinite coefficient values whenever the number of regressors matches or exceeds the sample size. However, the CCR model possesses alternative features that address this particular limitation. Additionally, this method is applied because it is a new methodological approach that brings innovative contributions to this study.

The remainder of the paper follows this structure in its subsequent sections. Section 2 includes a review of earlier studies, whereas data and methodology are described in Section 3. Section 4 delivers results and discussions and the conclusion of this paper is outlined in Section 5.

Literature Review

In this study, the literature review has been organized into two sub-sections: time series studies and cross-sectional studies.

Time Series Studies

Soytas et al. (2007) found a one-way causality from energy consumption to CO2 emissions in the USA. These results were also confirmed by other researchers, including: Joo et al. (2015) for Chile, Mohiuddin et al. (2016) for Pakistan, Wang et al. (2016) for China, Yang and Zhao (2014) for India, and Zhang and Cheng (2009) for China. Similarly, Nain et al. (2017) found a causality from electricity consumption to CO2 emissions by analyzing the data from 1971 to 2011 in India. In contrast, some other studies, such as Alam et al. (2011) for India, Hussain et al. (2012) for Pakistan, Lee and Yoo (2016) for Korea, Magazzino (2016) for Italy, and Mirza and Kanwal (2017) for Pakistan, found two-way causality between consumption of energy and emissions.

Gessesse and He (2020) concluded that energy consumption was directly linked to CO2 emissions in China. Similarly, Chandia et al. (2018) demonstrated that energy consumption positively influenced carbon emissions while utilizing data from 1971 to 2016 in Pakistan. These results were also confirmed by some other studies, including: Khan et al. (2019) for Pakistan, Raggad (2020) for Saudi Arabia Shahbaz et al. (2013) for Indonesia, and Shahbaz et al. (2014) for Bangladesh. On the other hand, Abbas et al. (2021) confirmed that traditional energy consumption, transportation, ecological footprint and urbanization enhanced emissions, whereas renewable energy use reduced it. Belaid and Youssef (2017) explored that non-renewable use resulted in increased emissions while renewable energy consumption caused emissions reductions in Algeria.

Some previous studies also investigated the impact of disaggregated energy consumption on environmental pollution in different countries. In these studies, Khan et al. (2020) found that coal and oil consumption were positively associated with emissions in the case of Pakistan. Kanat et al. (2022) empirically concluded that oil, gas and coal consumption were positively related to CO2 emissions in Russia. Ahmad et al. (2016) also found similar results by empirically investigating that aggregate energy, gas, oil, electricity and coal consumption were directly associated with emissions in India. Sahoo and Sahoo (2022) concluded that coal, gas and oil use were positively linked with CO2 emissions. Majeed et al. (2021) empirically examined that a positive shock in the consumption of total energy, coal and electricity inhibited the environmental quality, while a positive change in oil and a negative change in gas consumption enhanced the environmental quality. Moreover, economic development increased pollution (Awais, Kashif, & Raza, 2020; Awais, Malik, Bhatti, & Hashmi, 2022; Awais, Shah, & Abidy, 2018), while capital formation decreased it. Rahman and Ahmad (2019) empirically examined and concluded that capital formation and consumption of coal and oil resulted in increased CO2 emissions in Pakistan. In contrast, Alkhathlan and Javid (2013) empirically analyzed and concluded that consumption of total energy, oil and electricity were positively associated with CO2 emissions, while gas consumption was inversely related to environmental pollution in Saudi Arabia.

Cross-Sectional Studies

Gershon et al. (2024) empirically examined and concluded that energy use and real GDP exerted a positive influence on CO2 emissions, while FDI and population showed a negative influence for seventeen African countries. Osobajo et al. (2020) analyzed 70 nations to study the relationship between energy usage, population and capital formation along with their impact on emissions from 1994 to 2013. Their findings indicated that energy utilization, population and capital formation enhanced CO2 emissions. Mahapatra and Irfan (2021) explored the energy efficiency impact on emissions while utilizing data from 1990 to 2017 for 34 developing and 28 developed economies. A 1 percent increase in energy efficiency resulted in 1.19 emissions decrease in developing countries and 1.24 emissions decrease in developed countries according to their findings. Furthermore, a 1 percent decrease in energy efficiency enhances emissions by 1.06 percent and 0.37 percent for developing and developed countries, respectively. Alshehry and Belloumi (2023) indicated that both energy use and economic development increased environmental pollution in 17 countries. Ehigiamusoe (2020) explored the electricity generation and consumption influence on emissions in 25 African economies. Results suggested that consumption of electricity showed a positive influence on emissions, whereas electricity output from renewable sources was negatively linked with emissions. Moreover, gas, coal and oil-generated electricity indicated a detrimental influence on emissions, whereas the influence of hydro-generated electricity on emissions was negative. Mujtaba et al. (2022) authenticated that non-renewable consumption of energy and capital formation positively impacted CO2 emissions in 17 OECD nations. Behera and Dash (2017) empirically explored that energy use and FDI exerted a direct influence on CO2 emissions in seventeen Asian countries.

Table 1: Summary of Literature Review

Author	Methodology	Country	Data Period	Findings
Soytas et al. (2007)	TY	USA	1960-2004	EC Granger causes CO2 emissions.
Zhang and Cheng (2009)	TY	China	1960–2007	One-way causality from EC to emissions.
Yang and Zhao (2014)	Granger Causality	India	1970–2008	One-way causality from EC to carbon emissions and EG.
Joo et al. (2015)	Granger Causality, Cointegration and ECM	Chile	1965–2010	One-way causality from EC to CO2 emissions and EG.
Wang et al. (2016)	VECM and Granger Causality	China	1990–2012	One-way causality from EC to CO2 emissions and two-way causality between EG and EC.
Mohiuddin et al. (2016)	VECM	Pakistan	1971-2013	One-way causality from EC to CO2 emissions
Nain et al. (2017)	TY	India	1971-2011	Unidirectional causality from EC to GDP and CO2 emissions.
Alam et al. (2011)	TY	India	1971-2006	Bidirectional causality between EC and CO2 emissions.
Hussain et al. (2012)	Cointegration, VECM and Granger causality	Pakistan	1971-2006	Bidirectional causality between EC and CO2 emissions
Magazzino (2016)	TY	Italy	1970–2006.	Bidirectional causality between EC, EG and CO2 emissions.
Lee and Yoo (2016)	Cointegration and ECM	Korea	1971–2008.	Bidirectional causality between EC, EG and CO2 emissions.
Mirza and Kanwal (2017)	Cointegration, ARDL and Granger causality	Pakistan	1971-2009	Bidirectional causality between CO2 emissions, EC and EG.
Gessesse and He (2020)	ARDL	China	1971-2015	EC and GDP have positive effects on CO2 emissions.
Chandia et al. (2018)	OLS and VECM	Pakistan	1971-2016	EC and GDP positively impact CO2 emissions, two-way causality between CO2 emissions and EC.
Shahbaz et al. (2013)	ARDL and VECM Granger causality	Indonesia	1975-2011	EC and EG have positive impacts on CO2 emissions, Bidirectional causality between CO2 emissions, EC and EG
Shahbaz et al. (2014)	ARDL	Bangladesh	1975–2010	Electricity consumption positively impacted CO2 emissions.
Khan et al. (2019)	Dynamic ARDL	Pakistan	1971-2016	EC and FDI positively impacted CO2 emissions.

Raggad (2020)	NARDL	Saudi Arabia	1971-2014	Positive change in EC enhances CO2 emissions
Abbas et al. (2021)	ARDL	Pakistan	1970-2018	EC has a positive effect on CO2 emissions.
Belaid and Youssef (2017)	ARDL	Algeria.	1980–2012	Electricity consumption and EG have positive impacts on CO2 emissions.
Khan et al. (2020)	ARDL	Pakistan	1965-2015.	EC and EG have a positive influence on CO2 emissions.
Kanat et al. (2022)	ARDL	Russia	1990-2016	Oil, gas and coal consumption positively impacted CO2 emissions.
Ahmad et al. (2016)	ARDL and VECM	India	971–2014.	Total EC, consumption of electricity, oil, gas and coal were positively associated with CO2 emissions.
Sahoo and Sahoo (2022)	ARDL and TY	India	1965-2018.	Consumption of coal, gas and oil and GDP have positive impacts on CO2 emissions.
Majeed et al. (2021)	NARDL	Pakistan	1971-2014	An increase in oil and a reduction in total energy, coal and electricity consumption increase ecological footprint.
Rahman and Ahmad (2019)	NARDL	Pakistan.	1980–2016	Consumption of coal and oil, GDP per capita and capital formation have a positive influence on CO2 emissions.
Alkhathlan and Javid (2013)	ARDL and VECM	Saudi Arabia	1980-2011	Total EC, oil, gas and electricity consumption have a positive influence on CO2 emissions.
Gershon et al. (2024)	Fixed and Random effects models	17 African Countries	2000-2017	EC and real GDP enhanced CO2 emissions while population growth and FDI reduced it.
Osobajo et al. (2020)	Pooled OLS and Fixed Effect Model	70 Countries	1994-2013	EC, population and capital formation have positive impacts on CO2 emissions.
Mahapatra and Irfan (2021)	Nonlinear Panel ARDL	62 Countries	1990-2017	The reduction in CO2 emissions relied on an increase in energy efficiency but a decrease caused more emissions.
Alshehry and Belloumi (2023)	Linear and Nonlinear Panel ARDL	17 MENA Countries	1990-2020	EC and GDP increased CO2 emissions
Ehigiamusoe (2020)	DOLS and FMOLS	25 African Countries	1980-2016	Electricity consumption and electricity generated from oil, gas and coal have positive impacts on CO2 emissions.
Mujtaba et al. (2022)	ARDL and NARDL	17 OECD Countries	1970-2016	EC and capital formation have harmful influences on the environment.
Behera and Dash (2017)	DOLS and FMOLS	17 SSEA Countries	1980–2012	Primary and fossil fuel EC and FDI positively impacted CO2 emissions.

Note: EC = Energy Consumption, EG = Economic Growth, TY = Toda and Yamamoto, VECM = Vector Error Correction Model, ECM= Error Correction Model, ARDL =
Autoregressive Distributive Lag Approach, NARDL = Non-linear Autoregressive Distributive Lag Approach, DOLS = Dynamic OLS, FMOLS = Fully Modified OLS.

Data and Methodology

Data and Variables

This study analyzes data spanning from 1992 to 2022 while achieving its primary goal to understand how various sectors of oil, gas and coal consumption influence carbon dioxide (CO2) emissions in Pakistan. For this objective, this research is based on the following variables.

Dependent Variable

The analysis in the current research employs CO2 emissions as the environmental degradation proxy following earlier studies by: Alola and Kirikkaleli (2019), Apergis and Payne (2009), Lean and Smyth (2010), Razzaq et al. (2021) and Zafar et al. (2022).

Independent Variables

i. Oil Consumption

Previous researchers such as: Adebayo et al. (2021), Kanat et al. (2022), Kartal (2022), and Lim et al. (2014), have already studied how aggregated oil consumption influences CO2 emissions in various countries. Unlike these studies, the current research analyzes oil consumption across household, industrial, agricultural, transport, power and other government sectors.

ii. Gas Consumption

Several research works including: Adebayo et al. (2021), Amer et al. (2024), Dong et al. (2018), Kanat et al. (2022), and Kartal (2022) studied the link between gas consumption and CO2 emissions at an aggregated level. A study of disaggregated gas consumption across seven sectors makes up the main focus of the present paper which examines household, commercial, cement, fertilizer, power, industrial and transport sectors.

iii. Coal consumption

Many previous researchers (Adebayo et al., 2021; Amer et al., 2024Cheng et al., 2021; Kanat et al., 2022; Kartal, 2022; Pata, 2018) have investigated the association between aggregated coal consumption and CO2 emissions. Departing from these studies, the present study considers coal consumption in the power and brick kiln sectors as separate explanatory variables.

Control Variables

The current research includes population along with foreign direct investment and gross fixed capital formation as control variables. When FDI increases local production rises therefore manufacturers consume additional resources leading to increased environmental damage. This relationship was confirmed by earlier studies conducted by: Adeel et al. (2024), Al-mulali (2012), Amoah et al. (2023), Bakhsh et al. (2017), Behera and Dash (2017), and Kim and Seok (2023). CO2 emissions also increase with population growth which requires industrial expansion, higher energy consumption, additional transportation activities, more deforestation and land-use transitions for housing or agricultural purposes. Higher gross fixed capital formation is referred to as more investments in physical assets like machines, buildings and infrastructures. All these activities stimulate economic growth thereby causing more CO2 emissions.

Data Source

Data concerning CO2 emissions is sourced from our world in Data, while population, gross fixed capital formation and foreign direct investment are searched from the WDI. Moreover, the data related to all sectors of oil, gas and coal consumption is taken from the Pakistan Economic Dashboard. Table 2 summarizes the data source and variables

Table 2: Description of Variables

Name of Variables	Abbreviation	Measurement Unit	Source
CO2 Emissions	lnCO2	Kilotons	Our World in Data
Total Population	lnPOP	Numbers	WDI
Gross Fixed Capital Formation	lnGFC	Constant Local Currency Unit	WDI
Foreign Direct Investment	lnFDI	Current US Dollars	WDI
Households Sector Oil Consumption	lnHOILC	Tons	Pakistan Economic Dashboard
Industrial Sector Oil Consumption	lnIOILC	Tons	Pakistan Economic Dashboard
Agriculture Sector Oil Consumption	lnAOILC	Tons	Pakistan Economic Dashboard
Transport Sector Oil Consumption	lnTOILC	Tons	Pakistan Economic Dashboard
Power Sector Oil Consumption	lnPOILC	Tons	Pakistan Economic Dashboard
Other Govt. Oil Consumption	lnOGOILC	Tons	Pakistan Economic Dashboard
Households Sector Gas Consumption	lnHGC	Million Cubic Feet	Pakistan Economic Dashboard

Commercial Sector Gas Consumption	lnCGC	Million Cubic Feet	Pakistan Economic Dashboard
Cement Sector Gas Consumption	lnCEGC	Million Cubic Feet	Pakistan Economic Dashboard
Fertilizer Sector Gas Consumption	lnFGC	Million Cubic Feet	Pakistan Economic Dashboard
Power Sector Gas Consumption	lnPGC	Million Cubic Feet	Pakistan Economic Dashboard
industrial Sector Gas Consumption	lnIGC	Million Cubic Feet	Pakistan Economic Dashboard
Transport CNG Sector Gas Consumption	lnTCNGGC	Million Cubic Feet	Pakistan Economic Dashboard
Power Sector Coal Consumption	lnPCOALC	Thousand Metric Tons	Pakistan Economic Dashboard
Brick Kilns Sector Coal Consumption	lnBKCOALC	Thousand Metric Tons	Pakistan Economic Dashboard

Model Specification

The major objective of this study is to determine the sectoral consumption influence of oil, gas and coal on CO2 emissions in Pakistan while adopting a correlated component regression approach. The influence of aggregated consumption of energy, including oil, gas and coal, has been examined in the earlier empirical studies. In this study, we will extend the analysis to the sectoral level and attempt to seek the sectoral influence of oil, gas and coal consumption on CO2 emissions. This objective has been achieved by employing the STIRPAT model, abbreviated as Stochastic Impacts by Regression on Population, Affluence, and Technology. Previous studies, including the work by: Amer et al. (2024), Shaheen et al. (2022), Zmami and Ben-Salha (2020), and many other researchers have employed the STIRPAT model to determine the factors driving environmental degradation in different contexts. This study also utilizes the STIRPAT model to find out the sectoral influence of oil, gas and coal consumption on CO2 emissions in Pakistan. This model can be presented as follows:

$$I = \beta_0 P^{\alpha}.A^{\beta}.T^{\delta}.\varepsilon \qquad (1)$$

I in this equation indicates environmental degradation which is measured by CO2 emissions. The P is represented by the population size (POP) at a given point in time. As the population of a country grows, it leads to more deforestation and land clearing for commercial or agricultural purposes which requires more energy usage and hence causes greater environmental pollution. A is divided into two variables, including gross fixed capital formation (GFC) and foreign direct investment (FDI). Finally, T is decomposed into three crucial variables, such as oil consumption (OILC), natural gas consumption (GC) and coal consumption (COALC). By incorporating all aforementioned variables into equation (1), equation (2) is constructed as follows:

$$CO2 = \beta_0 POP^{\alpha}.GFC^{\beta1}.FDI^{\beta2}.OILC^{\delta1}.GC^{\delta2}.COALC^{\delta3}.\varepsilon \qquad (2)$$

Finding the sectoral influence of oil, gas and coal consumption on CO2 emissions is a fundamental purpose of this study. Therefore, the OILC is disaggregated into six components, including household sector oil consumption (HOILC), industrial sector oil consumption (IOILC), agriculture sector oil consumption (AOILC), transport sector oil consumption (TOILC), power sector oil consumption (POILC), and other government sector oil consumption (OGOILC). The GC has been divided into seven components, such as household sector gas consumption (HGC), commercial sector gas consumption (CGC), cement sector gas consumption (CEGC), fertilizer sector gas consumption (FGC), power sector gas consumption (PGC), industrial sector gas consumption (IGC) and transport sector (CNG) sector gas consumption (TCNGGC). Finally, power sector coal consumption (PCOALC) and brick kilns coal consumption (BKCOALC) are the two components of COALC. Incorporating the aforementioned fifteen energy consumption variables into equation (2), yields equation (3) as follows:

$$CO2 = \beta_0.POP^{\alpha}.GFC^{\beta1}.FDI^{\beta2}.HOILC^{\delta11}.IOILC^{\delta12}.AOILC^{\delta13}.TOILC^{\delta14}.POILC^{\delta15}.OGOILC^{\delta16}. HGC^{\delta21}.CGC^{\delta22}.CEGC^{\delta23}.FGC^{\delta24}.PGC^{\delta25}.IGC^{\delta26}.TCNGGC^{\delta27}.PCOALC^{\delta31}.BKCOALC^{\delta32}.\varepsilon \qquad (3)$$

Taking the natural log on both sides of equation (3) yields equation (4) as follows:

$$lnCO2 = ln\beta_0 + \alpha lnPOP + \beta_1 lnGFC + \beta_2 lnFDI + \delta_{11} lnHOILC + \delta_{12} lnIOILC + \delta_{13} lnAOILC + \delta_{14} lnTOILC + \delta_{15} lnPOILC + \delta_{16} lnOGOILC + \delta_{21} lnHGC + \delta_{22} lnCGC + \delta_{23} lnCEGC + \delta_{24} lnFGC + \delta_{25} lnPGC + \delta_{26} lnIGC + \delta_{27} lnTCNGGC + \delta_{31} lnPCOALC + \delta_{32} lnBKCOALC + ln\varepsilon \qquad (4)$$

Equation (4) can be used to determine the sectoral influence of oil, gas and coal consumption on CO2 emissions in Pakistan.

Methodology

The correlated component regression (CCR) technique, provided by Magidson (2013), was applied in this research to address a high degree of multicollinearity in the dataset. Magidson (2013) indicated that the CCR methodology enhances the reliability of estimated coefficients even when the independent variables are multicollinear. Scale invariant is an important advantage of the CCR methodology over the traditional methodologies, implying that it provides identical results whether explanatory variables are based on unstandardized or standardized regressors. Traditional methods like PLS-R and penalized regression algorithms along with Ridge Regression, Lasso and Elastic Net are predictor scaling-dependent and yield different results when using unstandardized and standardized predictors. The CCR technique also performs effectively when analyzing datasets with numerous predictors along with limited sample observations such as this study which contains 18 predictors and only 31 sample values. Traditional regression methods produce inaccurate and indefinite coefficient values whenever the number of regressors matches or exceeds the sample size. However, the CCR model possesses alternative features that address this particular limitation. Additionally, this method is applied because it is a new methodological approach that brings innovative contributions to this study.

In earlier research work, Alkerwi et al. (2015) applied the CCR model to study how various demographic and socioeconomic factors affect diet quality. Moreover, in the previous economic literature, some other studies (Bullock, 2021; Naveed & Hina, 2023; Naveed, Maqsood, & Cheema, 2024; Naveed, Maqsood, Cheema, & Yousaf, 2024) have also applied the CCR technique. This methodology has also been applied in this study to examine the sectoral impact of oil, gas and coal consumption on CO2 emissions. The general framework of the CCR methodology is as follows:

In the first stage, we will fit the regression equations utilizing OLS for every regressor separately. This is indicated as follows:

$$ln\hat{Y} = \hat{\gamma}_g^{(1)} + \hat{\lambda}_g^{(1)} lnX_g \qquad (5)$$

In equation (5), *ln* indicates the natural logarithm, Y represents the dependent variable and the symbol Xg signifies explanatory variables in which g takes values like 1, 2,…P and $\hat{\gamma}_g^{(1)}$ and $\hat{\lambda}_g^{(1)}$ represent constant coefficient as well as regression coefficients for a specific independent variable g. The first correlated component variable, lnS_1, captures the impacts of prime predictors, which have a direct impact on the outcome variable. It is the weighted sum of all 1-predictor impacts, considering the slope coefficients obtained from equation (5) as weights. It is defined as follows:

$$lnS_1 = \sum_{g=1}^{P} \hat{\lambda}_g^{(1)} lnX_g \qquad (6)$$

Regressing a basic OLS of lnY on lnS_1 yields the predictions for the explained variable Y (in the form of a natural logarithm) in the 1-component CCR model:

$$ln\hat{Y} = \hat{\alpha}^{(1)} + \hat{\beta}_1^{(1)} lnS_1 \qquad (7)$$

The second correlated component variable, lnS_2, is derived by first employing the following regression equation for each predictor using simple OLS:

$$ln\hat{Y} = \hat{\gamma}_g^{(2)} + \hat{\lambda}_{1,g}^{(2)} lnS_1 + \hat{\lambda}_g^{(2)} lnX_g \qquad (8)$$

The second component, lnS_2, then becomes the weighted sum of all the 2-predictor impacts and is calculated as follows:

$$lnS_2 = \sum_{g=1}^{P} \hat{\lambda}_g^{(2)} lnX_g \qquad (9)$$

Regressing a basic OLS of lnY on lnS_1 and lnS_2 produces the predictions for the outcome variable Y (in the form of a natural logarithm) in the 2-component CCR model:

$$ln\hat{Y} = \hat{\alpha}^{(2)} + \hat{\beta}_1^{(2)} lnS_1 + \hat{\beta}_2^{(2)} lnS_2 \qquad (10)$$

Accordingly, the aforementioned procedure for obtaining the correlated component variables can be followed over again until the optimal number of component variables is reached. Generally, for any component variable K (where K< P), we will fit the following regression equation for each regressor utilizing the OLS:

$$ln\hat{Y} = \hat{\gamma}_g^{(K)} + \hat{\lambda}_{1,g}^{(K)} lnS_1 + \hat{\lambda}_{2,g}^{(K)} lnS_2 + \cdots + \hat{\lambda}_{K-1,g}^{(K)} lnS_{K-1} + \hat{\lambda}_g^{(K)} lnX_g \qquad (11)$$

Finally, the last component variable, lnS_k, is then found using equation (12):

$$lnS_k = \sum_{g=1}^{P} \hat{\lambda}_g^{(k)} lnX_g \qquad (12)$$

Regressing a simple OLS of lnY on lnS_1, lnS_2…, lnSk yields the predictions for the explained variable Y in the k-component CCR model:

$$ln\hat{Y} = \hat{\alpha}^{(K)} + \hat{\beta}_1^{(K)} lnS_1 + \hat{\beta}_2^{(K)} lnS_2 + \cdots + \hat{\beta}_k^{(K)} lnS_k \quad (13)$$

To produce the values of regression coefficients, we can re-express the K-component CCR model by inserting equations (6), (9) and (12) into equation (13) as indicated in the following equation:

$$ln\hat{Y} = \hat{\alpha}^{(K)} + \hat{\beta}_1^{(K)} \left(\sum_{g=1}^{P} \hat{\lambda}_g^{(1)} lnX_g\right) + \hat{\beta}_2^{(K)} \left(\sum_{g=1}^{P} \hat{\lambda}_g^{(2)} lnX_g\right) + \cdots + \hat{\beta}_k^{(K)} \left(\sum_{g=1}^{P} \hat{\lambda}_g^{(k)} lnX_g\right) \quad (14)$$

Algebraic manipulation and simplification of equation (14) yields equation (15):

$$ln\hat{Y} = \hat{\alpha}^{(K)} + \sum_{k=1}^{k} \hat{\beta}_k^{(K)} \left(\sum_{g=1}^{P} \hat{\lambda}_g^{(k)} lnX_g\right) = \hat{\alpha}^{(K)} + \sum_{g=1}^{P} \hat{\beta}_g \, lnX_g \quad (15)$$

Thus, the estimated regression coefficient $\hat{\beta}_g$ is a weighted aggregate of the loadings. The regression coefficients of the K-component CCR model, as expressed in equation (13), serve as weights:

$$\hat{\beta}_g = \sum_{k=1}^{P} \hat{\beta}_k^K \hat{\lambda}_g^{(k)} \quad (16)$$

By replacing lnCO2 with lnY in equation (15) and incorporating all relevant explanatory variables, we yield an equation equivalent to equation (4), which we are trying to estimate.

Equation (16) provides the estimates of unstandardized coefficients, whereas the standard errors of estimated coefficients can be estimated using the following formula:

$$SE\left(\hat{\beta}_g\right) = \sqrt{\sum_{k=1}^{K} \left(SE\left(\hat{\beta}_k^K\right)\right)^2 \left(\hat{\lambda}_g^k\right)^2} \quad (17)$$

Where $\hat{\lambda}_g^k$ indicates the loadings on all correlated component variables and $SE\left(\hat{\beta}_k^K\right)$ denotes the coefficient's standard error for the K-component CCR model. The standardized regression coefficients in absolute values are employed to assess the relative significance of each explanatory variable concerning CO2 emissions. These coefficients are produced by applying the following formula:

$$\hat{\beta}_g^* = \left(\frac{\hat{\sigma}_g}{\hat{\sigma}_y}\right) \times \hat{\beta}_g \quad (22)$$

Where $\hat{\beta}_g^*$ and $\hat{\beta}_g$ respectively denote the standardized and unstandardized coefficients of each of the regressors with g equaling 1, 2, 3…, P. Furthermore, $\hat{\sigma}_g$ and $\hat{\sigma}_y$ measure the dispersion as a standard deviation for each regressor and explained variable, respectively, with g indicating 1, 2, 3…, P.

The standardized coefficients represent which explanatory variable has a higher influence on the explained variable. In this research, the relative contribution of each explanatory variable to CO2 emissions is measured through standardized coefficients in absolute values which are then presented as percentages of their absolute sum.

Results and Discussion

Figure 1 indicates the behavior of CO2 emissions from 1992 to 2022 in Pakistan. Figure 2a and 2b shows oil consumption pattern in various sectors, while gas consumed in the fertilizer, power, industrial, transport, household, commercial and cement sectors is presented in Figure 3a and 3b. Finally, power and brick kilns coal consumption behavior is shown in Figure 4.

Figure 1: CO2 Emissions

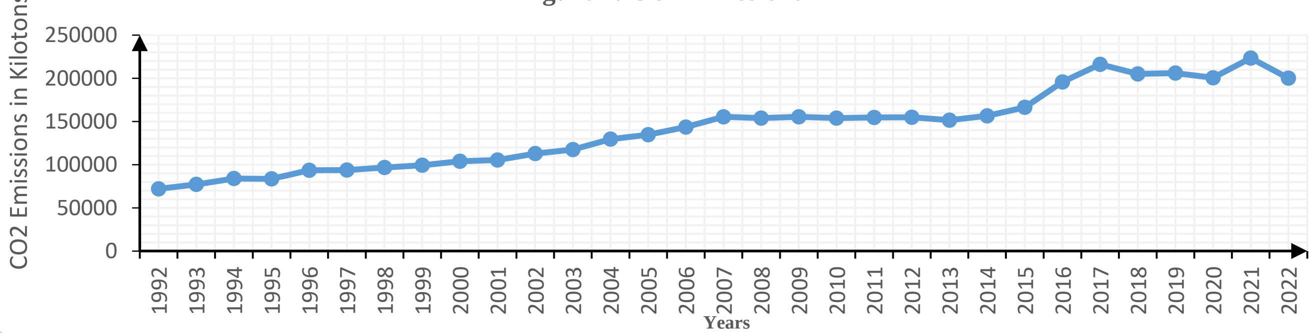


Figure 2a: Industrial (IOILC), Transport (TOILC) and Power (POILC) Sector Oil Consumption in Tons

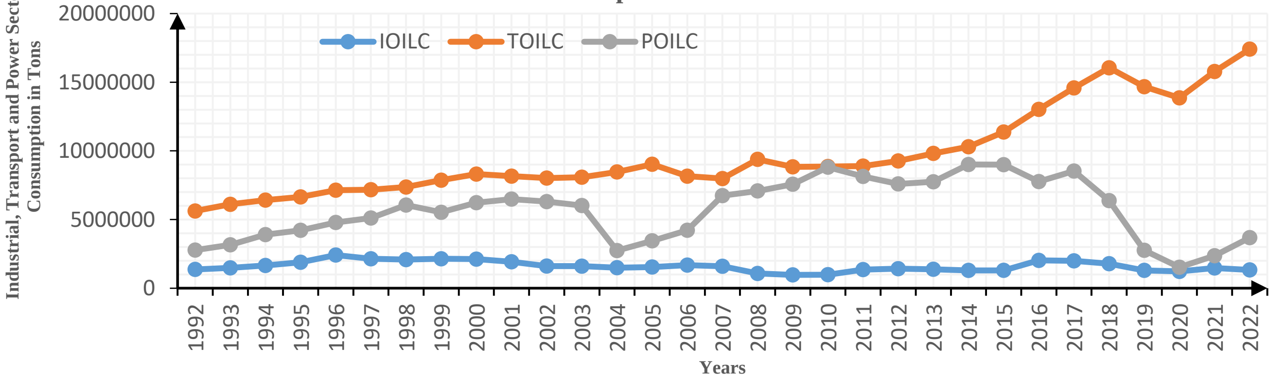


Figure 2b: Household (HOILC), Agriculture (AOILC) and Government (OGOILC) Sector Oil Concumption in Tons

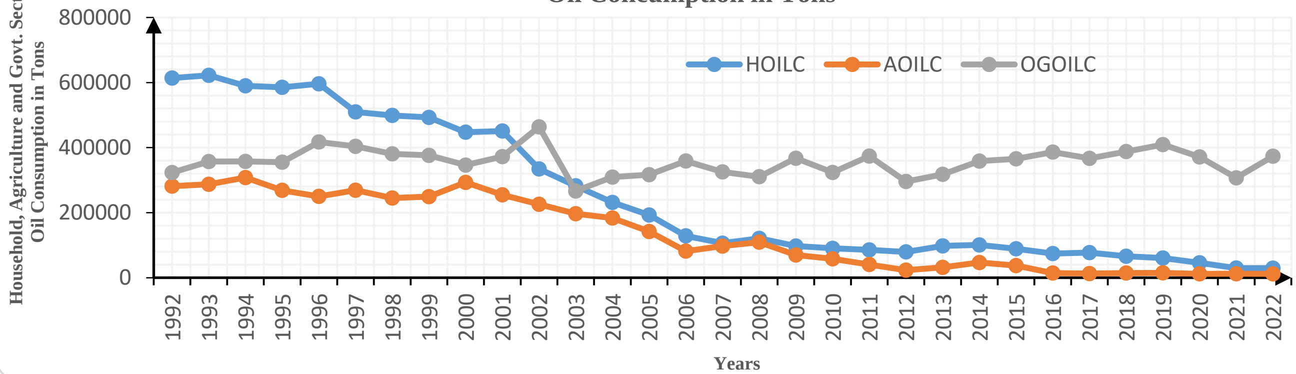


Figure 3a: Fertilizer (FGC), Power (PGC), Industrial (IGC) and Transport (TCNGGC) Sector Gas Consumption

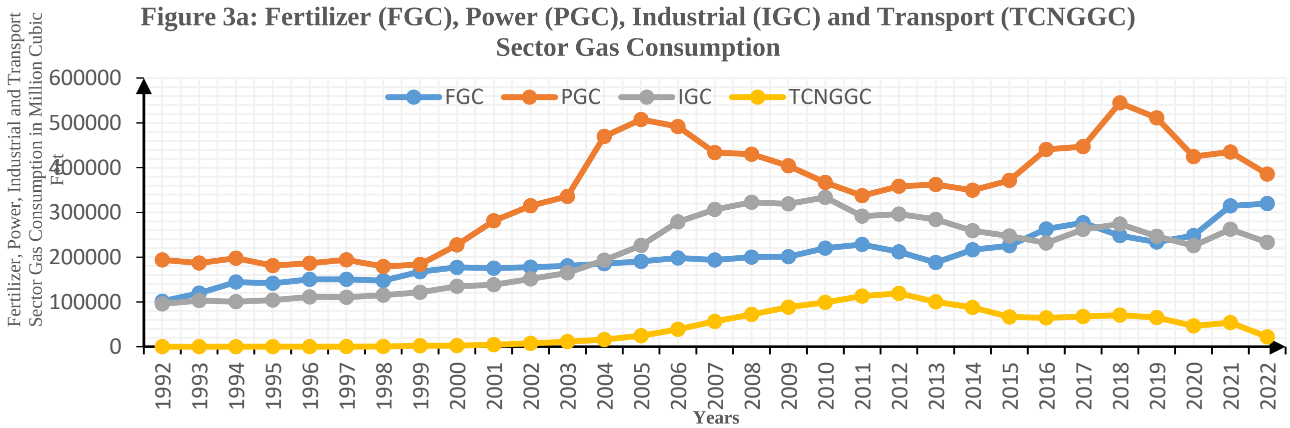


Figure 3b: Household (HGC), Commercial (CGC) and Cement (CEGC) Sector Gas Consumption

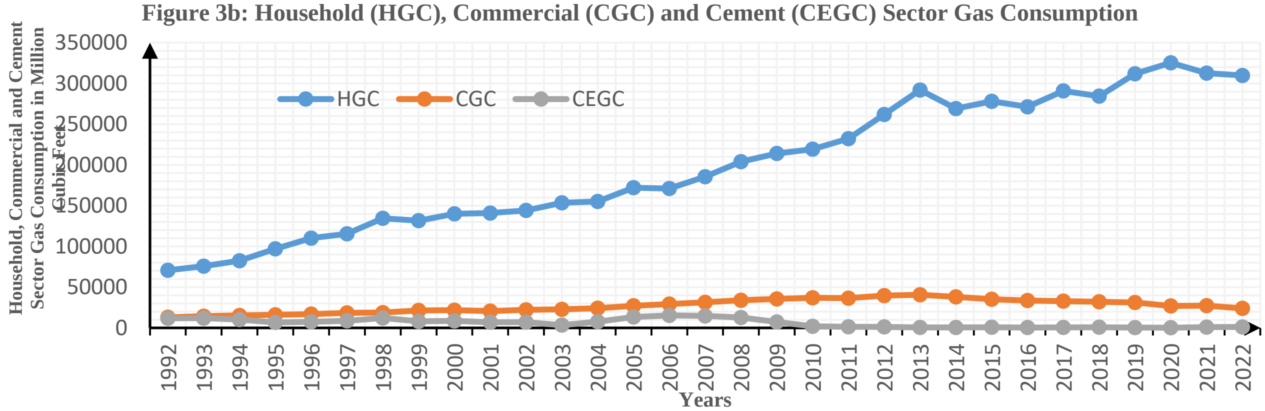
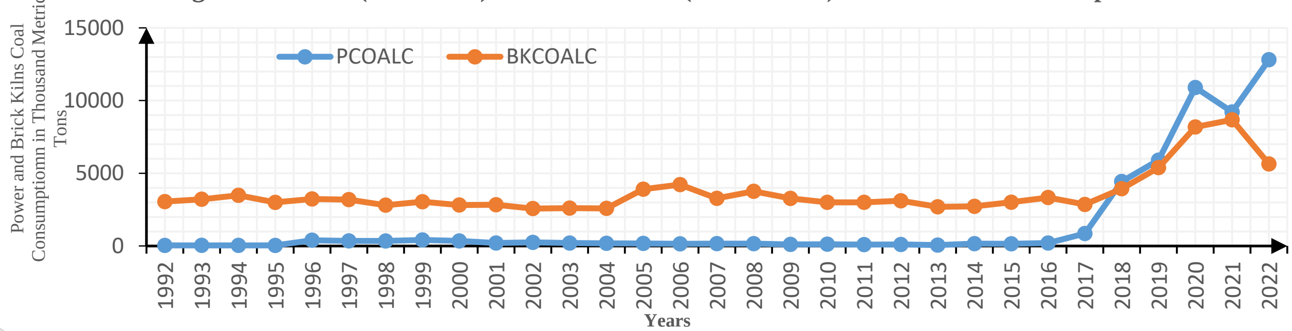


Figure 4: Power (PCOALC) and Brick Kilns (BKCOALC) Sector's Coal Consumption



Summary statistics (Table 3) results indicate that the mean of carbon dioxide (CO2) emissions, in the natural logarithm, is found to be 11.81 kilotons, with 12.32 and 11.18 kilotons as maximum and minimum values, respectively. The degree to which the CO2 emission differs from the mean, as expressed by the standard deviation in the natural logarithm, is calculated to be 0.33 kilotons. Among the six gas consumption sectors, AOILC and OGOILC show the highest and lowest absolute dispersion, respectively. Similarly, in the seven gas consumption sectors, TCNGGC exhibits the highest absolute dispersion, while FGC has the lowest. Furthermore, among the two sectors of coal consumption, PCOAL and BKCOALC indicate the highest and lowest dispersion, respectively. Moreover, the summary statistics results reveal that the median for all variables excluding lnGFC, lnHOILC, lnTOILC, lnPCOALC, and lnBKCOALC is greater than the mean, indicating a negative skewness as demonstrated by negative skewness coefficients observed for lnCO2, lnPOP, lnFDI, lnIOILC, lnAOILC, lnPOILC, lnOGOILC, lnHGC, lnCGC, lnCEGC, lnFGC, lnPGC, lnIGC, and lnTCNGGC. The kurtosis values concerning all variables excluding lnOGOILC, lnFGC, lnPCOALC, and lnBKCOALC fall below 3, implying a platykurtic distribution, while the kurtosis values for lnOGOILC = 3.20, lnFGC = 3.06, lnPCOALC = 3.36, and lnBKCOALC = 5.77 indicate a leptokurtic distribution for these variables. The Jarque-Bera analysis shows that observed data for all variables excluding lnPCOALC and lnBKCOALC follow the normal distribution at the 95% confidence level, whereas the distributions of lnPCOALC and lnBKCOALC are non-normal.

Table 3: Summary Statistics

Variables	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque Bera	Prob.	Obs.
lnCO2	11.81	11.93	12.32	11.18	0.33	-0.23	1.92	1.77	0.41	31
lnPOP	18.99	19.02	19.28	18.62	0.20	-0.35	1.91	2.17	0.34	31
lnGFC	28.85	28.89	29.34	28.48	0.28	0.07	1.56	2.71	0.26	31
lnFDI	20.91	21.01	22.44	19.55	0.82	-0.02	2.09	1.07	0.58	31
lnHOILC	12.02	11.70	13.34	10.29	0.97	0.01	1.70	2.18	0.34	31
lnIOILC	14.26	14.25	14.70	13.78	0.23	-0.14	2.41	0.55	0.76	31
lnAOILC	11.25	11.48	12.64	9.38	1.22	-0.36	1.57	3.29	0.19	31
lnTOILC	16.05	15.99	16.67	15.54	0.30	0.58	2.42	2.20	0.33	31
lnPOILC	15.46	15.62	16.01	14.24	0.46	-0.80	2.83	3.31	0.19	31
lnOGOILC	12.78	12.79	13.05	12.49	0.11	-0.20	3.20	0.26	0.88	31
lnHGC	12.11	12.13	12.69	11.17	0.45	-0.46	2.15	2.05	0.36	31
lnCGC	10.16	10.21	10.61	9.48	0.33	-0.45	2.07	2.14	0.34	31
lnCEGC	8.07	8.85	9.64	5.58	1.33	-0.41	1.58	3.50	0.17	31
lnFGC	12.17	12.17	12.68	11.53	0.26	-0.24	3.06	0.31	0.86	31
lnPGC	12.69	12.80	13.21	12.10	0.37	-0.50	1.78	3.25	0.20	31
lnIGC	12.18	12.35	12.72	11.47	0.42	-0.43	1.61	3.47	0.18	31
lnTCNGGC	9.10	10.57	11.69	3.22	2.80	-1.01	2.57	5.54	0.06	31
lnPCOALC	5.69	5.22	9.46	3.68	1.64	1.14	3.36	6.93	0.03	31
lnBKCOALC	8.14	8.04	9.07	7.85	0.30	1.84	5.77	27.48	0.00	31

The correlation coefficients in Table 4 indicate that some explanatory variables are positively associated, while some are negatively related to each other. Moreover, correlation coefficients between some variables have absolute values less than 0.80, while the values between several explanatory variables are extremely high and exceed 0.80 (Green values in Table 4) in absolute value. The high (0.80 or above) value of simple pairwise correlations among predictors indicates the presence of severe multicollinearity as highlighted by Willis and

Perlack (1978).

Table 4: Correlation matrix

Predictors	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
lnPOP 1	1																	
lnGFC 2	0.92	1																
lnFDI 3	0.70	0.82	1															
lnHOILC 4	-0.97	-0.94	-0.74	1														
lnIOILC 5	-0.44	-0.42	-0.42	0.53	1													
lnAOILC 6	-0.93	-0.92	-0.61	0.94	0.35	1												
lnTOILC 7	0.91	0.88	0.55	-0.88	-0.21	-0.92	1											
lnPOILC 8	0.14	0.06	0.13	-0.04	0.03	-0.01	-0.04	1										
lnOGOILC 9	-0.07	-0.03	-0.06	0.12	0.34	-0.01	0.09	0.03	1									
lnHGC 10	0.99	0.89	0.68	-0.94	-0.39	-0.91	0.89	0.20	-0.05	1								
lnCGC 11	0.85	0.75	0.73	-0.79	-0.48	-0.71	0.60	0.49	-0.18	0.87	1							
lnCEGC 12	-0.80	-0.69	-0.32	0.74	0.26	0.87	-0.80	-0.06	-0.08	-0.81	-0.59	1						
lnFGC 13	0.95	0.87	0.65	-0.92	-0.27	-0.88	0.93	0.12	0.00	0.93	0.74	-0.72	1					
lnPGC 14	0.84	0.85	0.80	-0.82	-0.47	-0.72	0.72	0.04	-0.21	0.80	0.78	-0.48	0.77	1				
lnIGC 15	0.87	0.84	0.84	-0.87	-0.60	-0.74	0.64	0.32	-0.26	0.86	0.95	-0.51	0.78	0.88	1			
lnTCNGGC 16	0.91	0.79	0.74	-0.85	-0.47	-0.73	0.70	0.35	-0.18	0.91	0.96	-0.58	0.83	0.87	0.95	1		
lnPCOALC 17	0.60	0.58	0.28	-0.58	0.02	-0.62	0.80	-0.40	0.25	0.58	0.17	-0.52	0.67	0.40	0.25	0.35	1	
lnBKCOALC 18	0.47	0.55	0.38	-0.58	-0.25	-0.57	0.60	-0.66	0.03	0.43	0.09	-0.37	0.51	0.37	0.26	0.22	0.75	1

The variance inflation factor (VIF) and the condition index (CI) are also applied to assess the multicollinearity. According to the VIF criterion, there is severe multicollinearity between the predictors if the VIF value is greater than10 (Kennedy, 2008; Kyriazos & Poga, 2023). In Table 5, all the VIF values excluding lnIOILC and lnOGOILC exceed 10, implying a harmful multicollinearity in the data. According to the CI method, multicollinearity is severe if the CI value is 15 or greater (Midi et al., 2010). In our findings, the CI has a maximum value of 217.84, which is larger than 15, indicating severe multicollinearity. Severe multicollinearity among explanatory variables produces unstable and statistically insignificant coefficient estimates (Paetzold, 1992). As a result, we need to use an econometric approach that is suitable for collinear datasets. Severely multicollinear dataset analysis benefits from the CCR method which produces reliable and precise coefficient estimates (Magidson, 2013). Therefore, this study adopts the CCR methodology for analyzing the sectoral contributions of oil, gas, and coal usage on CO2 emissions in Pakistan.

Table 5: Variance Inflation Factor and Condition Index

Predictors	Variance Inflation Factor (VIF)			Condition Index (C.I)	
	R_i^2	$1 - R_i^2$	**VIF**	**Eigen Values**	**C.I**
lnPOP	0.9996	0.0004	2754.8209	11.4843	1.0000
lnGFC	0.9897	0.0103	96.6651	2.5856	2.1075
lnFDI	0.9426	0.0574	17.4149	1.5101	2.7577
lnHOILC	0.9984	0.0016	619.5787	0.7983	3.7929
lnIOILC	0.8891	0.1109	9.0180	0.6253	4.2856
lnAOILC	0.9942	0.0058	171.9690	0.3106	6.0804
lnTOILC	0.9946	0.0054	185.5632	0.2496	6.7836
lnPOILC	0.9409	0.0591	16.9268	0.1693	8.2370
lnOGOILC	0.7473	0.2527	3.9569	0.0979	10.8324
lnHGC	0.9982	0.0018	564.6527	0.0692	12.8835
lnCGC	0.9952	0.0048	207.0393	0.0429	16.3642
lnCEGC	0.9792	0.0208	48.0354	0.0246	21.6153
lnFGC	0.9759	0.0241	41.5749	0.0147	27.9061
lnPGC	0.9821	0.0179	55.7351	0.0068	41.1260
lnIGC	0.9951	0.0049	204.4154	0.0049	48.6509
lnTCNGGC	0.9970	0.0030	333.5557	0.0035	57.5042
lnPCOALC	0.9725	0.0275	36.3994	0.0023	70.1007
lnBKCOALC	0.9131	0.0869	11.5023	0.0002	217.8432

Table 6 shows each predictor's loading upon four correlated component variables. All predictors excluding POILC and OGOILC exhibit significant loadings upon the first component variable, while the second component variable has only six significant loadings, such as the loading of HOILC, IOLC, TOILC, FGC, IGC and PCOALC. On the other hand, the third component variable has eight significant loadings, including IOILC, TOILC, CGC, PGC, IGC, TCNGGC, PCOALC and BKCOALC.

Table 6: Loadings on Correlated Component Variables

Predictors	lnS1	lnS2	lnS3	lnS4
lnPOP	1.6409*	-0.1040	-0.1696	-0.0767
lnGFC	1.1330*	0.1187	0.0365	0.0192
lnFDI	0.3082*	0.0019	0.0160	-0.0029
lnHOILC	-0.3278*	0.0713***	0.0414	-0.0270
lnIOILC	-0.5459**	0.1338*	0.0818***	-0.0024
lnAOILC	-0.2530*	-0.0089	0.0156	-0.0135
lnTOILC	1.0104*	0.1463*	-0.1998**	-0.0184
lnPOILC	0.0741	-0.0003	0.0193	-0.0063
lnOGOILC	-0.1362	0.0857	-0.0494	-0.0529
lnHGC	0.7034*	-0.0268	-0.0293	-0.0273
lnCGC	0.8321*	-0.0680	0.0795***	-0.0471
lnCEGC	-0.1861*	0.0024	0.0100	-0.0007
lnFGC	1.2085*	0.2248*	0.0687	0.0193
lnPGC	0.7721*	0.0249	0.0615***	0.0163
lnIGC	0.6765*	-0.0752***	0.1364*	-0.0329
lnTCNGGC	0.1050*	-0.0044	0.0124**	-0.0009
lnPCOALC	0.1261*	0.0108***	-0.0133***	-0.0019
lnBKCOALC	0.5580*	-0.0042	-0.0511**	-0.0119

*, ** and *** indicate that the loadings are significant at the 1%, 5% and 10% significance level, respectively.

Since each predictor shows insignificant loadings upon the fourth component variable, we omit the fourth component and proceed with the first three components. The identification of three components also follows the ascertain by Magidson (2010) that the CCR technique performs well with two, three, or four components. In addition to components, we have incorporated all explanatory variables to evaluate the sectoral impact of oil, gas, and coal utilization on CO2 emissions.

Table 7: Correlated Component Regression Model with K = 3

Component Variable	Un-Standardized Coefficients	Std. Error	T-Statistic	P-Value	Standardized Coefficients	Shares (%)
lnS1	0.091*	0.002	60.826	$<$ 0.000	1.040	83.788
lnS2	0.444*	0.068	6.567	$<$ 0.000	0.130	10.451
lnS3	0.194*	0.055	3.550	$<$ 0.010	0.072	5.761

*, ** and *** indicate that the coefficients are significant at the 1%, 5% and 10% significance level, respectively.

Table 7 indicates the estimated results concerning the correlated component regression model with three component variables. Our findings reveal that all component variable's coefficients are positive having a significant influence on the explained variable. The component variable, S1, captures the prime variable's (direct) effect, accounting for 83.788 percent of the total contribution. However, the second and third component variables S_2 and S_2 measure the suppressor variable's (indirect) effect. These two components comprise 10.451 and 5.761 percent of total shares. It is worth noting that the prime variables have a dominant share in determining the explained variable.

Table 8: Regression Results Based on the CCR Model

Predictors	Unstandardized Coefficients	Standard Error	T-Statistic	Prob.value	Significance	Standardized Coefficients	Contribution (%)
lnPOP	0.071	0.012	5.967	$<$ 0.001	*	0.042	3.41
lnGFC	0.163	0.008	19.347	$<$ 0.001	*	0.138	11.06
lnFDI	0.032	0.001	32.164	$<$ 0.001	*	0.080	6.41
lnHOILC	0.010	0.005	1.815	$<$ 0.100	***	0.028	2.29

lnIOILC	0.025	0.010	2.504	< 0.050	**	0.018	1.44
lnAOILC	-0.024	0.001	-21.635	< 0.001	*	-0.088	7.10
lnTOILC	0.118	0.015	8.008	< 0.001	*	0.108	8.68
lnPOILC	0.010	0.001	9.773	< 0.001	*	0.014	1.16
lnOGOILC	0.016	0.006	2.504	< 0.050	**	0.006	0.45
lnHGC	0.047	0.003	17.695	< 0.001	*	0.064	5.14
lnCGC	0.061	0.006	9.504	< 0.001	*	0.060	4.86
lnCEGC	-0.014	0.001	-22.104	< 0.001	*	-0.056	4.53
lnFGC	0.223	0.016	14.190	< 0.001	*	0.176	14.15
lnPGC	0.093	0.004	23.784	< 0.001	*	0.106	8.48
lnIGC	0.055	0.009	6.052	< 0.001	*	0.070	5.66
lnTCNGGC	0.010	0.001	13.257	< 0.001	*	0.085	6.83
lnPCOALC	0.014	0.001	13.089	< 0.001	*	0.068	5.47
lnBKCOALC	0.039	0.003	13.392	< 0.001	*	0.036	2.89
CONSTANT	-3.528	0.693	-5.088	< 0.001	*		

*, ** and *** indicate that the coefficients are significant at the 1%, 5% and 10% significance level.

After determining the two turning parameters including three components and eighteen explanatory variables, we go ahead and estimate the parameters of our concerned equation using the CCR model. The estimated regression results based on the CCR model are reported in Table 8. According to findings, population, capital formation and FDI have positive impacts on CO2 emissions. These results confirm that a 1 percent increase in population, capital formation and foreign direct investment enhance environmental pollution by 0.071, 0.163 and 0.032 percent, respectively. Oil consumption in the household sector (HOILC) has a positive impact on CO2 emissions, implying that environmental degradation rises with an increase in HOILC. More precisely, a 0.010 percent increase in CO2 emissions is associated with a 1 percent increase in HOILC. Oil consumption in the industrial sector (IOLC) also positively affects CO2 emissions. A 1 percent increase in IOILC leads to a 0.025 percent increase in CO2 emissions, indicating that environmental degradation increases with an increase in IOILC. The rise in agricultural sector oil use (AOILC) demonstrates a negative influence on CO2 emissions by generating a 0.024 percent decrement for every 1 percent increase in AOILC. This confirms that an increase in AOILC mitigates environmental pollution, while its decrease significantly damages the environmental quality. Oil consumption in the transport sector (TOILC) has a positive impact on CO2 emissions. According to the results, a 1 percent rise in TOILC leads to a 0.118 percent rise in CO2 emissions, suggesting that a positive change in TOILC increases pollution, while its negative change reduces pollution. Oil consumption in the power sector (POILC) also positively affects CO2 emissions. According to findings, a 0.010 percent increase in CO2 emissions is associated with a 1 percent increase in POILC, implying that environmental pollution increases due to an increase in POILC. Finally, oil consumption in the government sector (OGOILC) positively contributes to carbon emissions, suggesting a 0.016 percent increase in CO2 emissions due to a 1 percent rise in OGOILC.

Our results confirm that gas consumption in the household sector (HGC) has a positive effect on CO2 emissions, indicating that a 0.047 percent increase in CO2 emissions is associated with a 1 percent rise in HGC. Gas consumption in the commercial sector (CGC) also has a positive impact on CO2 emissions. A 1 percent increase in CGC leads to a 0.061 percent increase in CO2 emissions, showing that environmental degradation is associated with the increase in CGC. In contrast, gas consumption in the cement sector (CEG) has a negative effect on CO2 emissions, indicating a 0.014 percent decrease in CO2 emissions in response to a 1 percent increase in CEGC. This confirms that a higher CEGC mitigates environmental pollution, while its decline significantly damages the environmental quality. Gas consumption in the fertilizer sector (FGC) has a positive impact on CO2 emissions. According to empirical results, a 1 percent rise in FGC leads to a 0.223 percent rise in CO2 emissions. This confirms that a higher FGC increases pollution, while its reduction mitigates pollution. Similarly, gas consumption in the power sector has a positive influence on CO2 emissions. More precisely, a 0.093 percent increase in CO2 emissions is associated with a 1 percent rise in PGC. This implies that a higher PGC leads to higher environmental pollution, whereas its deterioration mitigates pollution. Gas consumption in the industrial sector (IGC) positively contributes to carbon emissions. According to estimated results, a 1 percent increase in IGC leads to a 0.055 percent increase in CO2 emissions. Finally, gas consumed in the transport sector (TCNGGC) has also a positive impact on CO2 emissions, showing that a 0.010 percent increase in CO2 emissions is associated with a 1 percent increase in TCNGGC. This confirms that environmental degradation in Pakistan is associated with higher gas consumption in TCNGGC.

Coal consumption in the power sector (PCOALC) has a positive influence on CO2 emissions. According to the results, a 1 percent positive rise in PCOALC leads to a 0.014 percent increase in CO2 emissions, implying that a higher PCOALC enhances environmental pollution. Similarly, coal consumption in the brick kilns sector (BKCOALC) also positively impacts CO2 emissions, showing a 0.039 percent increase in CO2 emissions following a 1 percent increase in BKCOALC. According to our results, positive change in BKCOALC increases environmental pollution, while negative change mitigates pollution.

Empirical findings concerning each predictor’s relative importance are also calculated. According to our findings, among the comprised explanatory variables, gas consumption in the fertilizer sector had the highest contribution at 14.151 percent, followed by gross fixed capital formation (11.059%), transport sector oil consumption (8.682%), power sector gas consumption (8.481%), agriculture sector oil consumption (7.103%), transport sector gas consumption (6.827%), foreign direct investment (6.409%), industrial sector gas consumption (5.657%), power sector coal consumption (5.473%), household sector gas consumption (5.145%), commercial sector gas consumption (4.857%), cement sector gas consumption (4.528%), population (3.408%), brick kilns coal consumption (2.895%), household sector oil consumption (2.289%), industrial sector oil consumption (1.436%), power sector oil consumption (1.157%) and other government sector oil consumption (0.445%).

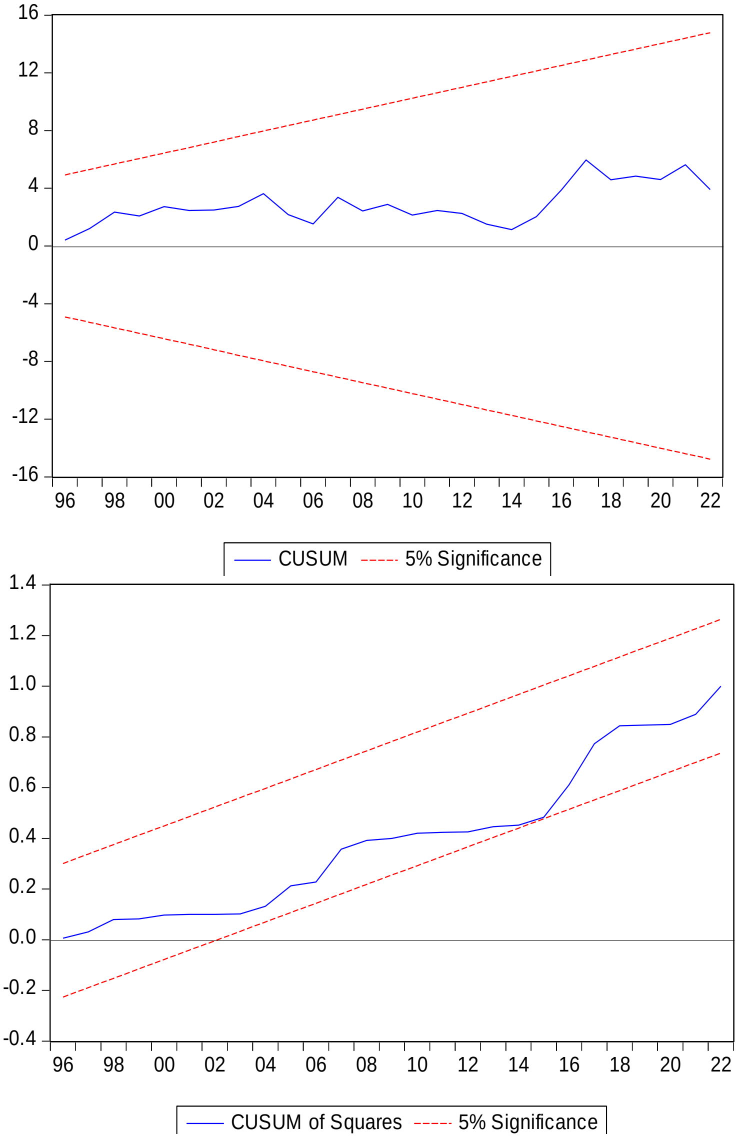
Table 9: Diagnostic Tests for the CCR Model

Name of Test	Critical value	Calculated value of Test Statistic	P-value
Normality Test (Jarque Bera)	$\chi^2_{0.05(2)} = 5.99$	1.06	0.59
Serial Correlation LM Test	$\chi^2_{0.05(1)} = 3.84$	1.15	0.28
ARCH Test	$\chi^2_{0.05(1)} = 3.84$	0.65	0.42
Ramsey Reset Test	$F_{0.05(1,26)} = 4.22$	2.68	0.11

Various diagnostic tests are used to confirm the validity and stability of the CCR model and the estimated results of these tests are presented in Table 9. We have checked the assumption of normally distributed residuals using the Jarque-Bera test. The residuals of the CCR model satisfy the normal distribution requirement according to our findings. The LM test has been applied to investigate the autocorrelation. The findings concerning the LM test show the absence of autocorrelation, implying that disturbances in one time period do not correlate with disturbances of another period. The problem of heteroscedasticity has been analyzed with the help of the ARCH test. This test confirms the absence of heteroscedasticity, indicating that all observations of the disturbances are drawn from the distribution having equal variability. The Ramsey Reset test has also been used to analyze the specification and misspecification concerning the CCR model. Based on the results of this test, it is possible to claim that the CCR model is correctly specified.

Figure 5 shows the cumulative sum (CUSUM) and squares cumulative sum (CUSUMSQ) of residuals to identify the parameter's stability and consistency of the CCR model. Both CUSUM and CUSUMSQ confirm structural stability since their graphs remain within 95% confidence level straight lines.

Figure 5: The CUSUM and the CUSUMSQ



Conclusion and Policy Recommendations

The basic objective of this study is to examine the sectoral impact of energy consumption on CO2 emissions in Pakistan. This research has analyzed data from 1992 to 2022 while adopting the correlated component regression methodology. According to our findings, a 1 percent increase in oil consumption across households, industries, transport, power and government sectors leads to an increase in CO2 emission by 0.010 percent, 0.025 percent, 0.118 percent, 0.010 percent and 0.016 percent, respectively. This indicates that an increase in oil consumption in these sectors leads to a corresponding increase in environmental pollution. In contrast, a 1 percent increase in agricultural oil use produces a 0.024 percent reduction in environmental pollution consistent with a negative impact on CO2 emissions. Furthermore, gas consumption in the household, commercial, fertilizer, power, industrial and transport sectors is found to have a positive impact on CO2 emissions. A 1 percent increase in gas consumption in the household, commercial, fertilizer, power, industrial and transport (CNG) sectors leads to an increase in environmental pollution by 0.047 percent, 0.061 percent, 0.223 percent, 0.093 percent, 0.055 percent and 0.010 percent, respectively. Conversely, gas consumption in the cement sector demonstrates a negative influence on CO2 emissions, showing that environmental degradation decreases by 0.014 percent following a 1 percent increase in cement sector gas consumption. Coal consumption in both the power and brick kiln sectors has a positive effect on CO2 emissions, showing a 1 percent increase in coal consumption in the power and brick kiln sectors leads to an increase in environmental pollution by 0.014 and 0.039 percent, respectively. Finally, population, capital formation and foreign direct investment also positively impact CO2 emissions, indicating that a 1 percent increase in population, capital formation and foreign direct investment leads to an increase in environmental pollution by 0.071, 0.163 and 0.032 percent, respectively. Our results concerning the relative contributions indicate that among the variables, fertilizer sector gas consumption contributed 14.151 percent to CO2 emissions, followed by capital formation (11.059%), transport sector oil consumption (8.682%), power sector gas consumption (8.481%), agriculture sector oil consumption (7.103%), transport sector gas consumption (6.827%), foreign direct investment (6.409%), industrial sector gas consumption (5.657%), power sector coal consumption (5.473%), household sector gas consumption (5.145%), commercial sector gas consumption (4.857%), cement sector gas consumption (4.528%), population (3.408%), brick kilns coal consumption (2.895%), household sector oil consumption (2.289%), industrial sector oil consumption (1.436%), power sector oil consumption (1.157%) and government sector oil consumption (0.445%).

Based on our findings, the following policy recommendations can be made to tackle the sector-specific effect of energy consumption on CO2 emissions in Pakistan. First, energy efficiency measures should be adopted in high emissions-intensive sectors, including transport, household, industrial, power, and government, to decrease oil consumption. People can achieve this through green technologies along with promoting other energy sources, like solar, wind, and electric vehicles. For gas-consuming sectors, including fertilizer, power, transport (CNG), industrial, household and commercial should shift towards less emissions-intensive sources, including hydrogen and biogas. Emissions from coal utilization in the power and brick kilns sectors can be best addressed by kicking out coal and transitioning its usage either toward green energy sources or less emissions-intensive technologies. Investment in renewable energy technologies such as wind-based, solar panel-based and hydropower-based technologies is an urgent need to achieve environmental sustainability. The government needs to create financial assistance through subsidies and tax cuts for residential and industrial users who choose renewable energy technologies. Since the fertilizer sector has the largest share of carbon emissions, the focus of policies should encourage low carbon-intensive technologies in fertilizer production and promote the utilization of organic alternatives. In the transport sector, the concept of public transportation should be promoted. Electric vehicle adoption should be supported by establishing motivational schemes for electric vehicle usage and necessary infrastructure development. This research delivers useful guidelines that also allow other developing countries to establish sector-specific policies and renewable energy transformations that reduce CO2 emissions effectively. These nations can achieve sustainable growth promotion and address climate change issues through the implementation of these strategies.

Adopting the proposed policies could bring important economic and social advantages for Pakistan. Moving towards renewable energy options including solar power and wind energy together with hydropower can reduce its reliance on imported fossil fuels which strongly improves national energy security and saves foreign exchange.

This shift to renewable energy can generate employment possibilities in the renewable technology systems which boost economic growth and further develop new technologies. Some social benefits can also be achieved with reduced CO2 emissions through cleaner energy infrastructures and green technologies that improve public health and provide better air quality as well as reduce healthcare costs and enhance life quality. Furthermore, adopting electric vehicles together with public transportation services can minimize traffic congestion and noise pollution which further leads to higher quality of living standards.

Despite the important sectoral analysis, the current study has the following limitations. First, it may include potential omitted variables bias due to its exclusion of important CO2 emissions determinants such as gross domestic product as well as renewable energy use and technological innovation. Second, the investigated model considers linear relationships while ignoring dynamic feedback effects within the data. In future research, better-estimated results can be achieved by incorporating these omitted variables and employing nonlinear estimation methods. Additionally, the results would gain more reliability through increased sample size along with the use of dynamic models for panel data analysis.

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