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Dynamic Impacts of Renewable Energy on Carbon Emissions: A Cross-Income Analysis Using Advanced Econometric Models

Abdul Salam Maftoon[1*], Kiran Afzal[2], Abdul Razzaq[3], Dr. Irfan Ullah Arfeen[4]

*[1]Lecturer, (Management Sciences) University of Loralai, Pakistan
[2]Senior Auditor, (PMAD) Ministry of Defence, Government of Pakistan
[3]Lecturer (QASMS), Quaid-i-Azam University Islamabad, Pakistan
[4]Associate Professor (QASMS), Quaid-i-Azam University Islamabad, Pakistan

***Corresponding Author:** Abdul Salam Maftoon
*Email: salam.kakar@gmail.com

Abstract
This paper aims to establish the long run and short run relationship between renewable energy consumption (REC) and carbon dioxide emissions (CO_2) in 126 countries within the period of 2001 to 2022 with the use of panel data that includes high income, upper-middle income, lower-middle income and low-income countries. To control for endogeneity, serial correlation and cross-sectional dependence, System GMM and CS-ARDL models are used in the analysis. This research also reveals that REC has a significant inverse relationship CO and the effect is most significant in low-income countries. The study also looks at the part played by natural resource rents, population density, foreign direct investment (FDI) and urbanization in determining emissions. The findings suggest that dependence on natural resources leads to emission of greenhouse gases especially in the low-income countries, while the effects of population density and FDI are mixed depending on the level of income. The study also affirms the need to promote the REC for climate change mitigation across the globe particularly in the developing countries while at the same noting the importance of the economic factors in policy making. Conclusions for future research and policy recommendations are discussed.

Keywords: System GMM, CS-ARDL, Natural resource rents, Foreign direct investment, Population density, Urbanization, Climate change mitigation

Introduction

Climate change mitigation has emerged as one of the biggest humanity's concerns of the current era mainly due to the increasing levels of CO_2 emissions (CO). CO_2 emissions are the major cause of global warming due to activities such as burning of fossil fuels, industrial processes and deforestation. The current levels of CO in the atmosphere are associated with negative effects on the environment such as global warming, sea level rise, and extreme weather conditions (Arias et al. 2021). Therefore, the reduction of carbon emissions has been recognized as one of the major goals of the international environmental protection policies, such as the Kyoto Protocol and the Paris Agreement that is designed to limit the increase in the global temperature by international cooperation in the reduction of greenhouse gas emission (UNFCCC 2015).

In this context, the shift towards renewable energy (RE) has become one of the most important measures for cutting greenhouse gas emissions. Wind, solar, hydro and biomass energy are RE sources which are not only cheaper than fossil fuels but also do not emit CO during their operation. The shift to the use of RE sources is deemed as important not only for the achievement of climate change goals but also for the sustainable development of the economies especially those that are dependent on the fossil fuel extraction("IEA" 2020).

The recognition of RE's importance is clear, and the relationship between renewable energy consumption (REC) and carbon emissions is not straightforward and varies by country's economy. In countries with effective and sophisticated energy systems, the consequences of renewable energy on CO2 emissions could be relatively insignificant. In contrast, in the low-income countries where the energy infrastructure is not fully developed and fossil fuels dominate, the addition of renewable energy can greatly cut emissions (Shahbaz et al., 2020). In addition, the connection between renewable energy and CO2 emissions could be bi-directional, with rising carbon emissions leading to the use of renewable energy to meet international climate change agreements and in response to public demand for cleaner energy sources (Marques and Fuinhas 2012).

The goal of this research is to identify the connection between REC and carbon dioxide emissions across different income levels and then to estimate that relationship using advanced econometric techniques to manage for endogeneity and heterogeneity that might exist in the relationship. The study uses System GMM and CS-ARDL models to investigate the relationship between renewable energy, natural resource rents, population density, urbanization, and FDI and CO2 emissions in high-income, upper-middle-income, lower-middle-income, and low-income countries.

The need for this research is based on the need to understand how the countries of different income levels and levels of development can decrease the CO_2 emissions and still maintain the economic growth. The transition from the conventional energy sources to the RE sources is crucial in the achievement of the sustainable development goals as well as the mitigation of the impacts of climate change. However, the success of this transition may be a function of the country's economic system,

energy consumption, and policy environment. In this study, the authors aim at determining the relationship between REC and CO_2 emissions with the aim of identifying the challenges and opportunities that are likely to be faced by countries in the process of reducing their CO_2 footprint. The following are the reasons why this research is important. First, it expands the current literature by providing a detailed analysis of the RE consumption and carbon emissions in different economic conditions. While the previous research has documented the contribution of RE in emission reduction, there is still a lack of research that examines the impact of RE on emission reduction by income groups. Second, the study employs System GMM and CS-ARDL to tackle endogeneity, cross-section dependence and other issues that could complicate the results of basic models. In this manner, the research ensures that the findings are reliable and accurate to make policy recommendations.
Lastly, the implications of the study are significant for policy makers especially in the developing world where there are special challenges in shifting from the conventional energy sources. Through the identification of the factors that affect carbon dioxide emissions in different economic systems, the study offers a way for countries to develop better policies that will help them attain their climate objectives while at the same time fostering sustainable development.

Literature Review

Carbon Emissions: Background and Understanding

CO_2 emissions are the primary cause of climate change, with carbon dioxide (CO_2) being the most common emission, which is released into the atmosphere through burning of fossil fuels, deforestation and industrial activities. CO_2 in the atmosphere leads to the heat being trapped thus causing global warming and its effects such as extreme weather, sea level changes, and changes in ecosystems (Arias et al. 2021). The need to tackle CO_2 emissions has been acknowledged in the scientific and policy literature and has resulted in international treaties such as the Kyoto Protocol and the Paris Agreement which seek to limit global warming by controlling greenhouse gas emissions (UNFCCC 2015).
There has been a significant increase in the number of researches that have been conducted on carbon dioxide emissions in the last few decades. Economic development, energy usage, industrialization, and population increase have been considered as the main determinants of carbon dioxide emissions (Shahbaz et al. 2013; Stern 2004). However, carbon dioxide emissions also have feedback effects on these factors and hence, create interdependencies that have to be well coordinated through policy and technological interventions.

Factors Affecting Carbon Emissions

***Economic Growth and Industrialization**:*
This is in accordance with the Environmental Kuznets Curve (EKC) hypothesis which states that emissions rise with economic development up to a certain point of development after which emissions fall as the economy moves to cleaner technologies and services (Grossman and Krueger 1995). Nevertheless, this relationship is not constant across all the countries and is influenced by factors such as energy intensity, structural change, and environmental standards (Dinda 2004).
***Energy Consumption**:*
Energy consumption is the most direct cause of carbon dioxide emissions especially in economies that are dependent on fossil fuels. The type of energy used, renewable or non-RE is another factor that greatly influences the level of emissions. Previous studies have shown that the consumption of fossil energy results in high CO_2 emissions while the consumption of RE results in low CO_2 emissions (Sadorsky 2009).
***Population Growth and Urbanization**:*
The population growth results in the higher consumption of energy, transportation, and industrial products that are associated with the emission of carbon dioxide (York, Rosa, and Dietz 2003). This trend may be amplified by urbanization in that economic activities and energy consumption are densified in cities. But urbanization can also offer chances for decreasing emissions via improved infrastructure and public transport systems (Jones and Kammen 2014).
***Foreign Direct Investment (FDI)**:*
The effect of FDI on carbon dioxide emissions is rather ambiguous and can be different in different cases. First, FDI may lead to emissions increase since it encourages the development of energy-intensive industries or exploits the low environmental standards in the host country (Zarsky & Gallagher, 2007). But, FDI can also bring cleaner technologies and practices and therefore can contribute to the reduction of emissions in the future (Eskeland and Harrison 2003).
***Natural Resource Dependence**:*
Some of the countries that are highly dependent on natural resources especially the fossil fuels are likely to emit more CO_2 due to the processes of extraction and burning of these resources (J. D. Sachs and Warner 2001). This relationship shows that there is a need to diversify the economy and the move towards cleaner energy to reduce emissions.

The Relationship Between REC and Carbon Emissions

REC and CO_2 emissions have been of interest to many authors especially in the context of climate change. Wind, solar, hydro and biomass energy sources are useful in combating climate change because they produce less CO_2 than the fossil fuels ("IEA" 2020).
***Impact of REC on Carbon Emissions**:*
A multitude of studies indicates that an increase in the share of renewable energy sources in the energy mix results in a major decrease in CO2 emissions. Al-Mulali et al. (2015) discovered that REC has a negative effect on CO2 emissions, and the relationship is statistically significant for both developed and developing countries. Apergis and Payne (Apergis and Payne 2010) found that in a panel of OECD countries, REC is negatively correlated with CO2 emissions, which means that RE can help in reducing pollution. Income inequality has role in the relationship of renewable energy and carbon emissions (Maftoon et al. 2024).

This is due to the change in energy source from fossil fuels, which is one of the leading causes of CO2 emissions around the world (Sadorsky 2009). Depending less on coal, oil, and natural gas for energy and using renewable energy resources (RE) instead helps to cut CO2 emissions during energy generation. Also, the performance of RE technologies has been advancing and cutting expenses, improving their power to decrease emissions (REN21 2021).

***The Role of Economic Context*:**

The economic context could provoke disparate effects of renewable energy on carbon dioxide emissions. In affluent countries, where energy systems function at higher levels of efficiency, the introduction of more RE could yield only slight results. While in nations with fragile energy systems and a major reliance on fossil fuels, the adoption of RE can provide a more significant reduction in emissions (Shahbaz, Balsalobre-Lorente, and Sinha 2019).

***Feedback Effect: Carbon Emissions on REC*:**

There is a possibility that RE and CO2 emissions are related in a feedback loop. Research findings show that higher carbon emissions may motivate the uptake of RE sources as governments and industries strive to counter the environmental effects of their actions and meet international climate change pledges (Marques and Fuinhas 2012). The increased global awareness of CO2 footprint has supported this feedback loop and has resulted in a significant investment of capital in RE technologies. As an illustration, policies designed to cut CO2 emissions, including CO2 pricing and emission trading schemes, can make fossil fuel energy production expensive, which in turn makes renewable energy (RE) cheaper (Böhringer and Rutherford 1997). In addition, increasing awareness among the public regarding how carbon emissions influence the environment will generate a market for clean energy, which will force governments and other organizations to augment their funding for renewable energy sources (Jones and Kammen 2014).

This is in agreement with Menyah and Wolde-Rufael (Menyah and Wolde-Rufael 2010) who found that the relationship between CO2 emissions and REC is reciprocal. There is a view that, while renewable energy (RE) can lessen CO2 emissions, the threats posed by climate change and the actions taken to counter those threats can stimulate the use of RE, resulting in a helpful feedback loop.

This interdependence points to the critical need for complementary policies that would encourage the adoption of RE, while also addressing the economic and infrastructural challenges that characterize the uptake of the technology. These actions might include delivering incentives—such as subsidies for renewable energy (RE)—while also raising carbon taxes and putting resources into the research and development needed to make RE technologies more efficient and capable of improved storage. Still, the change to RE has its own set of problems. The talk covers components that lead to variability in renewable energy sources, the major capital expenditures essential for infrastructure development, and the socio-political difficulties connected to the ongoing use of fossil fuels (Sovacool 2009). Also, in a number of developing countries, the costs of RE technologies and the problem of access to funding may slow down the adoption process and, consequently, may not have a major impact on CO2 emissions in the near term (Aklin et al. 2018).

Other Variables and Their Relationship with Carbon Emissions

Still, there are other important variables in this study, including economic growth, FDI, population density, and natural resource rents in relation to CO2 emissions.

***Economic Growth*:**

It should be recalled that the Environmental Kuznets Curve hypothesis suggests that emissions of carbon dioxide increase with economic development in the initial stage and then decline with further development and the use of cleaner technologies. But this relationship is not fixed and the decoupling of economic growth and CO_2 emissions is still a significant problem particularly in the emerging economies (Dinda 2004).

***Foreign Direct Investment (FDI)*:**

The relationship between FDI and carbon dioxide emissions has been analyzed in the literature. Some of the researches have indicated that FDI leads to increased emissions in the developing countries due to the encouragement of energy intensive industries (Gallagher and Zarsky 2007). On the other hand, some authors argue that FDI can lead to the decrease in emissions as it brings cleaner technologies and practices from the developed countries to the developing ones (Eskeland and Harrison 2003). The net impact of FDI on emissions is probably a function of the sectoral pattern of the investment and the stringency of environmental standards in the host country.

***Population Density and Urbanization*:**

This paper also finds that population density and urbanization are positively linked with CO_2 emissions. This is because high population density means that there is a higher population living in a small area and therefore there is efficient use of energy and resources in order to meet the needs of the population (Jones and Kammen 2014). But, the development of cities without proper infrastructure may result in high emissions especially in the developing countries where energy demand is higher than the supply (Poumanyvong and Kaneko 2010).

***Natural Resource Rents*:**

This is because countries that have a high dependence on natural resource rents especially from the fossil fuels tend to emit more CO_2. This is because these resources are extracted and used and, in the process, they release carbon dioxide gases into the atmosphere. The 'resource curse' theory explains the challenges that countries endowed with natural resources have in transforming to a more stable and diversified economy (J. D. Sachs and Warner 2001)(Sachs & Warner, 2001).

The literature on CO_2 emissions and RE shows that RE is instrumental in lowering the carbon footprint of the world. However, the impact of RE on emissions may not be the same in all the economies despite the relationship between these variables. Also, the correlation between CO_2 emissions and RE could be bidirectional, where the attempts to reduce emissions can lead to the increased utilization of clean energy. This is because as the world faces the challenges of climate change, it becomes important to understand these dynamics in order to come up with policies that can foster sustainable development while at the same time minimizing the negative impacts on the environment.

Research Gap

Despite the fact that there is a large body of research on the relationship between REC and CO_2 emissions, the literature is still quite limited in terms of explaining the nature of this relationship at different levels of income and economic development. Previous research has also shown that RE is capable of decreasing CO_2 emissions; however, most of the research has either been conducted on certain countries of the world like OECD countries or has considered the relationship as being same across all economies (Apergis and Payne 2010; Sadorsky 2009). This approach does not consider the possibility of differential effects of RE on countries with diverse economic systems, energy requirements, and policy frameworks.

However, there is still scant literature on the relationship between carbon dioxide emissions and REC and this is particularly so in developing and low-income countries (Menyah and Wolde-Rufael 2010). The feedback loop through which increasing CO_2 emissions may lead to the deployment of RE and increasing deployment of RE may lead to decreasing carbon emissions needs more research to identify the factors that could enhance or dampen this process of global energy transition.

A second limitation is that other macroeconomic variables such as natural resource rents, population density, urbanization and FDI have not been included in the analysis of their impact on CO_2 emissions. These variables are crucial in determining energy consumption and carbon dioxide emissions of a country but their link with RE in different income level countries has not been well explored.

This research aims at filling these gaps through analyzing the relationship between REC and carbon emissions in high income, upper middle income, lower middle income and low-income countries. To overcome the possible econometric issues like endogeneity and cross-sectional dependence, the study uses System GMM and CS-ARDL and hence the results are generalizable across various economic environments.

Theoretical Framework

The conceptual framework of this study is based on the Environmental Kuznets Curve (EKC) hypothesis, theory of economic development and the energy-environment relationship with emphasis on RE in reducing CO_2 emissions. The EKC hypothesis posits that the relationship between environmental degradation and economic growth follows an inverted U-shape: The level of environmental pollution increases with the growth of economy until a certain point and then it begins to decline as the economy turns to cleaner technologies and products (Grossman and Krueger 1995). This hypothesis suggests that at the early level of development, countries focus more on the economic growth than environmental conservation and therefore release more carbon dioxide. But as countries move from low income to higher income countries, they are likely to spend more on cleaner technologies, enforce pollution control and change their economies to produce less carbon emissions.

This study seeks to build on the EKC model to establish whether the development and expansion of RE sources can hasten the decline of the EKC especially in the middle- and low-income countries. The study also seeks to find out if high income countries that are expected to be on the downward part of the EKC still experience decline in CO_2 emissions with increased uptake of RE.

The energy consumption in relation to economic development is one of the most significant factors that determine carbon dioxide emissions. As the economies grow, the energy demand increases and this leads to emission of greenhouse gases especially where the energy is derived from fossil fuels. However, the transition to the RE source can free the economic development from the carbon emissions and hence the countries can develop without increasing the harm to the environment (Sadorsky 2009).

Energy-environment nexus theory holds that energy is one of the most critical determinants of the state of the environment. RE is one of the most significant factors in this connection because it provides a clean power source in comparison with the conventional non-RE sources. This paper aims at determining the role of income levels in the energy-environment relationship with emphasis on the role of REC in reducing CO_2 emissions. It also looks at how other aspects of the economy including FDI, natural resource rents and population density affect this relationship.

This research also applies the theoretical hypothesis that carbon dioxide emissions and REC are co-integrated, potentially in a uni-directional or bi-directional manner. In accordance with the thought that larger CO2 emissions might inspire policies that stimulate renewable energy (RE) adoption, this also incorporates carbon pricing, global climate pacts, and consumer calls for cleaner energy (Marques and Fuinhas 2012).

This feedback relationship points to the idea that while RE can be a weapon against CO2 emissions, rising emissions may foster increased RE adoption as countries pursue solutions for mitigating pollution and following international standards. This paper is particularly interested in this potential feedback loop, especially in low-income countries, where the move towards green energy is influenced by both external factors and the requirement to lower emissions.

This theoretical framework offers a model of the relationship between the variables of interest, REC and CO_2 emissions. This paper therefore aims at adding to the literature on the management of carbon footprint of countries at different levels of development through the analysis of the EKC hypothesis, the energy-environment link and the possibility of feedback between emissions and RE. The framework also guides the empirical analysis so that the study findings are grounded in economic and environmental theories while at the same filling the gaps identified.

Methodology

The methodology applied in this study is to examine the relationship between REC and carbon emissions in countries of different income status while other macroeconomic variables are included in the model. The study uses a panel data set of 126 countries over the period 2001–2022. This dataset was chosen because it contains the necessary information on the variables of interest for the countries and the years of interest in order to give a complete and recent view of the impact of RE on CO_2 emissions.

To account for these multiple channels in this relationship, the study employs two econometric models namely the System Generalized Method of Moments (System GMM) and the Cross-Sectional Autoregressive Distributed Lag (CS-ARDL). These methods are most suitable for panel data analysis since issues such as endogeneity, serial correlation, heteroscedasticity and cross-sectional dependence are prevalent.

Table 1: Description of variables and sources of data

Variable	Symbol	Type of variable	Description	Source
Carbon Emissions per capita	CO	Dependent Variable	CO_2 emissions (metric tons per capita)	World Bank
Renewable Energy	REC	Independent Variable	Renewable energy consumption (% of total final energy consumption)	World Bank
Natural Resources	NR	Control Variable	Total natural resources rents (% of GDP)	World Bank
Population Density	POPD	Control Variable	Population density (people per sq. km of land area)	World Bank
Foreign Direct Investment	FDI	Control Variable	Foreign direct investment, net inflows (% of GDP)	World Bank
Urbanization %	URB	Control Variable	Urban population (% of total population)	World Bank

To overcome the possible endogeneity problem that may arise from the use of lagged dependent variables and other endogenous variables, the System GMM is employed. This method is most suitable when handling panel data since past CO_2 emissions may have an impact on the current emissions. The System GMM estimator which was developed by Arellano and Bover (Manuel Arellano and Bover 1995) and Blundell and Bond (Blundell and Bond 1998) is a combination of the equations in levels and the equations in first differences to increase the efficiency especially when the instruments are not very good. The model specification for System GMM in this study can be expressed as follows:

$lnCO_{it}=\alpha lnCO_{it-1}+\beta_1 lnREC_{it}+\beta 2 lnNR_{it}+\beta_3 lnPOPD_{it}+\beta_4 lnURB_{it}+\beta_5 lnFDI_{it}+\gamma_i+\lambda_t+\epsilon_{it}$

In this model, CO_{it} is the carbon dioxide emissions per capita of country i at time t, RECit is the REC, NR_{it} is the natural resource rents, $POPD_{it}$ is the population density, URB_{it} is the urbanization rate and FDI_{it} is the foreign direct investment inflows. The variables γ_i and λ_t are country dummies and time dummies respectively while ϵit is the error term. The inclusion of the lagged CO_2 emissions ($lnCO_{it-1}$) in the model is important because emissions are not only persistent, but also dynamic.
To enhance the credibility of the results of the study, the CS-ARDL model has also been applied in the analysis of the data. This approach is particularly helpful when dealing with cross-sectional dependence that is a major issue in panel data where the shock or the trend in one country can easily affect the other countries. The CS-ARDL model extends the conventional ARDL model to include short run and long run dynamics in the context of cross-sectional data which is ideal in the analysis of the long run association between RE and CO_2 emissions across countries of different income status.
The CS-ARDL model can be specified as follows:

$$lnCO_{it} = \alpha_0 + \sum_{j=1}^{p} \alpha_j lnCO_{it-j} + \sum_{j=0}^{q1} \beta_j lnREC_{it-j} + \sum_{j=0}^{q2} \beta_j lnNR_{it-j} + \sum_{j=0}^{q3} \beta_j lnPOPD_{it-j} + \sum_{j=0}^{q4} \beta_j lnURB_{it-j} + \sum_{j=0}^{q5} \beta_j lnFDI_{it-j} + \lambda_i + \epsilon_{it}$$

The lagged terms of each variable ($lnCO_{it-j}$, $lnREC_{it-j}$, etc.) enable the estimation of both the short run and long run impacts of the variables on carbon emissions and the dynamic adjustments that occur in the levels of carbon dioxide emissions in response to changes in the level of REC and other control variables. The long-run relationship is crucial to understanding how the gradual shifts in the level of RE affect the carbon emissions in the long run, while the short-run analysis reveals the immediate impacts.
The analysis is done for high income, upper middle income, lower middle income and low-income countries to see the differences in the impact of RE in different income levels. This methodology considers that the economic development, energy consumption and policies of countries at different income levels may affect the ability of RE to cut carbon emissions.
In order to evaluate the validity of the models, several diagnostic tests are performed. The System GMM model undergoes testing for autocorrelation (Arellano-Bond test) and heteroskedasticity and over-identification (Hansen and Sargan tests) to evaluate the validity of the instruments applied in the model (Jann 2024). The CS-ARDL model undergoes cross-sectional dependence testing (Pesaran's test) and unit root tests to examine the null hypothesis of the presence of long-run relationships and to test for the stationarity of the variables.
Thus, the proposed System GMM and CS-ARDL models can be considered as a reliable method for the analysis of the impact of REC on carbon emissions. This approach not only addresses the possible econometric issues of panel data but also allows the examination of the heterogeneity of this relationship by income. The outcomes of these models are beneficial to policy makers who want to design good policies in reducing CO_2 emissions by promoting RE.

Results and Discussion

The results and discussion of this research paper aims to determine the relationship between REC and carbon emissions per capita with other variables such as natural resource rents, population density, urbanization and foreign direct investment. The analysis is done by using both the descriptive statistics, correlation analysis and advanced econometric models such as System GMM, CS-ARDL and quantile regression.

The descriptive analysis gives a general picture of the variables in the different income levels and helps in the understanding of the distribution and the central tendencies of the variables. Table 1 provides the descriptive statistics of the full sample and the results indicate that there is a high degree of variation in the carbon emissions (CO) across the countries with the mean of 3.91 metric tons per capita with the standard deviation of 4.04. The minimum and maximum values of 0 to 25.61 show that there is a huge difference in CO_2 emissions among countries due to differences in industrialization, energy use, and environmental standards (World Bank 2021).

Table 2: Descriptive Statistics (Full sample)

Variable	Obs	Mean	Std. dev.	Min	Max
CO	2,772	3.911204	4.036499	0	25.61044
REC	2,772	34.82696	27.86419	0	95.35
NR	2,772	4.983551	7.199865	0	79.43095
POPD	2,772	140.9938	219.7463	1.597867	1738.19
URB	2,772	57.02676	23.40178	8.461	100
FDI	2,772	5.61221	20.92474	-394.472	449.0828

The REC is also relatively volatile with the mean of 34. 83% and the standard deviation of 27. 86%. The range is from 0% to 95.35% which shows that different countries have different energy mix, some of which have a high proportion of RE while others still have a high proportion of fossil energy. This variation is crucial because it demonstrates that the adoption of RE can impact carbon dioxide emissions in a specific country in a specific way depending on the country's energy mix (IRENA 2022).

The control variables also show a high level of variation in their means. For instance, natural resource rents (NR) have an average of 4. 98% of GDP with a standard deviation of 7. 20% which indicates the level of dependence of the economy on natural resources. The level of natural resource rents in a country may also determine the path that the country will take in its energy transition and this can affect CO_2 emissions (J. Sachs 1995). Population density (POPD) and urbanization (URB) also show significant differences, which may suggest the different demographic and urbanization conditions that may influence energy use and emissions. The mean of FDI is 5. 61% of GDP, but the standard deviation is 20. 92%, which implies that investment is not evenly distributed across countries and may affect the spread of energy technologies and industrial practices.

Table 3: Correlation Analysis

	lnCO	**lnREC**	**lnNR**	**lnPOPD**	**lnURB**	**lnFDI**
lnCO	1					
lnREC	-0.6896	1				
lnNR	-0.4682	0.3225	1			
lnPOPD	0.0234	-0.2056	-0.4268	1		
lnURB	-0.0893	0.0401	0.0855	-0.0544	1	
lnFDI	0.0121	-0.094	-0.0229	0.0145	-0.0008	1

Table 2 also presents the income-level distribution which indicates that the average CO_2 emissions per capita in high income countries are 7. 79 metric tons while in low-income countries it is 0. 14 metric tons. This can be attributed to the differences in industrial production, energy consumption and environmental standards. Contrary to expectation, the REC is inversely related to the income level; the low-income countries have the highest mean REC (81.81%) while the high-income countries have the lowest (20.18%). This is in agreement with the argument that, the low-income countries may still depend on the traditional biomass and hydro power which are classified as RE sources but may not be sustainable or efficient in the long run (Pachauri and Spreng 2011).

Table 3 presents the correlation analysis which gives a general idea of the interrelation between the variables. The coefficient of the variable carbon dioxide emissions and REC is negative (-0. 6896) which suggest that when the consumption of RE increases, the carbon dioxide emissions decrease. This finding supports the hypothesis that one of the ways of reducing CO_2 emissions could be through increasing the share of RE in a country's energy mix (Sadorsky 2009). Also, the negative correlation between carbon emissions and natural resource rents (r = -0. 4682) may imply that countries with high natural resource rents are likely to have low carbon dioxide emissions per capita because such countries are less industrialized or use more non-fossil fuels.

Other control variables are also included in the model and their relationship with carbon emissions is not as close as the above variables. Population density is also weakly positively related to the variable with a correlation coefficient of 0.0234 while urbanization is weakly negatively related with a correlation coefficient of -0.0893. The correlation coefficient between carbon emissions and FDI is 0.0121 which is weak positive indicating that foreign investment in general may not be a significant

contributor to CO_2 emissions although this may not be the case in all instances and types of investments (Gallagher and Zarsky 2007).
The descriptive and correlation analyses used in this paper can be followed by a more elaborate econometric analysis. The relationships that were estimated can be employed to state the hypothesized impacts of REC and other control variables on carbon dioxide emissions. But they also argue that more robust methods have to be employed in order to address the issues of endogeneity, omitted variable bias and other factors that may undermine these relationships.

Diagnostic Tests

The diagnostic tests conducted in this study are crucial in determining the econometric properties of the panel data used in this study and hence it is appropriate to use System GMM and CS-ARDL models. These tests are useful in establishing the reliability of the regression models that were used in establishing the relationship between REC and CO_2 emissions.

Heteroskedasticity and Autocorrelation

The null hypothesis of homoscedasticity is also rejected by the Modified Wald test for groupwise heteroskedasticity in the fixed effects regression model at 1% level of significance (chi2(126) = 2.7e+05, Prob > chi2 = 0.0000). This result is in line with the assumption of heteroscedasticity which entails that the variance of the error terms is not constant in the different countries. This is because heteroskedasticity leads to inefficiency in the estimators and the standard errors which in turn affects hypothesis testing and confidence intervals (White 1980). It is therefore important to control for heteroskedasticity especially in panel data with cross-sectional units that are different in terms of their economic development and energy consumption patterns.
The Wooldridge test for autocorrelation also does not support the null hypothesis of no first-order autocorrelation (F(1, 125) = 203.799, Prob > F = 0.0000). The existence of autocorrelation means that the errors are correlated over time within the same group and this is a source of endogeneity if not handled properly, it leads to biased and inefficient estimators (Wooldridge 2010). Due to the fact that carbon emissions and REC are time-varying, autocorrelation is expected, since past values of these variables can affect the present results. Hence, it is crucial to employ methods such as System GMM that takes into consideration such endogeneity by including lagged dependent variables as instruments.

Multicollinearity

The VIF test results also indicate that the problem of multicollinearity is not evident in the model given that all the VIF values are below the recommended threshold of 10 with an average of 1. 14. This shows that the independent variables are not very much related to each other and hence there is no problem of multicollinearity which is a situation where two or more independent variables are highly correlated and this can lead to large standard errors and one cannot be able to determine the contribution of each variable (Gujarati 2009). The low VIF values are reassuring in that they suggest that the relationships observed between the variables are not the result of multicollinearity.

Table 4: Variance Inflation Factor (VIF) Test

Variable	VIF	1/VIF
lnNR	1.32	0.757248
lnPOPD	1.23	0.812408
lnREC	1.13	0.882801
lnFDI	1.01	0.991094
lnURB	1.01	0.992154
Mean VIF	1.14	

Endogeneity

The Durbin-Wu-Hausman (DWH) test for endogeneity is quite powerful and the results of the test show that endogeneity is a problem in the model as the residuals are statistically significant (t = 8. 36, P > t = 0.0000). The sources of endogeneity include omitted variables, measurement errors, and simultaneity, and endogeneity leads to inefficient and biased OLS estimates. This is because REC and carbon dioxide emissions could be endogenous if the two are determined simultaneously or if there are other factors that influence both variables. The high level of endogeneity that is revealed by the DWH test means that System GMM is appropriate to use since it is designed to handle endogeneity by using internal instruments which are based on lags of the endogenous variables (Manuel Arellano and Bond 1991; MANUEL Arellano and Bond 1991).

Cross-sectional Dependence

The Pesaran test for cross-sectional dependence and the CD tests for each variable reveal that the null hypothesis of cross-sectional independence cannot be accepted with p-values close to zero for all tests. The cross-sectional dependence implies that the errors are correlated across different entities (countries) which may be attributed to common shocks, global economic conditions or spillover effects in RE policies and carbon emissions (Pesaran 2004). For example, the prices of energy in the global market or the international climate change treaties may affect CO_2 emissions and the use of RE in several countries at the same time. This is because the data is cross-sectional and therefore there is the need to use methods such as the Cross-Sectional ARDL (CS-ARDL) which can help to account for such dependencies and give more accurate estimates in the presence of cross-sectional correlation.

Table 5: Cross Sectional Dependence (Pesaran)

Variable	CD-test	p-value	average joint	mean ϱ	mean abs(ϱ)
lnCO	37.78	0.00	22	0.09	0.57
lnREC	4.784	0.00	22	0.01	0.59
lnNR	93.472	0.00	22	0.22	0.38
lnPOPD	189.523	0.00	22	0.46	0.9
lnURB	238.426	0.00	22	0.57	0.84
lnFDI	37.754	0.00	22	0.09	0.26

Unit Root and Cointegration

The Harris-Tzavalis unit root test shows that most of the variables are stationary at level while lnCO, lnPOPD, and lnURB are stationary at first difference. Non-stationarity is a major problem in time-series and panel data analysis because non-stationary data can produce what is known as spurious regression, where a relationship between variables appears to exist when in fact it does not (Phillips 1988). The non-stationarity of the variables is tested using unit root tests and the results show that the variables are stationary, thus allowing the use of econometric models that require stationary data such as System GMM and CS-ARDL.

Table 6: Unit root test

	Harris-Tzavalis			
Variable	**rho**	**z**	**p-value**	**at**
lnCO	-0.0245	-70.5134	0.00	1st Diff.
lnREC	0.7354	-11.1212	0.00	Level
lnNR	0.7686	-8.3747	0.00	Level
lnPOPD	0.5281	-26.639	0.00	1st Diff.
lnURB	0.5364	-25.981	0.00	1st Diff.
lnFDI	0.0588	-67.2274	0.00	Level

From the Kao test, it is seen that there is co-integration in the long run as the p-values in the Dickey-Fuller test statistics are significant. Cointegration is a concept which states that even though the variables are integrated of order one, they have a long run equilibrium relationship and are said to be cointegrated (Engle and Granger 1987). This finding is important for the study as it indicates that REC, CO_2 emissions and other control variables are interlinked in the long run and thus supports the use of advanced dynamic models such as CS-ARDL that can capture both short run dynamics and long run relationships.

Table 7: Cointegration test (Kao)

	Statistic	**p-value**
Modified Dickey–Fuller t	4.0264	0.00
Dickey–Fuller t	2.5588	**0.0053**
Augmented Dickey–Fuller t	2.1406	0.0162
Unadjusted modified Dickey–Fuller	3.2567	0.0006
Unadjusted Dickey–Fuller t	1.7805	0.0375

Implications for Advanced Econometric Approaches

These diagnostic tests show that the data is quite intricate and that more sophisticated econometric techniques are required. The existence of heteroskedasticity, autocorrelation, endogeneity, cross-sectional dependence, and the identification of cointegration relationships support the use of System GMM and CS-ARDL in assessing the effects of RE on carbon emissions. These models are able to handle the econometric problems mentioned above and therefore provide better and faster estimates that reflect the relationships between the variables in question. In addition, the use of quantile regression, which will be discussed later, makes it possible to study the relationships at different points of the distribution and, therefore, to consider the potential heterogeneity of the effects of RE at different levels of CO_2 emissions.

Thus, the study avoids these econometric problems and the results obtained are not only statistically significant but also economically relevant, which can help to understand the possibilities of using RE to reduce carbon emissions in different economies.

System GMM

The System GMM estimation results presented in the table show the long run and short run relationship between REC, CO_2 emissions and other macroeconomic variables across countries. The findings are discussed in relation to the previous research, with consideration of the convergent and divergent findings.

The coefficient of the lagged dependent variable (lnCOt−1) is positive but does not reach statistical significance (β=0. 1148, p>0. 64). This suggests that the present carbon emissions are not reliant on past CO2 emissions, provided that the other variables in the model remain unchanged. This result is somewhat surprising because earlier studies often report that carbon emissions are enduring over time as a result of energy system stickiness and slow technological change (Apergis and Payne

2010; Ur Rehman, Wang, and Mirza 2017). Likely, this result is due to the model's potential to include additional considerations that can shape the findings, which might have reduced the relevance of the lagged emissions.

Table 8: Dynamic panel-data estimation, two-step system GMM

lnCO	**Coefficient**	**Corr. std. err.**	**T**	**P>t**	**[95% conf. interval]**	
L1.lnCO	0.114769	0.245088	0.47	0.64	-0.37029	0.599828
lnREC	-0.55914	0.220042	-2.54	0.012	-0.99463	-0.12366
lnNR	0.099251	0.043448	2.28	0.024	0.013261	0.18524
lnPOPD	0.600544	0.550462	1.09	0.277	-0.48889	1.689976
lnURB	-5.97877	3.330304	-1.8	0.075	-12.5699	0.612314
lnFDI	0.059235	0.27443	0.22	0.829	-0.4839	0.602367
_cons	22.74351	12.48041	1.82	0.071	-1.95677	47.4438

The coefficient of the natural logarithm of REC (lnREC) is also negative and statistically significant with the coefficient estimate of β=-0. 5591 and p-value of less than 0. 05. 012. This is in line with the literature which has stressed on the need to adopt RE sources in order to minimize carbon footprint. Some of the RE sources are wind, solar and hydroelectric power which are known to emit little or no carbon dioxide as opposed to the fossil fuels (Al-Mulali, Saboori, and Ozturk 2015; Sadorsky 2009). The coefficient estimate also reveals that the REC has a negative effect on the CO_2 emissions and the relationship is statistically significant, thus, one percent increase in the REC will reduce the CO_2 emissions by approximately 0. A decrease of CO_2 intensity by 56 percent, with all other factors held constant. This is in agreement with the statement that the shift towards the use of RE is one of the most important strategies for combating climate change ("IEA" 2020).

The coefficient for natural resource rents (lnNR) is positive and statistically significant (β=0. 0993, p<0. 024), which imply that natural resource rents enhance carbon emissions. This finding is in consonance with the so called "resource curse" theory which posits that countries that are blessed with natural resources are likely to have slow rates of economic growth and environmental degradation because of dependence on natural resources (J. D. Sachs and Warner 2001). Natural resource rents are higher when there is high utilization of the fossil fuels and this leads to more emission of CO_2 (Frankel 2012). This is a clear indication that there is need to diversify economies especially those that are dependent on natural resources for the sake of environmental conservation.

Population density (lnPOPD) has a positive coefficient but it is not significant at 5% level of significance (β=0.6005, p>0.277). This means that population density does not have a significant direct impact on carbon dioxide emissions in this respect. This could be due to the fact that other factors such as rate of urbanization, energy consumption per capita and availability of infrastructure may not be well represented by population density (Martínez-Zarzoso and Maruotti 2011). Some of the studies have indicated that high population density may result to low emissions per capita due to efficient transport systems and low energy use per capita (Jones and Kammen 2014). However, since the findings are inconclusive in the literature, this may explain the non-significant result obtained in this study.

Urbanization (lnURB) is also negative and has marginal statistical significance (β=−5.9788, p=0.075). This result suggests that as the level of urbanization increases, there may be a reduction in carbon emissions but the relationship is not very robust. Urbanization can also contribute to the reduction of CO_2 emissions per capita through the benefits of large-scale production, energy efficiency and concentration of public services as pointed out by Poumanyvong and Kaneko (Poumanyvong and Kaneko 2010). However, the borderline significance suggests that there could be a possibility of non-linear relationship between urbanization and carbon emissions and the relationship could be different at different levels of urbanization and different structure of the economy.

The coefficient for foreign direct investment (lnFDI) is positive but statistically insignificant (β=0. 0592, p>0. 829). This implies that there is no a clear direct relationship between FDI and CO_2 emissions in this sample. The current literature on FDI and environmental impact is rather ambiguous with some studies supporting the pollution haven hypothesis that states that FDI results in increased emissions while others suggest that FDI can introduce cleaner technologies and practices thus reducing emissions (Cole, Elliott, and Zhang 2011; Eskeland and Harrison 2003). This may be due to the fact that these two forces are neutralizing each other or it may be due to the fact that there are other variables that moderate the relationship between FDI and carbon dioxide emissions that have not been captured in the model.

Year fixed effects (dy2 to dy22) are included to control for year specific effects which may be regarded as the overall trends in CO_2 emissions over the years. Some of these dummies are statistically significant from dy10 and onwards, which means that there has been a shift in the level of carbon emission over the years due to factors such as economic fluctuations, technological advancement and international treaties. The positive and significant coefficients in the later years (e. g., dy16, dy20) may be due to the general increase in emissions that has been encouraged by industrialization in emerging economies although there is increased uptake of RE sources (Peters et al., 2012).

The Arellano-Bond test for AR(1) and AR(2) indicates that there is no significant first-order or second-order serial correlation in the first differences of the error terms (AR(1): p>It is greater than 0. 473; AR(2): p>0. 088). This is because if serial correlation is found, it implies that the instruments employed in the GMM estimation are invalid and this will lead to the biased estimates (Manuel Arellano and Bond 1991).

The Sargan and Hansen tests for restrictions of overidentifying also favour the model that has been employed in this study. The Sargan test (chi2(17) = 5. 75, p>0. 995) and the Hansen test (chi2(17) = 25. 47, p>0. Both F0. 085 and F1. It can be seen from the results of the chi-square tests for 085 that the instruments used are valid because the null hypothesis of instrument validity cannot be accepted. The difference-in-Hansen test also supports the exogeneity of the instrument subsets, which also supports the System GMM results.

The System GMM results also offer additional support to the notion that REC is associated with reduced carbon dioxide emissions, which is crucial in fighting climate change. This means that countries that rely on resources are likely to have special challenges in cutting emissions and this underlines the significance of diversification. The results also indicate that population density, urbanization, and FDI have ambiguous and contingent effects on carbon emissions.

These results are important for the current body of literature on the causes of CO2 emissions and give a new angle on the effects of RE and natural resource extraction. The study provides evidence that there is need to invest more on RE technologies in the fight against global carbon emissions. But it also suggests that policy interventions have to factor in the economic structures and the level of development of various countries in the world in order to be effective.

The findings also offer evidence for the application of System GMM in estimating dynamic panel data models especially when there is endogeneity, serial correlation and cross section dependence. The policy recommendations made from this analysis are supported by the diagnostic tests used in this analysis because the findings are accurate.

CS-ARDL

The CS-ARDL model estimates reveal the short-run and long-run dynamics between CO_2 emissions (lnCO) and the other variables of interest; REC (lnREC), population density (lnPOPD), urbanization (lnURB), foreign direct investment (lnFDI) and natural resource rents (lnNR). This method considers the heterogeneity and cross-sectional correlation among countries, rendering it a fit method to examine trends in carbon emissions.

Short-Run Estimates

In the short run, the coefficient for the lagged dependent variable (L.lnCO) is positive but does not reach statistical significance ($\beta=0.0166$, $p>0.506$). This result shows that in the near term, the earlier levels of CO emissions do not affect the current levels of emissions. This is in accordance with the System GMM results, which showed that lagged CO2 emissions were statistically insignificant. This might be because other influences, such as REC and economic markers, have a more distinct impact on carbon emissions.

In the short run, the coefficient for REC is also negative and statistically significant at the 1 percent level ($\beta=-1.2954$, $p<0.000$). In the near term, there is a strong negative correlation between the REC and CO2 emissions. The correlation between RE and carbon emissions also indicates that RE is an important means of combating climate change. The coefficient size shows that a one percent variation in REC causes a one percent variation in CO2 emissions. A 3 percent reduction in CO2 emissions. This is in accord with earlier studies that have also supported the use of RE in reducing emissions (Sadorsky 2009; Shahbaz, Balsalobre-Lorente, and Sinha 2019).

Table 9: CS-ARDL

lnCO Coef.	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
Short Run Est.						
Mean Group:						
L.lnCO	0.165675	0.024919	0.66	0.506	-0.03227	0.065407
lnREC	-1.29543	0.190669	-6.79	0.00	-1.66914	-0.92173
lnPOPD	-1.49883	1.062688	-1.41	0.158	-3.58166	0.583997
lnURB	-2.71204	6.076751	-0.45	0.655	-14.6223	9.198169
lnFDI	0.041472	0.087952	0.47	0.637	-0.13091	0.213855
lnNR	-0.01033	0.01062	-0.97	0.331	-0.03115	0.010484
Adjust. Term						
Mean Group:						
lr_lnCO	-0.98343	0.024919	-39.47	0.00	-1.03227	-0.93459
Long Run Est.						
Mean Group:						
lr_lnFDI	-0.01831	0.094938	-0.19	0.847	-0.20439	0.167763
lr_lnNR	-0.00483	0.013378	-0.36	0.718	-0.03105	0.021393
lr_lnPOPD	-1.58563	1.17629	-1.35	0.178	-3.89112	0.719854
lr_lnREC	-1.47498	0.237244	-6.22	0.00	-1.93998	-1.00999
lr_lnURB	-2.83443	8.550977	-0.33	0.74	-19.594	13.92518

The coefficient of population density in the short run is negative ($\beta=-1.4988$) but it is not significant at the 0. 158 level. This result suggests that there is a possibility of population density reducing carbon dioxide emissions, however, the non-significance of the results means that this is not a long-term solution. Another factor that is directly related to CO_2 emissions is population density since high population density can lead to high efficiency through the use of public transport and low carbon dioxide emissions per capita as well as high emissions due to congestion and increased energy consumption (Jones and Kammen 2014). This could be due to the fact that there are counterbalancing forces that are at work and which are evidenced by the fact that the insignificance of the short run.

The short run coefficient for urbanization is negative and statistically insignificant (β=−2.7120, p>0.655). This therefore means that the short run impacts of urbanization on CO_2 emissions in this sample are relatively mild. This is contrary to some of the previous researches that have suggested that urbanization results to emission of more gases because of high energy use (Poumanyvong and Kaneko 2010). However, the insignificance here could be due to the fact that the level of urban infrastructure and energy intensity may vary across countries and thus may dampen the overall effect of urbanization on emissions.

The coefficient of FDI in the short run is positive but statistically insignificant with a coefficient of 0.0415 and a p-value greater than 0.637. This means that FDI does not have a significant direct impact on the carbon emissions. This insignificance may be attributed to the fact that FDI has both positive and negative impacts on the environment where it can have a positive impact by bringing in cleaner technologies while at the same time it can have negative impacts by promoting polluting industries depending on the host country's policies and industrial focus (Eskeland and Harrison 2003; Zhang 2011).

The coefficient for natural resource rents is also negative and statistically insignificant in the short run (β=−0.0103, p>0.331). This finding suggests that natural resource dependence does not exert a negative effect on CO_2 emissions in the short-run. This could be due to the fact that the impact of natural resources on emissions may not be visible in the short run as the natural resource endowed countries may take time to shift their economies to cleaner energy sources (J. D. Sachs and Warner 2001).

Long-Run Estimates

The adjustment term (lr_lnCO) is inverse and highly significant (β=−0.9834, p<0.000), indicating strong long-run convergence. This term suggests that any deviation from the long-run equilibrium in carbon dioxide emissions is adjusted in the same period with almost all the adjustment being done in the same period. The size and the value of the adjustment term are also an indication of the system's tendency to return to the long-term equilibrium, which is in agreement with the theory of cointegration as postulated by Engle and Granger (Engle and Granger 1987).

In the long run, the RE consumption continues to have a highly significant negative impact on CO_2 emissions (β=−1.4750, p<0.000). The long-run coefficient is slightly higher than the short-run coefficient, which implies that the impact of RE on CO_2 reduction is even more robust in the long run. This is in line with the argument that long term investments in RE systems lead to deeper reductions in CO_2 emissions (Apergis and Payne 2010; Sadorsky 2009). The short and long run negative relationship between RE and CO_2 emissions implies that there is need to encourage the use of RE as a way of fighting climate change.

The coefficient for population density in the long run is also negative but it is not statistically significant (β=−1.5856, p>0.178). This means that, as in the short run, population density does not influence CO_2 in the long run either. It is possible that this insignificance reflects a mediation of the relationship between population density and emissions by other elements, including physical infrastructure, technological progress, and energy efficiency, which have been found to differ among countries (Martínez-Zarzoso and Maruotti 2011).

In the long term, urbanization is still negative but does not reach statistical significance (β=-2.8344, p>0.740). This result implies that urbanization does not have a lasting effect on carbon emissions in this situation. The ambiguous and potentially influenced relationship between urbanization and emissions, as shown by the inconclusive empirical studies, suggests that urban infrastructure quality and the energy endowment of urban areas play a role (Poumanyvong and Kaneko 2010).

The long-run coefficient for FDI is also statistically insignificant (β=-0.0183, p>0.847), which suggests that FDI has no effect on carbon dioxide emissions over the long run. This result is in accord with the claim that the environmental impacts of FDI may depend on the investment type, the institutional environment, and the level of development (Cole, Elliott, and Zhang 2011; Zhang 2011). Also, there is no co-integration between natural resource rents and CO2 emissions over the long haul (β = -0. 0048, p > 0. 718).ical infrastructure, technological advancement and energy efficiency which are known to vary across countries (Martínez-Zarzoso and Maruotti 2011).

Urbanization remains negative but not statistically significant in the long run (β=−2.8344, p>0.740). This finding suggests that urbanization does not have a long-term effect on carbon emissions in this case. The inconclusive results of the empirical studies on the link between urbanization and emissions indicate that the relationship could be rather ambiguous and may be influenced by the quality of the urban infrastructure and the energy endowment of the urban areas (Poumanyvong and Kaneko 2010).

The long-run coefficient for FDI is also statistically insignificant (β=−0.0183, p>0.847), which implies that FDI has no long run impact on carbon dioxide emissions. This finding is in agreement with the assertion that the environmental impacts of FDI may be a function of the type of investment, the institutional context and the level of development (Cole, Elliott, and Zhang 2011; Zhang 2011).

Likewise, there is no co-integration between the natural resource rents and CO2 emissions in the long run (β = -0. 0048, p > 0. 718). This suggests that in the long run, resource dependence on carbon emissions may either fall or even be exceeded by other factors, including technological developments or policies designed to control emissions.

The R-squared values indicate that the model has a reasonable fit in explaining CO_2 emissions, with the Mean Group R-squared (R2MG = 0. 96) indicating that the model is a good fit for all groups. The Root Mean Squared Error (Root MSE) was 0. This is also evident from the 04 where the predicted values are almost equal to the actual values, thus indicating that the model is well fitted.

The CD statistic (13. 05, p<0. 000) indicates that there is cross-sectional dependence which is well addressed by the CS-ARDL model. This makes the estimates to be accurate and not to be influenced by cross-sectional correlations that may be due to global shocks that affect all countries in the panel (Pesaran 2006).

The CS-ARDL results show that REC has a negative effect on carbon dioxide emissions in the short and long run. This is in agreement with other research works to confirm the effectiveness of the use of RE in the fight against climate change. Other variables such as population density, urbanization, FDI and natural resource rents do not have a clear link with emissions and the results indicate that there is a complex interdependence between economic development and environmental conservation. These findings provide evidence for the need to enhance the use of RE technologies and the policies that enable sustainable energy transitions. However, other variables' non-significant coefficients reveal that a one size fits all approach may not be the most appropriate and that policies should be developed with consideration of the economic and environmental situations of the respective countries.

Quantile Regression

The findings of the quantile regression analysis show the type of the effect of the CO_2 emission (lnCO) and the control variables at different percentiles of the carbon emission distribution. Quantile regression is different from the OLS regression which provides the average effect of the explanatory variables on the dependent variable. This approach is appropriate when testing the moderating effect of the variables such as lnREC, lnNR, lnPOPD, lnURB and lnFDI at different levels of CO_2 emissions in countries.

Table 10: Quantile Regression

	0.1		*0.25*		*Median*		*0.75*		*0.9*	
lnCO	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t
lnREC	-0.83878	0.00	-0.85642	0.00	-0.8842	0.00	-0.77684	0.00	-0.72715	0.00
lnNR	-0.2608	0.00	-0.31338	0.00	-0.27697	0.00	-0.25338	0.00	-0.24709	0.00
lnPOPD	-0.29876	0.00	-0.28155	0.00	-0.27408	0.00	-0.34597	0.00	-0.37423	0.00
lnURB	-0.40852	0.00	-0.20843	0.00	-0.10066	0.003	0.119662	0.001	0.013684	0.753
lnFDI	-0.2783	0.005	-0.24181	0.00	-0.27335	0.025	-0.12989	0.00	-0.04422	0.039
_cons	6.170776	0.00	5.885858	0.00	6.153881	0.00	5.315034	0.00	5.783472	0.00

The coefficients for REC are negative and statistically significant in all quantiles meaning that the consumption of RE reduces carbon dioxide emissions. However, the coefficients are slightly different across the quantiles with a higher impact at the lower quantiles 0. 1 and 0. 25 and slightly lower impact at the higher quantiles 0.75 and 0.9. Specifically:

- At the 0.1 quantile, the coefficient is $\beta=-0.8388$, indicating that a 1% increase in REC is associated with a 0.84% reduction in CO_2 emissions.
- At the median (0.5 quantile), the coefficient is $\beta=-0.8842$, suggesting a stronger impact compared to the lower and upper quantiles.
- At the 0.9 quantile, the coefficient decreases to $\beta=-0.7271$, indicating a slightly weaker impact of RE on emissions among countries with the highest levels of carbon emissions.

These results indicate that the REC is most efficient in reducing the CO_2 emissions for the countries that have moderate emissions. It may be due to the fact that these countries may be more evolved in terms of transition towards the usage of RE sources in their energy mix and hence may have been able to achieve higher reductions in emissions. For the countries that are at the higher end of the emissions spectrum, the effect of RE remains negative but the effect is not as severe, this could be because the countries depend more on the use of fossil fuels or have a higher energy consumption (Al-Mulali, Saboori, and Ozturk 2015; Sadorsky 2009).

Natural resource rents also have a consistently negative and statistically significant effect on carbon dioxide emissions across all quantiles, but the impact is relatively smaller compared to REC. Natural resource rents also have a negative and statistically significant effect on CO_2 emissions in all quantiles but the magnitude of the effect is much lower than that of REC:

- The coefficients range from $\beta=-0.2608$ at the 0.1 quantile to $\beta=-0.2471$ at the 0.9 quantile.

This result indicates that countries with higher natural resource rents emit less carbon dioxide at every level of emissions. This result is rather paradoxical, as one might expect the resource-dependent economies to have higher emissions because of intensive fossil fuel extraction and consumption. However, this negative relationship could be explained by the fact that some of the countries endowed with natural resources may use their resource rents to fund cleaner technologies, or may have lower industrial emissions due to a less diversified economy (Frankel 2012).

Population density has a negative and statistically significant effect on CO_2 emissions across all quantiles:

- The coefficients range from $\beta=-0.2988$ at the 0.1 quantile to $\beta=-0.3742$ at the 0.9 quantile.

This means that the higher population density is in a country, the lower the levels of carbon dioxide emission and this is more pronounced at the higher quantiles. The negative effect of population density could be explained by better resource and energy utilization in densely populated areas and less energy per capita due to the centralization of infrastructure and public transport (Jones and Kammen 2014). The results also show that the impact of population density is relatively larger at the higher percentiles suggesting that population density is more effective in controlling CO_2 emissions in countries with higher emissions.

The effect of urbanization on carbon dioxide emissions is more complex and varies significantly across the quantiles:

- At the lower quantiles (0.1 and 0.25), the coefficients are negative and statistically significant, indicating that urbanization is associated with lower CO2 emissions ($\beta=-0.4085$ at the 0.1 quantile and $\beta=-0.2084$ at the 0.25 quantile).

- At the median quantile, the coefficient is still negative but smaller (β=−0.1007) and statistically significant.
- At the 0.75 quantile, the effect of urbanization turns positive (β=0.1197) and is statistically significant, suggesting that at higher levels of emissions, urbanization is associated with an increase in carbon dioxide emissions.
- At the 0.9 quantile, the coefficient is close to zero and statistically insignificant (β=0.0137).

Such variability of the impacts considered indicates the twofold nature of urbanization as a factor affecting CO_2 emissions. In countries with low emission level, urbanization could have positive effect on emissions resulting from efficient use of energy and better structures and access to cleaner technologies. However, in countries emitting relatively higher levels of carbon dioxide, urbanization could further the energy demand, traffic jam and pollution if the urbanization process is not complemented by infrastructural development and policies on clean energy (Poumanyvong and Kaneko 2010).
FDI also exhibits varying effects across the quantiles:
At the lower quantiles (0.1 and 0.25), the coefficients are negative and statistically significant, suggesting that FDI is associated with lower CO2 emissions (β=−0.2783 at the 0.1 quantile and β=−0.2418 at the 0.25 quantile).
At the median quantile, the coefficient remains negative and significant (β=−0.2734).
At the higher quantiles (0.75 and 0.9), the negative effect diminishes, and at the 0.9 quantile, the coefficient is small and only marginally significant (β=−0.0442).
This pattern suggests that FDI has a negative impact on carbon dioxide emission in low to moderately emitting countries, which could be attributed to technology transfer of cleaner technologies and better practices. However, in the case of higher emission countries, the correlation between FDI and emissions reduction is insignificant, which may be due to the fact that FDI in such countries is still biased towards energy intensive industries or may not necessarily be linked to strict environmental performance (Zhang 2011).
The constant term is positive and statistically significant in all quantiles with the values of 5.31 to 6.17. This provides the level of CO_2 emissions when there is no change in the explanatory variables and it is observed that the baseline emissions are slightly higher at the lower end of the distribution.
The findings from the quantile regression analysis show that the link between REC, natural resource rents, population density, urbanization, and FDI and CO_2 emissions is not straight forward and varies across the different levels of emissions. The regression analysis of the relationship between REC and carbon emissions shows that the former has a negative effect on the latter and decreases with the increase in the quantile level especially at the lower and median quantile levels. Population density and natural resource rents also aid in reducing the emissions while the effect of urbanization and FDI depends on the emission level.
Hence, it can be stated that these variables should be treated as heterogeneous when designing policies at different stages of emission. The measures that are to be put in place to promote the use of RE and sustainable urbanization should be in conformity with the emission rates of the countries in order to achieve the best results in the reduction of carbon dioxide emissions.

Analysis by Income Level Classification
The System GMM and CS-ARDL results give a clear picture of how the co-integration between CO_2 emissions and the other control variables including REC, natural resource rents, population density, urbanization and FDI varies depending on the income status of the countries. The analysis shows that these influences shape CO2 emissions in various manners reliant on a country's economic status, implying a sophisticated method is required for formulating environmental policy.
The results from System GMM estimation for high-income countries show that lagged carbon dioxide emissions are strongly persistent and that past emissions have a positive and significant effect on current emissions. This is probably because the energy systems that exist today are not readily adaptable. The study shows that REC has a negative effect on carbon emissions, but this is not statistically significant, which may be because these countries have already put in place efficient energy technologies. In addition, natural resource rents and population density do not influence emissions, which could be due to the fact that the economy has matured and the cities have been built more effectively. One can say the same about urbanization, which shows no statistically significant relationship with emissions in these countries.
The findings from the System GMM reveal that upper-middle-income countries exhibit lower persistence in CO2 emissions, and REC has a negative but statistically insignificant effect on emissions. In a corresponding manner, natural resource rents and population density fail to impact emissions, which implies that these countries could be in a shift period where diversification and industrialization decrease the impacts. With a positive coefficient but lack of statistical significance, this implies that foreign direct investments have no important effect on CO2 emissions.
In the lower-middle-income countries, the carbon dioxide emissions persistence is much less pronounced, and the REC begins to have a more pronounced effect. The relatively small contribution of RE in the reduction of emissions suggests its increasing importance in these countries where energy transitions are still ongoing. Nonetheless, natural resource rents, population density, and FDI are still small, which means that these factors are not yet significant sources of emissions in these economies.
However, the System GMM analysis reveals a different picture for the low-income countries. In this case, REC has a negative and significant impact on CO_2 emissions, which implies that the use of RE could be of great value in reducing emissions. On the other hand, natural resource rents have a positive and significant correlation with emissions, which shows the resource curse in these countries and the problems associated with the use of fossil energy sources. Population density also has a positive effect on emissions, which may be attributed to poor infrastructure and energy intensity. Notably, urbanization and FDI are excluded from the model, probably because of data limitations or multicollinearity, which are issues in the data for LINs.
The CS-ARDL analysis builds on these insights by offering both the short-run and long-run impacts. The short-run persistence of carbon dioxide emissions is low in high-income countries, as evidenced by the insignificant and negative coefficient of

lagged emissions. The findings show that REC has a negative and statistically significant effect on emissions in both the short and long terms, which backs the role of RE in the reduction of emissions. For both short and long periods, the coefficients relating to natural resource rents, population density, urbanization, and FDI are inconsequential, demonstrating that these variables have little effect on CO2 emissions in these affluent countries.

The CS-ARDL model results for upper middle-income countries indicate a strong short-run persistence of carbon emissions, but REC has a markedly negative effect on emissions in both the short and long terms. This indicates that RE could play a key role in reducing emissions as these countries persist in their industrialization. Still, natural resource rents and population density are not important in affecting emissions, and FDI, although significant only in the long run, may cause an increase in emissions because of industrialization or less sustainable practices.

The CS-ARDL analysis for lower-middle-income countries shows that the consumption of RE has a negative effect on emissions in both the short and long terms, which stresses the critical role of RE in these economies. Importantly, variables including natural resource rents, population density, urbanization, and FDI are not significant, which suggests that the transition to RE sources might be the optimal method for reducing emissions in these countries.

The CS-ARDL findings for low-income countries confirm that RE is important, with a highly significant negative effect on emissions in both the short and long terms. This is due to the fact that RE holds the promise of reducing emissions in economies that are still in the development phase of their energy systems. The robustness of the effects of natural resource rents and population density is not very strong because these two variables are not significant, which might be a result of the fact that the infrastructure and governance in these countries are still relatively new.

In summary, the results imply that RE is a viable option for lowering emissions across all income levels, but it shows the greatest promise for benefiting low-income countries. These countries are probably going to benefit most from the policies designed to boost RE source usage because they are still in the process of building their energy systems. The paper also concludes that natural resource rents are a challenge for low-income countries because the consumption of fossil fuels raises emissions, thus, supporting the 'resource curse' hypothesis. The impact of population density is also not uniform; the low-income countries are most impacted due to lack of infrastructure and energy intensity. It is also important to mention that urbanization and FDI do not have a strong impact on emissions in most of the countries which belong to different income levels; this means that the effects of these variables can be mediated by other factors, for example, governance, the structure of investment, or the quality of the infrastructure.

These results suggest that there is a need to have a policy that is sensitive to the economic environment of the various countries. For the lower-income countries, the policies related to the emissions reduction should be directed towards the RE while for the high-income countries, the efforts may have to be directed towards the fine-tuning of the existing technologies and energy systems. Mitigating the resource dependency of low-income nations will be important for emission reduction and sustainable development. Finally, the study highlights the need for policy solutions that are sensitive to the context in which the key economic and demographic variables operate in relation to CO_2 emissions.

Conclusion

The aim of this paper is to investigate the link between REC, carbon dioxide emissions and a number of macroeconomic variables in low, middle and high income countries. The System GMM, CS-ARDL and Quantile Regression analysis show that RE has the potential of reducing CO_2 emissions in all income groups. Interestingly, the effect of RE is felt most in the low and lower-middle-income countries where the shift to the use of RE sources is a potential way of reducing emissions. However, the use of natural resource rents results in high carbon emissions especially in the low-income countries because these countries' economies are based on the use of fossil fuels. The impacts of other variables like population density, level of urbanization and FDI are also observed to vary with income level; this implies that the impacts of these variables on CO_2 emissions are contingent on the level of economic development and are also influenced by other factors.

The study also has implications of supporting the idea that RE should be promoted as one of the ways of fighting climate change. But the study also reveals that there is need for more specific and targeted policies. While the use of RE is the most significant factor in the fight against emissions across all the income levels, other factors like natural resource intensity and population density have different effects depending on the economic condition. This shows that policy makers should take into consideration the situation of each country particularly the developing countries that are in the process of shifting from the use of conventional energy sources.

In the light of the above findings, the following are the policy implications of this study. First, the use of RE should be encouraged in all the income levels with a special focus on the expansion of RE facilities and investment avenues. Therefore, in the low and lower-middle-income countries, it will be crucial to depend on the international assistance in the form of financial support and technology transfer in order to overcome the barriers for the adoption of RE. Second, the link between natural resource rents and carbon dioxide emissions in low-income countries suggests that there is a need for diversification of the economy and proper management of resources. These countries should be encouraged to cut down their dependence on the fossil fuels and shift to other activities that are more sustainable. In addition, the differences in the effects of population density can be understood as meaning that the positive effects of population increase can be achieved by developing the level of urban infrastructure and promoting the use of energy efficient public transport in low-income countries. Policy makers should also ensure that FDI is in line with environmental protection goals by imposing measures that would require foreign investment to support emission reductions particularly in the developing countries.

However, there are some limitations which can be noticed in the study and these are as follows: Some of the limitations of data used in the study include the use of panel data which may not be sufficient to explain the nature of the association between RE consumption and CO_2. It would be helpful to have more disaggregated information, for instance, information at the city level or by industry, to explain these trends in the future studies. However, the econometric models employed in this study address some issues such as endogeneity and cross-sectional dependence, the models still have some assumptions that may not hold the true nature of the relationships. These trends could be better understood with the help of non-parametric or machine learning methods.

A third limitation is that the study supposes that the members of the same income group are more or less identical in terms of policy effects, energy systems, and governance. Future research could thus further investigate this heterogeneity by doing country-level or case-level analyses. In addition, the ability of technology in establishing the link between energy consumption and emissions has not been well explained. Subsequent research may also explore how the energy storage and smart grid technologies that are relatively nascent will influence the energy-emission relationship. However, the last but not the least, the viability of RE sources in the future has to be assessed. It is, however, important to note that this study has only focused on the direct impacts of RE and therefore future research should also take into account the external costs of expanding the use of RE sources in the future.

Hence, from this study, it can be concluded that RE has the ability of reducing CO_2 emissions in the economy irrespective of the level of development. However, the findings also show the difficulties of sustainable development since the natural resource and population density impact the income categories in different ways. Therefore, the future research may contribute to the identification of the ways to achieve the low-carbon sustainable future overcoming the limitations of the present study.

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Appendices

Table 1A: Descriptive Statistics (Income Level Classification)

	High Income				**Upper Middle Income**				**Lower Middle Income**				**Low Income**			
Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
CO	7.792536	4.138527	1.355235	25.61044	3.754793	2.681383	0.665546	15.34125	1.43395	1.699508	0	7.570578	0.140536	0.070172	0.051341	0.441454
REC	20.18399	16.64681	0	82.79	21.73432	14.93617	1.04	69.84	44.20499	27.21727	0	93.46	81.81379	10.10343	47.32	95.35
NR	1.110493	2.310476	0	17.34885	4.168089	6.444091	0	43.04068	7.455398	8.833462	0.042858	79.43095	11.07818	6.52451	2.489562	36.3206
POPD	165.5286	235.4584	2.508975	1620.425	143.2707	247.8033	2.254858	1738.19	127.7315	203.0748	1.597867	1301.039	103.5683	109.9831	6.781134	545.6785
URB	55.4135	23.22169	8.461	100	55.99956	25.53886	14.303	100	59.29903	20.16838	16.632	100	58.23306	25.26942	14.698	100
FDI	8.538941	36.1722	-394.472	449.0828	4.674087	5.219322	-5.68397	55.07288	3.264187	4.65498	-37.1727	43.91211	5.889456	11.1386	-4.84583	103.3374

Table 2A System GMM Classification

	High Income				***Upper Middle Income***				***Lower Middle Income***				***Low Income***			
lnCO	Coefficient	Corr. std. err.	t	P>t	Coefficient	Corr. std. err.	t	P>t	Coefficient	Corr. std. err.	t	P>t	Coefficient	Corr. std. err.	t	P>t
lnCO																
L1.	0.480954	0.236166	2.04	0.049	0.714132	0.467819	1.53	0.136	0.074883	0.182892	0.41	0.685	0	(omitted)		
lnREC	-0.29776	0.25137	-1.18	0.244	-0.04719	0.395459	-0.12	0.906	-0.9704	0.542744	-1.79	0.082	-1.63898	0.139607	-11.74	0
lnNR	-0.03392	0.041429	-0.82	0.418	0.014826	0.043378	0.34	0.735	0.058533	0.152982	0.38	0.704	0.783625	0.174874	4.48	0.001
lnPOPD	-0.41517	0.272207	-1.53	0.135	0.056208	0.140898	0.4	0.692	0.304576	0.273234	1.11	0.273	0.853873	0.077133	11.07	0
lnURB	-0.47864	0.873357	-0.55	0.587	0.565166	0.607859	0.93	0.359	-0.32105	1.187294	-0.27	0.788	0	(omitted)		
lnFDI	-0.0476	0.054427	-0.87	0.387	0.089457	0.422845	0.21	0.834	0.796106	0.712946	1.12	0.272	0	(omitted)		

Table 3A CS ARDL Classification

	High Income				***Upper Middle Income***				***Lower Middle Income***				***Low Income***			
lnCO	Coef.	Std. Err.	z	P>z	Coef.	Std. Err.	z	P>z	Coef.	Std. Err.	z	P>z	Coef.	Std. Err.	z	P>z
Short Run Est.																
Mean Group:																
L.lnCO	-0.08276	0.054116	-1.53	0.126	0.122014	0.047143	2.59	0.01	0.015698	0.052768	0.3	0.766	0.109368	0.079443	1.38	0.169
lnREC	-0.4531	0.075372	-6.01	0	-0.65067	0.163708	-3.97	0	-1.76365	0.374074	-4.71	0	-4.24446	0.774898	-5.48	0
lnPOPD	-0.51437	1.098964	-0.47	0.64	-0.30631	1.82186	-0.17	0.866	1.866845	1.689012	1.11	0.269	-1.29295	3.937859	-0.33	0.743
lnURB	14.13619	11.53584	1.23	0.22	13.52288	23.34066	0.58	0.562	5.145514	5.279166	0.97	0.33	-12.8236	10.81924	-1.19	0.236
lnFDI	-0.00951	0.073842	-0.13	0.898	0.255094	0.154433	1.65	0.099	0.154401	0.21461	0.72	0.472	0.170559	0.199851	0.85	0.393
lnNR	-0.0019	0.018695	-0.1	0.919	-0.01229	0.015916	-0.77	0.44	0.005429	0.014981	0.36	0.717	0.020881	0.030271	0.69	0.49
Adjust. Term																

Mean Group:																
lr_lnCO	-1.08276	0.054116	-20.01	0	-0.87799	0.047143	-18.62	0	-0.9843	0.052768	-18.65	0	-0.89063	0.079443	-11.21	0
Long Run Est.																
Mean Group:																
lr_lnFDI	0.009595	0.095922	0.1	0.92	0.448445	0.211686	2.12	0.034	0.093227	0.235623	0.4	0.692	0.215171	0.277604	0.78	0.438
lr_lnNR	-0.01031	0.029619	-0.35	0.728	-0.01482	0.020595	-0.72	0.472	0.022016	0.021847	1.01	0.314	0.048104	0.036281	1.33	0.185
lr_lnPOPD	-0.62632	1.21189	-0.52	0.605	0.173392	2.500692	0.07	0.945	2.006155	1.922758	1.04	0.297	-1.59449	4.177202	-0.38	0.703
lr_lnREC	-0.48665	0.093648	-5.2	0	-0.82594	0.20152	-4.1	0	-2.18303	0.516182	-4.23	0	-5.39848	1.087529	-4.96	0
lr_lnURB	12.07869	12.36777	0.98	0.329	24.62508	42.13324	0.58	0.559	5.797754	5.866472	0.99	0.323	-21.9873	18.10722	-1.21	0.225

Table A4**: Dynamic panel-data estimation, two-step system GMM**						
Group variable: CountryID			Number of obs	=	2646	
Time variable : Year			Number of groups	=	126	
Number of instruments = 44			Obs per group: min	=	21	
F(28, 125) = 9.07			avg	=	21	
Prob > F = 0.000			max	=	21	

lnCO	**Coefficient**	**Corr. std. err.**	**t**	**P>t**	**[95% conf. interval]**	
lnCO						
L1.	0.114769	0.245088	0.47	0.64	-0.37029	0.599828
lnREC	-0.55914	0.220042	-2.54	0.012	-0.99463	-0.12366
lnNR	0.099251	0.043448	2.28	0.024	0.013261	0.18524
lnPOPD	0.600544	0.550462	1.09	0.277	-0.48889	1.689976
lnURB	-5.97877	3.330304	-1.8	0.075	-12.5699	0.612314
lnFDI	0.059235	0.27443	0.22	0.829	-0.4839	0.602367
dy_2	-0.1954	0.111442	-1.75	0.082	-0.41596	0.025159
dy_3	-0.1446	0.085637	-1.69	0.094	-0.31409	0.024887
dy_4	-0.09941	0.058345	-1.7	0.091	-0.21488	0.016061
dy_5	-0.04275	0.029706	-1.44	0.153	-0.10154	0.016041
dy_7	0.044457	0.028401	1.57	0.12	-0.01175	0.100666
dy_8	0.079652	0.052475	1.52	0.132	-0.0242	0.183506
dy_9	0.146861	0.08317	1.77	0.08	-0.01774	0.311465
dy_10	0.216712	0.106068	2.04	0.043	0.006792	0.426633
dy_11	0.250138	0.131106	1.91	0.059	-0.00934	0.509613
dy_12	0.311995	0.156591	1.99	0.049	0.002082	0.621908
dy_13	0.382258	0.182598	2.09	0.038	0.020874	0.743643
dy_14	0.430507	0.20481	2.1	0.038	0.025163	0.835851
dy_15	0.510843	0.226871	2.25	0.026	0.061836	0.959849
dy_16	0.553941	0.249867	2.22	0.028	0.059423	1.048459
dy_17	0.587374	0.26951	2.18	0.031	0.05398	1.120768
dy_18	0.646487	0.295085	2.19	0.03	0.062478	1.230497
dy_19	0.694447	0.318062	2.18	0.031	0.064963	1.32393
dy_20	0.690317	0.346897	1.99	0.049	0.003764	1.376869
dy_21	0.691869	0.355541	1.95	0.054	-0.01179	1.395528
dy_22	0.734179	0.37766	1.94	0.054	-0.01326	1.481615
_cons	22.74351	12.48041	1.82	0.071	-1.95677	47.4438

Arellano-Bond test for AR(1) in first differences: z = 0.72 Pr > z = 0.473
Arellano-Bond test for AR(2) in first differences: z = 1.71 Pr > z = 0.088
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Sargan test of overid. restrictions: chi2(17) = 5.75 Prob > chi2 = 0.995
(Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(17) = 25.47 Prob > chi2 = 0.085
(Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
GMM instruments for levels
Hansen test excluding group: chi2(16) = 24.10 Prob > chi2 = 0.087
Difference (null H = exogenous): chi2(1) = 1.37 Prob > chi2 = 0.242