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Impact of Energy Consumption on Environmental Quality in Asian Countries: An Econometric Analysis

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ABSTRACT

This study examined the impact of energy consumption on environmental quality across Asian economies using panel data from 2000 to 2023. The analysis applied Quantile Regression to explore how renewable energy consumption and nonrenewable energy consumption influence environmental indicators, including CO_2 emissions and ecological footprints. Results revealed that renewable energy consumption significantly reduced environmental degradation in both high-income group of Asian countries and low-income Asian economies, with stronger effects in High income Asian nations. Conversely, nonrenewable energy consumption consistently increased CO_2 emissions and ecological pressure across all quantiles. Institutional quality showed a mitigating role, improving environmental outcomes by strengthening governance and policy enforcement. GDP growth was positively linked with emissions, though its adverse effects were partly offset by renewable energy adoption. The findings highlight the need for energy diversification, stronger institutions, and targeted policies promoting renewable sources to achieve sustainable growth and enhance environmental quality across Asian economies.

Keywords: *Energy Consumption, Environmental Quality, Renewable and Nonrenewable Energy Consumption, Asian Countries*

INTRODUCTION

Energy consumption (EC) is essential for fostering economic progress since it enables manufacturing using labour and capital. Energy use and financial development contribute to increased output and economic progress, but also negatively impact the environment by increasing carbon emissions (Siddique, 2017). Energy usage is essential for promoting economic activity, but it also harms the environment by increasing carbon emissions and resource depletion. Developing countries must move rapidly to promote economic growth in this circumstance. They have used fossil fuel energy for decades to support economic and developmental operations. The environmental deterioration that emerging countries endure results from using energy derived from fossil fuels to increase economic activity. In order to boost economic growth in emerging nations, these activities must be expanded, but environmental quality (EQ) must also be preserved. When this happens, industries use fossil fuels to spur economic expansion, worsening environmental circumstances due to their high energy needs and the need to meet those needs through the usage of fossil fuels. Environmental deterioration, according to Wolde-Rufael & Menyah (2010), is brought on by excessive CO_2 emissions brought on by the use of nonrenewable energy. Solving these environmental issues can be achieved using renewable energy sources like solar, wind, and hydropower. By replacing nonrenewable technology and non-degrading environmental norms, using renewable energy can meet energy production needs, enhance EQ, and prevent pollution (Akella et al., 2009).

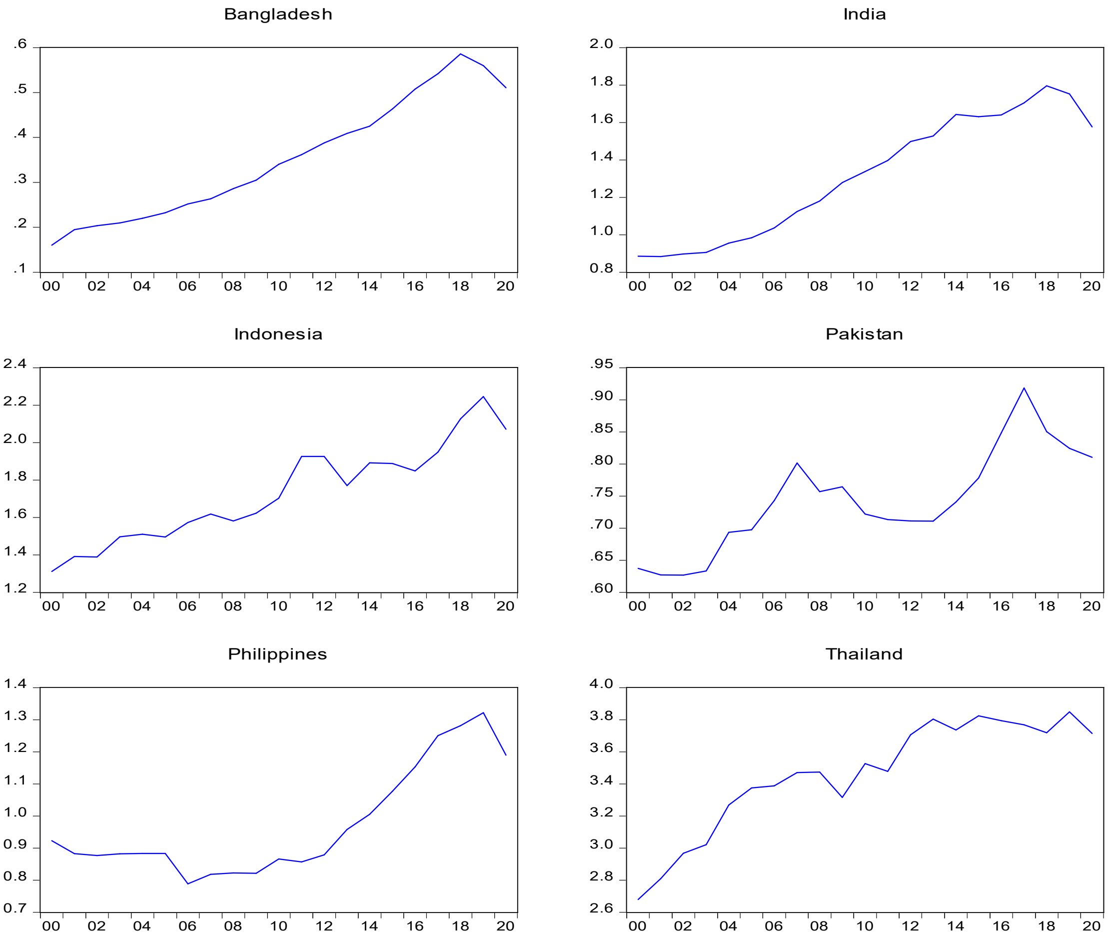

Figure 1: Trends of CO_2 Emissions in Asian Countries

Asia is the largest region on earth and provides concentrations of inexpensive labor, with more than 4.4 billion people (or 60% of the world's population). With a vibrant and varied roster of 48 countries, Asia is divided into five subregions: South Asia, Central Asia, Southeast Asia, East Asia, and West Asia. Based on GDP per capita, these are further divided into low, lower-middle, upper-middle, and high-income countries. With the biggest land area and population in the globe, as well as developing economies, this region is extremely dynamic, but it also faces the problem of environmental sustainability (ADB, 2015). Asia's social well-being and economic development are in jeopardy due to environmental problems such as pollution, climate change, biodiversity loss, global warming, and ecosystem degradation. These environmental issues are also hampering the pursuit of a sustainable development route. The general definition of environmental degradation is the decline in both the quantity and quality of the environment. Figure 1 shows the CO_2 emissions in Asian countries, including Indonesia, the Philippines, Bangladesh, India, Pakistan, and Thailand. The study focuses on Indonesia, Bangladesh, Pakistan, the Philippines, India, and Thailand because these countries represent diverse emerging economies in Asia with significant economic growth and environmental challenges. They are among the largest recipients of foreign direct investment (FDI) in the region and have rapidly expanding financial sectors, making them relevant for analyzing the impact of FDI and financial development on EQ. Additionally, these countries have substantial EC patterns that directly influence their environmental sustainability. The selection of these nations allows for a balanced examination of economies with different levels of industrialization, population sizes, and energy dependencies. The figure shows a rising trend of CO_2 emissions however, in 2019, the trend is declining due to COVID-19, which restricts economic activities. Rapid industrialization and urbanization in these nations are the main causes of the rising trend. Unavoidable social and economic effects have also resulted from the rising average temperature, particularly in Asia. The primary cause of climate change and global warming, which is causing natural disasters, is Asia's increasing trend of CO_2 emissions.

Energy consumption, a key driver of industrialization, significantly affects EQ, especially in regions heavily dependent on fossil fuels. By analyzing these interconnected factors, the study provides valuable insights into how Asian economies can balance economic progress with environmental sustainability. The findings can guide policymakers in designing regulations that attract responsible FDI, strengthen financial sectors for sustainable investments, and promote cleaner energy sources. Ultimately, this research contributes to global sustainability efforts by offering region-specific strategies that help mitigate environmental degradation while fostering economic growth, making it highly relevant for governments, international organizations, and economic researchers.

LITERATURE REVIEW

A good literature review is essential for any research, as it helps build on existing knowledge and identifies areas for further exploration, so there are given some literature review in this section.

Dagar et al., (2022) used the data from 1995 to 2019 to assess the influence of financial development, natural resources, industrialization, REC, and total reserve on environmental degradation (ED) in 38 OECD economies using dynamic panel data models. The results of the one-step difference GMM, one-step system GMM, and two-step system GMM analyses showed that in OECD countries, consumption of renewable energy and use of natural resources help to decline ED whereas financial development, industrialization, and reserves lead to an increase ED. Similarly, Duong & Ngo (2022) explored the effects of agricultural development on ED. The study chose several EC indicators, including GDP, fossil fuels, electricity, EC, and energy import. The study obtained secondary data from ASEAN nations from 1991 to 2020. To evaluate the link between particular constructs, the study also considered the QARDL technique. Results showed that fossil fuels consumption, GDP, and energy import directly related to ED, while RE use and ED were inversely related in the ASEAN economies. Furthermore, Kartal et al., (2022) explored the influence of energy use on environmental deterioration in the USA. The study performed non-linear techniques using Wavelet Coherence and used data from 1989 to 2021. The findings demonstrated that use of energy has a substantial influence on ED. Therefore, the empirical findings highlighted the importance of using renewable energy to enhance EQ by reducing CO2 emissions at aggregated and disaggregated levels. The findings suggested that to reduce CO2 emissions, US officials should prioritise efforts to increase renewable sources while decreasing fossil fuel sources.

The study by Magazzino et al. (2022) examined the causality association between renewable energies, ED, and GDP employing a dataset of five Scandinavian nations from 1990 to 2018. The empirical research findings suggested that consuming renewable energy was a valuable policy tool to lower CO2 emissions without negatively impacting GDP growth. The study suggested that lowering CO_2 emissions through increased reliance on renewable energy sources may ensure high levels of energy efficiency and economic expansion. In addition, Nan et al. (2022) analyzed the relationship between ecological footprints and energy from renewable sources. The asymmetry and heterogeneity between the EF of energy from wind and biomass sources were tested using the quantile regression approach. The results demonstrated that RE has a protracted adverse effect on the EF. There was no Granger causal link between the RE and energy efficiency. The most variable reduction in energy usage was caused by wind energy, followed by biomass energy and solar energy. Additionally, the effects of wind and biomass EC on the energy EF varied depending on the energy EF distribution parameters. In contrary, Agbede et al. (2021) employed a panel PMG/ARDL modelling method, the Granger causality test, and a period ranging from 1971 to 2017 to study the effect of EC on EQ in the MINT countries. The outcomes maintained that the factors used had a long-run nexus. The findings also showed that economic growth, EC, and bio-capacity positively and significantly impacted environmental deterioration over the long run. This implied that the ecological footprint of energy use has a detrimental influence on EQ. The outcome also implied that EQ declines due to larger ecological footprints as MINT countries expanded their energy usage to quicken the pace of EG. The causality test showed a unidirectional causal connotation between EG, energy use, urbanization and EF, and EG and biocapacity. The outcomes also indicated a two-way causal association between bio-capacity, ecological footprint, and EG.

The study by Khan et al. (2021) investigated the effect of RE, trade, FDI, and tourism on ED in industrialized and developing nations using data from 1985 to 2018. OLS, fixed effect, and system GMM models were utilized in the analysis to explore the dynamic association between variables. The results showed that, using more RE deleteriously and significantly impacts ED in both developed and developing nations. It suggests that using more renewable energy improves the EQ in both samples. FDI has a negative and noteworthy impact ED in developing nations, whereas it has a positive and substantial influence in developed nations, suggesting that FDI reduces and increases ED in developing nations. Similarly, Khan et al. (2021) investigated the importance of diverse energy sources and financial development in enhancing EQ in 21 developing countries using data from 1970 to 2018. The dynamic estimator used in the analysis demonstrated that RE sources improve EQ when likened to NREC and its sources. The results show that financial growth also lowers EQ. The study suggested lowering carbon emissions through the use of new technologies and less fossil fuel-based energy, attracting foreign clean energy investors who can provide clean technology for eco-friendly production, and investing in renewable energy sources to avoid using NRE sources. In addition, Vo (2021) explored the energy-environment-growth nexus in the ASEAN region using data from 1990 to 2014. The research revealed that renewable energy increases ED and responds to population. Second, a sizable amount of the change in EC can be attributed to EG and RE sources. Third, bidirectional Granger causation existed in each association between ED, EG, and EC. It was stated that attaining sustainable EG in the ASEAN region depends on limiting population expansion and increasing the REC. Andjarwati (2020) examined the effects of EC, population size, EG, urbanization, industrialization, and poverty on ED in Malaysia using data from 1995 to 2017. The investigation outcomes were examined using the ARDL approach. The study concluded that EC has both short-term and long-term beneficial effects on environmental damage. Urbanization negatively impacts the environment, whereas population growth, industry, and poverty have favorable effects. Only in the short term can economic expansion contribute favourably to ED.

Furthermore, Belaid & Zrelli (2019) used a panel of 9 Mediterranean nations between 1980 and 2014 to inspect the causal connection between REC and NREC, GDP, and ED. The results showed that there was short-term bidirectional causality between GDP, REC, and CO_2 emissions, as well as between NREC, GDP, and REC. The outcome for the long-term causal link showed a bidirectional causal association between ED and NREC. There was evidence of one-way causal links between GDP, NREC, and ED, as well as between renewable electricity use and ED. According to the findings, EG and the consumption of NREC both increase ED in the southern and northern Mediterranean countries, whereas renewable energy usage lowers them. Similarly, Mensah et al. (2019) used a panel of 22 African countries to analyze the causal relationship between ED, fossil fuel EC, ED, and oil prices from 1990 to 2015. Using panel econometric methods, the results revealed a bilateral causal relationship between the FFEC and EG and between the FFEC and ED. However, there was only a bilateral causal association between the FFEC and ED in the long term for oil exporting nations. Appiah (2018) scrutinized the association between ED, energy use, and EG in Ghana. The data used in this study ranged from 1960 to 2015. Granger causality's findings established a link between energy use, economic expansion, and CO_2 emissions. The results of the causality tests showed a causal link between EG and, EC and CO_2 emissions. There was a causal connection between ED and, EC and economic expansion. Policymakers should develop an energy conservation strategy to limit Ghana's EC and ED. The study also suggested that Ghana's government concentrate on clean technologies and REC to promote sustainable EG and a healthy environment rather than use fossil fuels. Lastly, Karasoy & Akçay (2018) investigated the effects of EC and trade on ED in Turkey from 1965 to 2016. The study employed unit root tests, the Zivot-Andrews unit root test, to consider a potential structural break. The vector error correction and autoregressive distributed lag techniques were used to inspect the relations between the variables. The results supported the EKC theory. Additionally, increases in trade and the use of NRE sources result in long-term increases in ED, whereas using RE sources results in short- and long-term decreases. According to the causality analysis, there were long-term causative relationships between the use of NRE and ED and between trade and these ED. The conservation hypothesis only holds for the non-REC-income nexus in the long run, while the neutrality hypothesis only holds in the short term.

DATA AND METHODOLOGY

In this section, the data and research methodology used to examine the relationship between EC and EQ in Asian countries are discussed.

Data Sources

This analysis examines the effect of EC on EQ in Asian economies from 2000 to 2023. Out of the 57 Asian economies, 40 were picked for present study depends on data availability. The World Bank sorts economies of countries into various income groups—ranging from low-income to high-income—determined by their per capita GDP. Pursuing Ali et al. (2021), we categorized Asian economies into three groups. The first group comprises all Asian economies and is referred to as the overall-Asian group (Asian-OIG). Whereas the second group includes both lower-income and low-middle-income nations of Asia, termed the lower-income Asian group (Asian-LIG). The third group combines the higher-middle-income and higher-income Asian economies, denoted to as the high-income Asian group (Asian-HIG). Based on the studies of Azam et al., (2021); Sarkodie (2020) and Ali et al., (2022) the following models are developed to analyze the effect of EC on EQ:

$$\ln CO_{2it} = \alpha_0 + \alpha_1 \ln REC_{it} + \alpha_2 \ln NREC_{it} + \alpha_3 \ln TOP_{it} + \alpha_4 \ln GDP_{it} + \alpha_5 \ln INQ_{it} + \varepsilon_{it} \quad (1)$$

$$\ln ECF_{it} = \alpha_0 + \alpha_1 \ln REC_{it} + \alpha_2 \ln NREC_{it} + \alpha_3 \ln TOP_{it} + \alpha_4 \ln GDP_{it} + \alpha_5 \ln INQ_{it} + \mu_{it} \quad (2)$$

Where;

CO_2 = Carbon dioxide emissions

ECF = Ecological footprints

INQ = Institutional quality

ε = Error term

Table 1: Variables' Descriptions

Variables	Narration	Unit of Measurement	Data Sources
GDP	Per capita GDP	Constant 2010 US$	WDI
CO_2	Carbon dioxide emissions	Kilo ton (kt)	WDI
ECF	Ecological footprint	Global hectares (gha)	Global Footprint Network
TOP	Trade openness	Imports plus exports divided by GDP	WDI
INQ	Institutional quality	Index	International Country Risk Guide (ICRG
NREC	Nonrenewable energy usage	KG of oil equivalent per capita	WDI
REC	Renewable energy consumption	Proportion of final energy usage	WDI

Data Estimation Approaches

In this section different data estimation approaches are discussed which are as follows.

Cross-Sectional Dependence Tests

To assess cross-sectional dependence (CSD) in panel data, several methods are utilized, such as the LM test, CD test, and both the scaled-LM test and its adjusted form. The standardized version of the LM test, originally introduced by Breusch & Pagan(1980), can be represented as follows:

$$LM_{BP} = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij}^{2} \tag{3}$$

In this context, ρ_{ij}^{2} shows the estimated test value of the paired correlation coefficients. This test is reliable for datasets with a greater time dimension (T) and relatively small cross-sections (N). However, it may provide inaccurate results when the average of the median paired correlations approaches zero. To address this limitation, Pesaran (2004) introduced a scaled version of the test.

$$Scaled\ \text{LM Test} = \sqrt{\left(\frac{1}{N(N-1)}\right)}\left[\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T\,\hat{\rho}_{ij}^{2}-1\right)\right] \tag{4}$$

The test indicates significant distortions when N exceeds T. To address this, Pesaran (2004) developed another test, the CD test, that is reliable when N > T or T < N.

$$\text{CD} = \sqrt{\left(\frac{2T}{N(N-1)}\right)}\left[\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right] \tag{5}$$

The CD test, defined by N→∞ and T→∞, follows an asymptotic normal distribution. Unlike the LM test, it uses the scaled mean of correlation coefficients rather than their squared values. This test is robust to multiple breaks in slope coefficients and delivers reliable outcomes for dynamic panel data with heterogeneity. In a subsequent study, Baltagi, Feng, & Kao (2012) enhanced the CD test by introducing more accurate estimates for the variance and mean of the LM statistics.

$$\mathrm{LM}_{adj} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{v_{Tij}^2}} \qquad (6)$$

In this case, v^2_{Tij} and μ_{Tij} indicate the exact variance and mean of $(T-k)\hat{\rho}_{ij}^2$.

Slope Homogeneity Tests

The SH test functions like a detective examining two hypotheses: one where the slopes are all the same (homogeneous) and another where the slopes vary (heterogeneous). Swamy (1970) introduced a test using a specific number of cross-sections (N) and time periods (T) to explore this. Later, Pesaran & Yamagata (2008) enhanced the test for situations involving a large number of N and T. A key condition for the Pesaran & Yamagata (2008) test is that the disturbance term must follow a normal distribution.

$$\tilde{S} = \sum_{i=1}^{N} (\hat{\beta}_i - \tilde{\beta}_{WFE})' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2} (\hat{\beta}_i - \tilde{\beta}_{WFE}) \qquad (7)$$

The notation $\hat{\beta}_i$ represents the coefficient estimated using the pooled ordinary least squares (OLS) method, while $\tilde{\beta}_{WFE}$ denotes the coefficient estimated through the fixed effect weighted pooled estimator. Furthermore, $\tilde{\sigma}_i^2$ represents the estimated variance. The SD statistic for the SH test can be calculated using the following formula:

The notation $\hat{\beta}_i$ represents the coefficient estimated using the pooled ordinary least squares (OLS) method, while $\tilde{\beta}_{WFE}$ denotes the coefficient estimated through the fixed effect weighted pooled estimator. Furthermore, $\tilde{\sigma}_i^2$ represents the estimated variance. The SD statistic for the SH test can be calculated using the following formula:

$$\bar{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \qquad (8)$$

$\bar{\Delta}$ test follows an asymptotic normal distribution with a standard distribution under the null hypothesis as (T, N) $\rightarrow \infty$ and $\sqrt{N/T} \rightarrow \infty$. The bias-adjusted version of the SH test ($\bar{\Delta}_{adj}$) can be represented as follows:

$$\overline{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\overline{z}_{it})}{\sqrt{\operatorname{var}(\overline{z}_{it})}}\right) \quad (8)$$

In simple terms, this test uses two symbols, $E(\overline{z}_{it}) = k$ for the average and $\operatorname{var}(\overline{z}_{it}) = 2k(T-k-1)/T+1$ for the variance. It helps determine whether the coefficients of the cross-sections are heterogeneous or homogeneous in the long run.

Panel Unit Root Tests

Traditional or 1st generation unit root tests failed to account for heterogeneity and CSD, leading to unreliable results when the variables being analyzed exhibited CSD and/or heterogeneity. In contrast, the 2nd generation unit root test, recognized as the CIPS test, established by Choi (2006) and Pesaran (2007), provides more accurate results by effectively addressing both CSD and heterogeneity issues.

Panel Cointegration Tests

The use of 1st generation cointegration tests can result in ambiguous results as they overlook key factors such as heteroskedasticity, serial correlation, and CSD. In contrast, the Westerlund (2007) test, recognized as the 2nd generation cointegration test, is highly reliable since it addresses all of these concerns. This test effectively evaluates the presence of cointegration or long-run relationships among variables and performs well even with small datasets or structural breaks (Westerlund, 2007). The testing methodologies involve both panel-based and group mean-based statistical approaches. Panel-based statistics focus on the error-adjusted component for the entire panel, while group mean-based statistics assess the weighted average of the error-adjusted component. These statistics examine long-run relationships by incorporating the error-correction mechanism for both the panel and individual cross-sections.

Quantile Regression (QR) Approach

Koenker & Bassett (1978) initially developed the quantile regression (QR) method. This approach utilizes various quantile points to fully leverage the significant benefits of the sample data for regression analysis. QR estimates the independent variable's average impact on different quantiles of the dependent variable (Koenker & Bassett, 1978). Consequently, QR provides conditional estimates of quantiles, where each function distinctly represents the behavior at specific points within the conditional distribution (Koenker & Bassett, 1978; Koenker, & Hallock, 2001). The basic framework of the QR model can be outlined as follows:

$$Y_t = X'_t \rho_\varphi + \pi_{\varphi t'}, 0 < \varphi > 1 \quad (9)$$

$$Quant_\varphi(\frac{Y_t}{X_t}) = X_t \rho_\varphi \quad (10)$$

In this model, Y is the dependent variable, and X represents the vector of explanatory variables. π is the stochastic error term with a conditional quantile distribution centered at zero. Consequently, $Quant_\varphi(\frac{Y_t}{X_t})$ indicates that φ^{th} quantile for Y, the dependent variable. The QR method allows for the analysis of the effects of covariates across different positions in the distribution of the dependent variable.

The φ^{th} estimator for QR is $\hat{\rho}_{\varphi}$, which is determined by solving the following equation:

$$\min \sum_{Y_t > X_t' \rho} \varphi \left| Y_t - X_t' \rho \right| + \sum_{Y_t > X_t' \rho} \varphi \left(1 - \varphi\right) \left| Y_t - X_t' \right| \tag{11}$$

The solution to the equation above is derived through linear programming. Specifically, median regression is a particular QR computed assuming that ϕ = 0.5. As equation three shows, various quantiles are obtained by assigning different values to ϕ. In order to explore the relationship between the independent variables and the different forms of the conditional distribution of the dependent variable, the study considers the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} quantiles. In the context of QR, the regression equation for our study can be expressed as follows:

$$LNGDP_t(\tau) = \beta_0(\tau) + \beta_1(\tau)LNREC_t + \beta_2(\tau)LNNREC + \beta_3(\tau)LNTOP_t + \beta_4(\tau)LNHC_t + \beta_5(\tau)LNINQ_t + \beta_6(\tau)LNGFCF_t + \varepsilon_t(\tau) \tag{12}$$

$$LNCO_{2t}(\tau) = \beta_0(\tau) + \beta_1(\tau)LNREC_t + \beta_2(\tau)LNNREC + \beta_3(\tau)LNTOP_t + \beta_4(\tau)LNGDP_t + \beta_5(\tau)LNINQ_t + \varepsilon_t(\tau) \tag{13}$$

Where RH(τ) represents the τ^{th} quantile of RH, $\beta_0(\tau)$ is the quantile-specific intercept, $\beta_1(\tau)$, $\beta_2(\tau)$, $\beta_3(\tau)$, $\beta_4(\tau)$, and $\beta_5(\tau)$ are the quantile-specific coefficients for the independent variables (LNREC, LNNREC, LNTOP, LNHC, LNGFCF and LNINQ). $\varepsilon_t(\tau)$ is the quantile-specific error term. This model allows the relationship between independent variables and the different quantiles of the dependent variable (RH) distribution.

DATA ANALYSIS

This section provides a comprehensive analysis of the data used to explore the relationship between EC and EQ in Asian countries.

Descriptive Analysis

Table 2 summarizes the key attributes of the dataset through presenting descriptive stat values regarding variables. The mean values for CO_2, ECF, GDP, TOP, INQ, REC and NREC are 5.39, 57886498, 7246.17, 1.82, 0.57, 15.92 and 1635, correspondingly. Skewness measures the extent and way of a distribution's symmetry, though kurtosis indicates the tails' heaviness. Skewness values suggest all variables are platykurtic having positive skewed distributions. Kurtosis values reveal that CO_2, ECF, GDP, TOP and INQ have leptokurtic distributions, while REC and NREC indicate platykurtic distributions.

Table 2: Descriptive Statistics

	CO_2	ECF	GDP	TOP	INQ	REC	NREC
Mean	5.39	57886498	7246.17	1.82	0.57	15.92	1635
Median	2.61	22253592	2746.83	1.86	0.55	14.51	1662
Minimum	0.08	1245639	339.14	0.85	0.41	12.76	1179
Maximum	44.64	389000000	72444.08	3.23	0.75	22.98	2119
Skewness	2.14	1.97	2.65	3.30	1.90	0.98	-0.02
Std. Dev.	7.51	72409720	10000.18	0.23	0.20	3.46	322.50
Kurtosis	7.35	6.96	11.79	54.86	3.89	2.45	1.63
Observations	600	600	600	600	600	600	600

Cross-Sectional Dependence Analysis

CSD might increase due to many factors, including shared social or economic networks, unobserved variables, spatial effects, and others (Chudik & Pesaran, 2015). It is widely recognized that failing to address CSD in panel dataset analysis can lead to inconsistent and biased estimations (Ali et al., 2021). To assess the presence of CSD throughout cross-sectional units, we employed scaled CD, bias-adjusted scaled LM (BAS-LM), and scale-LM (SLM) tests as detailed in Table 3. The results affirm the existence of CSD throughout the cross-sectional units. These findings from CSD tests perform a vital role in assessing the appropriate analytical approach and are essential for selecting the most relevant CIPS-test in a CSD framework.

Table 3: Outcomes of CSD tests

Variables	CD Test	SLM	BAS-LM
$lnCO_2$	90.53*	110.05*	111.50*
lnECF	69.36*	89.40*	90.22*
lnGDP	55.55*	105.10*	110.40*
lnTOP	130.35*	420.60*	422.61*
lnINQ	70.70*	150.30*	155.70*
lnREC	40.75*	109.60*	110.50*
lnNREC	60.90*	120.53*	122.70*

*Note: * and ** displays 1% and 5% P-value, correspondingly.*

Panel Unit Root Analysis

Table 4 presents the results of the CIPS test, a second-generation unit root test known for its accuracy in the presence of CSD. The findings indicate that LNINQ and LNREC are stationary at their first differences, whereas all other variables lnCO2, lnECF, lnGDP, lnTOP and lnNREC are stationary at their levels.

Table 4: Outcomes of CIPS Unit Root Test

Variables	Level	1st Difference
$lnCO_2$	-3.97*	-6.75*
lnECF	-3.85*	-6.20*
lnGDP	-3.83*	-5.20*
lnTOP	-3.59*	-6.40*
lnINQ	-1.89	-5.92*
lnREC	-1.75	-5.10*
lnNREC	-2.98*	-5.50*

*Note: * and ** denote to the P-values of 1% and 5%, correspondingly.*

We utilize a slope heterogeneity (SH) test to ascertain the presence of SH within the data. The findings obtained by the SH test are presented in Table 4. The null hypothesis proposes uniform slope coefficients, whereas the alternative hypothesis indicates slope heterogeneity. Across whole ASIAN groups, the t-statistic values for both the SH test ($\overline{\Delta}$) and its adj delta ($\overline{\Delta}_{adj}$) give compelling ground to accept the H_1 and reject the H_o, indicating the presence of CS SH in panel data.

Table 5: Findings of heterogeneity/slope homogeneity test

	$\overline{\Delta}$	$\overline{\Delta}_{adj}$
ASIAN-OIG	3.33*	4.36*
ASIAN-LIG	4.83*	5.78*
ASIAN-HIG	4.22*	6.01*

*Note: * and ** designate significance levels at 1 and 5 %, correspondingly.*

Panel Cointegration Analysis

Table 6 displays the findings of the Westerlund (2007) test, emphasizing the significance of the Group-α, Group-Ʈ, and Panel-α statistics. This significance indicates the presence of a long-term relationship among the variables examined. These results are consistent with Xue et al. (2021), who applied the same test and confirmed a long-run association between the variables.

Table 6: Findings of Westerlund Cointegration Test

H_0: no cointegration	ASIAN-OIG	ASIAN-LIG	ASIAN-HIG
Group- Ʈ	-6.10*	-5.84*	-4.36*
Group- α	-4.32*	-4.53*	-3.76*
Panel- Ʈ	-6.83*	-6.44*	-8.32*
Panel- α	-6.10*	-4.54**	-5.33*

***Note:** * and ** designate the significance level at 1% and 5%, correspondingly.*

Quantile Regression Analysis

Table 7 displays the outcomes of the QR analysis, highlighting the impact of EC and control variables on environmental performance. This approach uncovers varying effects across different quantiles, providing a deeper insight beyond average impacts. Table 7 shows that in high-income Asian economies, REC negatively impacts various quantiles of CO_2, starting from the 25th (low medium) quantiles and becoming more pronounced at the 90^{th} (highest) quantile, indicating a stronger reduction in CO_2 at higher levels. However, the impact of REC on ECF is insignificant at lower and lower-mid quantiles of ECF in high-income Asian economies. For ASIAN-LIG economies, REC has negative and significant impact on both CO2 and ECF at all quantiles except 75^{th} (upper-medium) quantiles of CO_2 and 10^{th} (lower) quantiles of ECF. The negative impact of REC on pollution is consistent with the studies of (Iram et al., 2024; Asghar et al., 2024; Sibt-e-Ali et al., 2023). For NREC, the impact on CO_2 emissions was positive and significant across all quantiles, reflecting that increased use of nonrenewable energy raises emissions at all levels of CO2 intensity. At low quantiles (10th), the effect of NREC was moderate, indicating that its contribution to emissions is consistent even at lower CO_2 levels. At the lower-mid quantile (25^{th}), the impact slightly increased, showing stronger emissions sensitivity. At the mid quantile (50^{th}), the effect remained stable, while at the upper-medium (75^{th}) and high (90^{th}) quantiles, the impact became more pronounced, emphasizing the substantial role of NREC in driving emissions in high-emission contexts. The positive impact of NREC on pollution is supported by (Kartal et al., 2022; Depren et al., 2022; Rani et al., 2023).

Table 7: Results of QR Estimation

Variables	QR (10th Quantile)	QR (25th Quantile)	QR (50th Quantile)	QR (75th Quantile)	QR (90th Quantile)	Pseudo R^2
Dependent Variable: CO_2						
High-income Asian Economies						
Intercept	10.987*	12.563*	13.432*	15.133*	16.121*	0.674
LNREC	0.049	-0.085*	-0.076*	- 0.099*	-0.111*	0.592
LNNREC	0.109*	0.112*	0.091*	0.113	0.126	0.459
LNTOP	0.087*	0.107*	0.159*	0.169*	0.170*	0.671
LNGDP	0.677*	0.847*	0.880*	0.958*	0.991*	0.521
LNINQ	0.046**	-0.076**	-0.095*	-0.097*	-0.122*	0.776
Low-Income Asian Economies						
Intercept	7.688*	8.688*	9.332*	10.024*	12.024*	0.738
LNREC	-0.169*	-0.183*	-0.174*	-0.297	-0.211*	0.570
LNNREC	0.0507*	0.060*	0.068*	0.094	0.097	0.679
LNTOP	0.017*	0.027*	0.109*	0.108*	0.121*	0.591
LNGDP	0.317*	0.447*	0.588*	0.698*	0.711*	0.639
LNINQ	0.026*	-0.046***	-0.065*	-0.060*	-0.081*	0.596
Overall Asian Economies						
Intercept	9.588*	11.586*	10.230*	12.920*	13.920*	0.748
LNREC	1.277	-0.125*	-0.126*	-0.147*	-0.171*	0.670
LNNREC	2.208	0.081*	0.085*	0.113	0.136	0.658
LNTOP	-0.105	0.055*	0.123*	0.122*	0.141*	0.651
LNGDP	0.455*	0.506*	0.658*	0.757*	0.801*	0.641
LNINQ	-0.036**	-0.056***	-0.074*	-0.084*	-0.091*	0.667
Dependent Variable: ECF						
High-income Asian Economies						
Intercept	9.488*	10.479*	11.122*	11.820*	13.820*	0.838
LNREC	-0.089	-0.091	-0.106*	-0.119*	-0.120*	0.786
LNNREC	0.127	0.121*	0.131*	0.150*	0.152*	0.769
LNTOP	-0.004	0.070*	0.083*	0.103*	0.111*	0.730
LNGDP	0.557	0.647*	0.788*	0.808*	0.822*	0.722
LNINQ	-0.016***	-0.046***	-0.066*	-0.075*	-0.100*	0.767
Low-Income Asian Economies						
Intercept	6.567*	7.345*	7.8976*	9.084*	11.980*	0.658
LNREC	0.090	-0.153*	-0.160*	-0.209*	-0.221*	0.703
LNNREC	0.040*	0.050*	0.059*	0.070	0.094	0.668
LNTOP	0.014*	0.025*	0.110*	0.128*	0.131*	0.330
LNGDP	0.207*	0.130*	0.408*	0.508*	0.601*	0.620
LNINQ	0.022*	-0.040***	-0.056*	-0.058*	-0.071*	0.754
Overall Asian Economies						
Intercept	8.500*	9.550*	9.830*	10.755*	11.567*	0.638
LNREC	1.450	-0.110*	-0.120*	-0.134*	-0.131*	0.472
LNNREC	0.080	0.071*	0.105*	0.120*	0.140*	0.455
LNTOP	-0.095	0.066*	0.103*	0.112*	0.130*	0.533
LNGDP	0.475*	0.539*	0.600*	0.720*	0.731*	0.523
LNINQ	-0.040**	-0.050***	-0.080*	-0.089*	-0.108*	0.560

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

For TOP, the positive and significant relationship with CO_2 emissions was evident across all quantiles. At low quantiles (10^{th}), TOP's effect was moderate, suggesting that trade contributes to emissions even in less industrialized or lower-emission settings. The impact intensified at the lower-mid (25^{th}) and mid (50^{th}) quantiles, reflecting increased trade-related emissions as economic activity scales up. At upper-medium (75^{th}) and high (90^{th}) quantiles, TOP showed the strongest effects, highlighting its greater influence in economies or situations with higher CO2 levels. For ECF, the positive impact of TOP became significant from the lower-mid quantile (25^{th}) onward, growing progressively stronger at mid (50^{th}), upper-medium (75^{th}), and high (90^{th}) quantiles, showing its increasing contribution to EQ metrics in high-performance scenarios. The positive and significant impact of TOP on CO_2 and ECF is supported by the studies of (Udeagha & Ngepah, 2022; Le et al., 2016).

GDP demonstrated a significant and positive association with both CO_2 emissions and ECF across all quantiles. At low quantiles (10^{th}), GDP's contribution to emissions was moderate, reflecting early-stage economic development effects. As the quantiles progressed to lower-mid (25^{th}), mid (50^{th}), upper-medium (75^{th}), and high (90^{th}), the effect of GDP became stronger, showcasing the dual role of economic expansion in driving emissions while also providing resources for improving environmental conditions. For ECF, the impact of GDP followed a similar pattern, with a steady increase across quantiles, highlighting its importance in both low and high-performance contexts. The positive and significant impact of GDP on CO_2 and ECF is supported by the studies of (Asghar et al., 2024; Sibt-e-Ali et al., 2023; Weimin et al., 2022).

INQ had a consistently negative and significant impact on CO_2 emissions across all quantiles, showing that better governance reduces emissions irrespective of the level. At low quantiles (10th), the reduction was moderate, growing stronger at lower-mid (25^{th}), mid (50^{th}), upper-medium (75^{th}), and high (90^{th}) quantiles, emphasizing the critical role of institutional frameworks in curbing emissions at all intensities. For ECF, the negative effect of INQ was more pronounced at higher quantiles (mid to high), suggesting that stronger institutions are crucial for maintaining EQ in more advanced or resource-intensive economies. However, its impact was weaker at lower quantiles in low-income economies, indicating limited institutional influence in such contexts. The negative and significant impact of INQ on CO_2 and ECF is supported by the studies of (Ahmed et al., 2020; Warsame et al., 2022).

CONCLUSIONS AND POLICY RECOMMENDATIONS

The analysis of the impact of EC on EQ across Asian economies highlights significant variations depending on the type of energy consumed, income levels, and environmental indicators. Using QR, the study examines the effects of REC, NREC, and control variables such as trade openness (TOP), institutional quality (INQ), and GDP growth on EQ indicators, including carbon dioxide (CO_2) emissions and ecological footprints (ECF).

In high-income Asian economies, REC demonstrates a consistently negative impact on CO2 emissions, particularly at higher quantiles, indicating that increased REC significantly reduces pollution in scenarios of high environmental degradation. The effects of REC on ECF are also negative, though less pronounced, reflecting its role in promoting sustainable practices. Conversely, NREC shows a positive and significant effect on both CO_2 emissions and ECF across all quantiles, highlighting its contribution to environmental degradation. The positive impact of GDP growth on environmental degradation in high-income economies is offset to some extent by stronger institutional frameworks, which promote the adoption of cleaner energy technologies and stricter environmental regulations.

In ASIAN-LIG economies, REC exhibits a negative impact on both CO_2 emissions and ECF at most quantiles, though the effects are weaker compared to ASIAN-HIG economies. This indicates that while renewable energy contributes to improving EQ, its potential is not fully realized due to infrastructural and institutional limitations. NREC, on the other hand, has a consistently positive and significant impact on environmental degradation across all quantiles, reflecting the reliance on polluting energy sources. INQ plays a mitigating role in ASIAN-LIG economies, with improved governance reducing the environmental harm caused by EC.

The overall results for Asian economies reveal that REC generally reduces environmental degradation, while NREC exacerbates it. The strength of these effects varies based on income levels and quantile positions, with high-income economies benefiting more from renewable energy and institutional frameworks than their low-income counterparts.

The findings underscore the need for tailored energy and environmental policies across different income groups. High-income Asian economies should continue their transition toward renewable energy by investing in advanced clean technologies, enhancing grid efficiency, and promoting energy-efficient practices. Policymakers should enforce stricter environmental regulations and incentivize green investments to further reduce the environmental impact of EC. For ASIAN-LIG economies, capacity building and institutional reforms are critical to reducing the reliance on nonrenewable energy and fostering the adoption of renewable energy sources. International cooperation, financial assistance, and technology transfer can play a pivotal role in enabling these countries to transition toward sustainable EC.

Across all income groups, integrating sustainability into energy policies is essential to align EC with EQ goals. This includes developing frameworks for carbon pricing, promoting public awareness of energy efficiency, and encouraging investments in renewable energy infrastructure. Strengthening institutional quality by improving governance, transparency, and enforcement mechanisms is crucial to ensuring that EC supports environmental sustainability.

In conclusion, the impact of EC on EQ varies significantly across Asian economies, driven by income levels, energy types, and institutional capacities. By adopting targeted strategies and prioritizing renewable energy and institutional improvements, Asian economies can achieve a sustainable balance between energy needs and environmental protection, contributing to long-term ecological and economic stability.

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