

The Interplay Between Clean Energy, Fossil Fuels, and Load Capacity Factor: Evidence from Asian Developing Countries

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Abstract

The attainment of the Sustainable Development Goals (SDGs) is a crucial concern for decision-makers not only in developed countries but also in developing countries. The Sustainable Development Goals (SDGs) encompass a range of comprehensive environmental objectives, including addressing air, water, and soil pollution and safeguarding natural resources to mitigate this pollution. To accomplish these objectives, the analysis of carbon emissions and ecological footprint can offer some direction, but they need to consider the supply aspect of nature. The load capacity factor allows for the simultaneous analysis of biocapacity (the natural supply) and ecological footprint to determine if countries surpass the sustainability threshold and identify the elements contributing to this limit. This study aims to analyze the impact of clean and fossil energy consumption along with natural resource rent, foreign direct investment, population and income on the load capacity factor for developing Asian countries from 1990 to 2024. To accomplish this objective, the study uses the novel method of moment quantile regression (MMQR) and examines the load capacity curve hypothesis. Following a U-shaped pattern, our results support the validity of the LCC hypothesis. The MMQR findings indicate that clean energy, NRR, and FDI contribute

to environmental quality, whereas population and fossil fuels harm environmental quality. In addition, robustness test by Driscoll-Kraay standard errors validate our earlier results.

Keywords: Load capacity factor; renewable energy consumption, Fossil fuel energy consumption, natural resources rent, foreign direct Investment

1. Introduction

Extreme weather events are becoming more common, putting millions of people at risk of food and water shortages. Many places and communities in Asia, Africa, Central and South America, LDCs, and the Arctic have felt the brunt of this problem (IPCC, 2023). Since the turn of the century, air temperatures have increased throughout Asia. Social and economic sustainability are more threatened than ever before due to the significant warming. Rising global temperatures significantly raise the probability of extreme climate-related events across Asia. These include increased heatwaves, prolong droughts in the arid and semi-arid zones of South and Central Asia, and delayed South Asian monsoons, intensified flooding across Southeast, East, and South Asia, and accelerated retreat in the Hindu Kush Himalayan (Shaw *et al.*, 2022).

Asian countries are facing a warmer summertime environment, which, combined with population growth, is driving up energy demand for cooling. Less precipitation affects energy use as well. Desalination, pumping underground water, and additional energy-intensive practices are more commonly used to supply water. Potential energy savings from relatively reduced wintertime heating demands could be offset by summertime energy demands. Energy insecurity and increased risk associated with industry remain prevalent across eleven of the thirteen highest energy-consuming developing nations in Asia (Shaw *et al.*, 2022).

Considering the environmental degradation caused by human activity, the Brundtland Commission acknowledged this in 1987 and stressed that economic growth should take place within environmentally sustainable bounds. Due to rapid industrialization, expanding population, and robust economic growth, Asia represents a major contributor to global emissions and air pollution. The nation that emits the most carbon dioxide globally is China. In 2019, China was responsible for an estimated 28% of worldwide carbon dioxide (CO₂) emissions, as reported by the Global Carbon Project. More than 80% of Asian metropolitan residents are subjected to poor

air quality as compared to the World Health Organization's standards (Srivastava, 2022). In addition to having a negative effect on biodiversity and water resources, this climate change in Asia threatens human health by degrading food quality, water quality, and seasonal distribution.

Environmental assessments primarily focus on carbon dioxide (CO₂) emissions and, more recently, the ecological footprint (EF). These two indicators focus on human environmental degradation and ignore nature's response. EF measures population consumption sustainability in global hectares. EF solely measures human pressure on the environment, neglecting nature's supply side. Load capacity factor (LCF), which represents biocapacity (BC) to EF ratio, was proposed by Siche (2010) as a method for evaluating the impact of human activities on the resilience of soil, water, air, and natural resources.

The diversity of environment-income interactions has given rise to new ideas and theories. The LCC (Load Capacity Curve) hypothesis states that socioeconomic factors have both short- and long-term effects on environmental quality. An ecosystem's ecological quality is determined by the interactions between its agents and services. The ecosystem's resilience to various social and economic disruptions is demonstrated by the LCF. Environmental quality is said to follow a U-shaped curve that decreases as income increases. According to the LCC hypothesis, countries degrade the environment at first because they raise their need for fossil fuel energy to sustain their economic expansion. However, once they reach a turning point, EF grows, and BC drops. Once per capita income reaches a certain level, environmental quality (LCF) can be improved by technical advancements, improved ecological awareness, and the use of renewable energy sources, which in turn raise BC and lower EF. This U-shaped association indicates that income has the potential to enhance LCF in the long run. Although excessive consumption can lead to disastrous ecological disasters and ecosystem service management is essential, scholars have not given much consideration to LCC or LCF in the literature. In light of this fact, we have conducted this study for the developing countries of the Asian region using a nexus of factors including GDP, GDP Squared, renewable energy consumption (REC), fossil fuel energy consumption (FFuel), natural resource rents (NRR), foreign direct investment (FDI), population and LCF.

Limited research has been conducted on the determinants of LCF for developing countries in Asia, despite a growing number of studies that have explored LCF. Numerous contributions are made

by this investigation to the body of knowledge: (i) investigation of the LCC hypothesis for developing countries of Asia is the main objective of this empirical study. By examining a different hypothesis, the study enables a far more comprehensive analysis of environmental sustainability. The simultaneous analysis of BC and EF in developing Asian countries encourages the assessment of ecological economics knowledge from a different and more comprehensive aspect. (ii) We must investigate newly discovered concepts and theories in order to establish strong policies capable of significantly restoring the biocapacity surplus while maintaining the mutually beneficial interaction of human beings and the environment. An intriguing concept, the LCC hypothesis explains an occurrence that contradicts the EKC theory and demonstrates how an excessive reliance on ecosystem services can be deceiving regarding long-term environmental sustainability. We may utilize the concepts of the LCF and LCC curve to evaluate the progress of various countries in meeting their Sustainable Development Goals (SDGs), given that a number of the goals (including goals 7, 8, 13, and 16) are predominantly contingent on the management of ecosystem services and the environment. (iii) We investigate the relationships between GDP, GDP Squared, Renewable energy consumption (REC), fossil fuel energy consumption (FFuel), natural resource rent (NRR), foreign direct investment (FDI), Population and LCF in Asia (iv) Further, we apply MMQR for the estimation to explore the relationships between variables following nonnormal distribution. MMQR is employed to estimate quantiles in a dataset. In contrast to alternatives like the least squares method, MMQR is not dependent on the assumption of a normal distribution of data, enhancing the robustness of our analysis. Driscoll-Kraay standard errors validates the findings of MMQR.

The structure of the analysis is as follows: A review of the relevant literature is provided in Section 2, while the data, model, and theoretical framework are introduced in Section 3. In Section 4, the empirical methodology is described. Section 5 lists the findings and discussion. While conclusion and policy implications are presented in section 6.

2. Literature Review

One of the key factors influencing the environment is economic development. The EKC hypothesis has been used in many studies to examine how per capita income affects environmental degradation (Jalil and Mahmud, 2009; Shahbaz et al., 2016; Wang et al., 2017; Pata, 2018; Hassan et al., 2019; Danish et al., 2019; Sarkodie et al., 2020; Isik et al., 2020; and Zhang et al., 2021).

The EKC hypothesis, which is founded on the seminal work of Grossman and Krueger (1991), posits that there exists an inverse U-shaped relationship between income and environmental deterioration.

A considerable body of research has investigated the consequences of per capita fossil fuel consumption, a significant contributor to environmental contamination (see, for instance, Mensah et al., 2019; Pata, 2021a). Renewable energy sources are considered sustainable due to their inherent replenishability and absence of greenhouse gas emissions and other pollutants (Shahzad et al., 2023a,b Rehman *et al.*, 2023; Adebayo et al., 2023). Furthermore, in comparison to traditional energy sources, renewable energy sources are often associated with diminished water and land use impacts (Woltjer & Kuiper, 2014). Renewable energy sources can aid in the reduction of the environmental impact of energy production by minimizing waste generated during the manufacturing process (Weitzel et al., 2019). By promoting sustainability and mitigating the negative environmental impacts of human activity, renewable energy sources have the potential to assist in the reduction of our ecological footprint.

There is often a close correlation between economic growth and environmental degradation (Grossman & Krueger, 1995; Luo et al., 2023). There is the potential for economic expansion to rise living standards, generate employment, and increase prosperity. However, it should not be overlooked that climate change, habitat degradation, and increased pollution are all detrimental environmental impacts (Ghosh et al., 2022). Resource depletion and environmental degradation have ensued as a consequence of the conventional paradigm for economic expansion, which has prioritized the release of contaminants into the atmosphere and the consumption of natural resources (Dogan et al., 2022). The utilization of fossil fuels in transportation and industry, for instance, has significantly amplified the release of greenhouse gases and the consequential impacts of climate change. However, an increasing number of individuals are coming to the understanding that economic growth and environmental protection are not equivalent. Zafar et al. (2020) argue that the concept of sustainable development underscores the imperative of reconciling economic advancement with social and environmental sustainability. This requires an economic transition toward resource efficiency and reduced carbon emissions, in addition to the implementation of sustainable practices in fisheries, forestry, and agriculture.

Furthermore, empirical evidence supports the notion that allocating resources towards environmental restoration and preservation can yield long-term financial benefits, including reduced healthcare expenditures, enhanced productivity, and job creation within the green sector (Bezdek *et al.*, 2008; Fleishman *et al.*, 2009; Zhang & Jiang, 2019, Fareed *et al.*, 2022;). It is of the utmost importance to recognize that economic development and environmental sustainability are not incompatible, and that policies and strategies can be developed to promote both. More attention has been paid in the streaming literature (Ahmed *et al.*, 2020; Bello *et al.*, 2018; Cui *et al.*, 2022) to the correlation between economic activities and environmental sustainability via ecological footprint or CO₂ emissions. These studies have postulated that unregulated economic activities have the potential to cause short-term and long-term damage to environmental quality. However, there has been a dearth of research examining the relationship between economic activity and load capacity factor (LCF) via revenue generation.

Moreover, the aforementioned conclusions were corroborated by Pata and Isik (2021) for China, Pata and Kartal (2023) for South Korea, Zhao *et al.* (2023) for BRICS-T, Guloglu *et al.* (2023) for OCED and the Dai *et al.* (2023) for ASEAN countries. Pata & Pata, (2025) used US data from 1990-2022 to explore the impact of disaggregated renewable energy on LCF and sustainable developed. Based on the findings of the Fourier approach, the study reveals that biofuel, wind and solar energy contribute to EQ and SD, while hydropower has no significant impact on EQ and SD. (U. K. Pata, 2025) explored how environmental quality is affected by ICT, Institutional quality amid energy and climate uncertainties. Using monthly data from 2003 to 2022 and utilizing Fourier causality, the results show that ICT and IQ have a beneficial impact on ecological quality, while both uncertainties are deleterious for the LCF. In a recent study for Japan, (Awosusi & Ozsahin, 2026) examined the LCF in the context of innovation related to renewable energy, political risk, and economic growth. Using wavelet quantile, the study found that renewable energy innovation enhances EQ, while growth has a harmful effect on LCF.

While prior empirical literature has evaluated ecological metrics using isolated subsets of variables, significant gaps persist regarding the joint interaction of economic growth, energy composition, demographic dynamics, and resource extraction across developing Asia. First, existing studies often rely on single-sided proxies such as carbon emissions, ignoring the ecological supply capacity (biocapacity) of ecosystems. By employing the Load Capacity Factor,

this study evaluates both supply and demand dimensions of environmental quality. Second, previous LCC studies frequently omit either population dynamics or the explicit trade-off between renewable and fossil fuel energy, leading to potential omitted variable bias. Third, by leveraging Method of Moments Quantile Regression alongside Driscoll-Kraay robust standard errors, this study provides a distributional framework that captures non-linear, quantile-specific behavior while accounting for cross-sectional dependence across 18 Asian developing nations (1990–2024).

3. Description of Data, Theoretical Framework and Empirical Model

3.1. Data

The current study utilizes annual data from 2090-2024 for developing Asian countries to explore how the environment quality is impacted by renewable energy (REC) vs fossil energy (FFuel), natural resource rents, foreign direct investment, population, GDP, and the square of GDP. The selection of variables is based on existing literature. The list of countries is given in Appendix A.

This study uses the Load capacity factor (LCF) to measure environmental quality, which is calculated by biocapacity divided by ecological footprint. Variables definition and sources are provided in Figure 1.

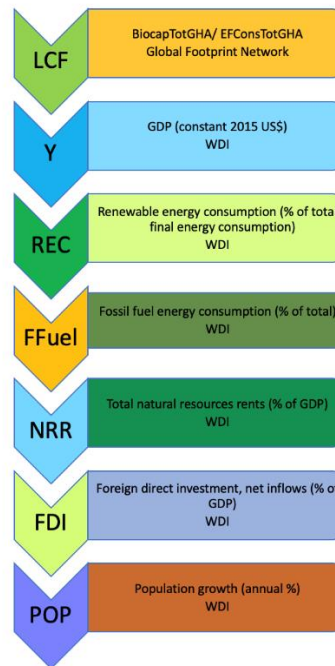


Figure 1: Variables definition and source

3.2. Theoretical Framework

We look closely at how explanatory variables affect the LCF in this part. The literature on environmental economics has grown significantly since the 1990s, making it one of the hottest subjects of the twenty-first century. In theory, ecological quality is impacted by income via three unique mechanisms, as Grossman and Krueger (1991) have illustrated. To begin with, the phrase “scale effect” pertains to the phenomenon wherein a greater quantity of inputs is utilized to generate a greater quantity of output, resulting in the depletion of natural resources and a substantial increase in waste. This procedure results in an adverse effect on environmental quality.

Furthermore, ecological quality improves as income surpasses a critical threshold. This phenomenon can be elucidated through the mechanisms of composition effect and technical effect. When adjusting the structure of economic activities, the composition impact is utilized to account for the proportions of the service and industry sectors, as evidenced by the experiences of numerous nations. The pollution and debris produced by the service sector are inferior to those of the industrial sector. The proportion of non-polluting services will consequently increase as income levels rise, leading to a gradual enhancement in environmental quality. Lastly, as the economy grows, additional funds might be allocated towards research and development (R&D). Subsequently, efforts will be made to develop devices that are more energy-efficient, thereby diminishing resource wastage and energy usage, and ultimately enhancing environmental conditions.

In other words, the scale effect demonstrates that negligent utilization of natural resources and the combustion of fossil fuels reduce the LCF. When income reaches a certain threshold, the interplay between composition, technical effect, and income growth promotes sustainable technologies and increases eco-awareness, thereby enhancing LCF.

The renewable energy consumption through the reduction of the environmental impact associated with conventional energy sources can positively influence the ecological load capacity factor. However, the LCF might be negatively impacted by renewable energy sources. Infrastructure and a robust finance system are necessary for renewable resources. Nonetheless, some developing Asian countries lack the means to make significant investments in renewable energy sources. The nations surpassing the income milestone are the ones that are shifting from using fossil fuels to

intensive renewable energy. Therefore, information about whether Asian economies have eliminated the scale effect can be found by looking into the relationship between renewable energy and ecological quality. Energy utilization from fossil fuels release CO_2 and other pollutants that contribute to climate change, ecosystem degradation, and biodiversity loss. Fossil fuel consumption represents a negative externality that damages the environment. Therefore, the expected sign of fossil fuel is negative.

Natural resources, the third independent variable, can impact the ecosystem either favorably or unfavorably. The first stage of income growth is characterized by an increase in environmental degradation due to extensive usage of natural resources. But as wealth rises, so too can individual awareness of the environment and the government's use of technology to extract natural resources, which can amplify the benefits of natural resources. The panel's present energy import level may also have an impact on how natural resources are used in the environment. The impact of FDI on the environment can be explained by the Pollution Haven (PHA) and Pollution Halo (PHO) hypotheses. According to the PHH hypothesis, multinational organizations relocate their production to those economies that have weak environmental law leading to worse EQ, while PHO argues that FDI transfers cleaner technology and thus contributes to EQ.

3.3. Empirical model

Based on the previous discussion, the estimation model can be presented as follows in equation 1

$$LCF_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \beta_3 REC_{it} + \beta_4 FFuel_{it} + \beta_5 NRR_{it} + \beta_6 FDI_{it} + \beta_7 POP_{it} + e_{it} \quad (1)$$

In equation 1, LCF, Y, Y^2 , REC, FFuel, NRR, FDI, and POP represent the load capacity factor, GDP, GDP square, renewable energy consumption, fossil fuel energy consumption, natural resource rent, foreign direct investment and population, respectively.

4. Empirical Methodology

Before performing the final estimation, some diagnostic tests are first performed. Starting with descriptive statistics that describe the nature of the data set, the study performed the cross-sectional dependence (CSD). CSD shows the relationship between co-movement in more than one unit. This tendency is more pertinent in panel data analysis, where the omission of CSD typically results in

findings based on explanations that are biased and inconsistent (Pesaran, 2021). Therefore, it is necessary to check CSD when dealing with panel data. Thus, we have considered the cross-sectional dependence (CD) technique proposed by Pesaran, (2004).

The equation for the CD test is as follows:

$$CD = \left[\frac{2T}{N \cdot (N-1)} \right]^{1/2} \cdot \left[\sum_{i=1}^{N-1} \sum_{k=i+1}^N \hat{\theta}_{ik} \right] \quad (1)$$

In the next step, the slope heterogeneity approach proposed by Pesaran & Yamagata, (2008) is performed. The expression for slope heterogeneity is as follows.

Slope heterogeneity is conceptualised as follows:

$$\tilde{\Delta} = \text{sqrt}(N/2K) \cdot (N^{-1}\tilde{S} - k) \quad (2)$$

The bias-adjusted $\tilde{\Delta}$ stats can be computed as follows:

$$\tilde{\Delta}_{adj} = \text{sqrt}(N) \cdot \left(\frac{2k(T-k-1)}{T+1} \right)^{-\frac{1}{2}} (N^{-1}\tilde{S} - 2k) \quad (3)$$

After performing CD and SH, stationarity of the study variable is analyzed. As recommended by Pesaran, (2007), this study uses the CIPS and the CADF to verify their statistical validity. These approaches are crucial, particularly when the data exhibits cross-sectional dependency, which might skew the stationary characteristics of the unit root tests. Therefore, the analysis can effectively evaluate potential non-stationarity bias for linked data series due to the applicability of these tests. Using these tests to examine non-stationarity yields robust statistical results that remain accurate regardless of the dataset or condition used by researchers. Further, the study checks the long-run relationship among LCF and its covariates by employing Kao, Pedroni, (2004), and Westerlund cointegration tests. At the final step method of moments quantile regression is performed to check the association between LCF and Y, Y2, REC, FFuel, NRR, FDI, and Pop.

Method of moments Quantile regression proposed by Machado & Silva, (2019) is superior to simple quantile regression. Unlike previous methods like least squares, quantile regression

utilizing the technique of moments does not require the data to have a normal distribution. Because it is less vulnerable to outliers, this method becomes more dependable. In this regard, Koenker & Bassett Jr, (1978) developed the Panel Quantile Regression approach, which uses the values of the explanatory parameters to calculate the dependent variance and conditional mean. Quantile regression yields accurate estimates when the distribution features of the dataset are irregular. The novel MMQR has been used in this study due to the non-normal distribution of the data. This method looks at the various and distributional properties of quantile numbers (Sarkodie & Strezov, 2019).

To achieve this, we have employed the following equation to approximate the conditional quantile location-scale, $Q_Y[\tau|Z]$ variant:

$$Y_{it} = \theta_i + \beta Z_{it} + [\delta_i + \phi W_{it}] \psi_{it} \quad (4)$$

$p(\delta_i + \phi W_{it} > 0) = 1$ is the probability part, while estimated coefficients are represented by θ, β, δ , and ϕ . The fixed effect is expressed by (i), *i varies from 1 to n*.

In addition, Term Z kth dimension vector is denoted by W , while $\mathbb{I}$ shows the variation counterpart, as expressed below

$$W\mathbb{I} = W\mathbb{I}(Z), \mathbb{I} = 1, 2, \dots, k \quad (5)$$

For each i and t , Z_{it} follows independent and uniform distribution. The final form of MMQR is expressed in equation 6 by combining equations 4 and 5 and take into account the information of equation 7.

$$Q_Y(\tau|Z_{it}) = (\theta_i + \delta_i q(\tau)) + \beta Z_{it} + \phi W_{it} q(\tau) \quad (6)$$

Where, Z_{it} refers to the vector of each regressor. Lastly, sample quantiles are signified by $q(\tau)$, i.e., from 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th. Therefore, the quantile equation for this study in general form is expressed as follows.

$$\min_q \sum_i \sum_t \eta_\tau (Z_{it} - (\delta_i + \phi W_{it}) \cdot q) \quad (7)$$

In this context, $\eta_{\tau}(A)$, represents a check function, defined as $(\tau - 1)AI[A \leq 0] + \tau AI[A > 0]$.

To check the validity of MMQR estimates, Driscoll-Kraay standard errors with fixed effect is performed.

5. Findings and Discussion

The descriptive statistics of the study variables are displayed in Table 2. All variables have positive mean, minimum and maximum except FDI and POP. The REC shows the highest mean value, followed by FFuel, Y, NRR, Fi, pop, and LCF. The volatile nature of the variables is shown by the SD, the most volatile variable is REC and then FFuel, NRR, FDI, Y, pop, and LCF, respectively. LCF mean value (0.654) is below 1, indicating an ecological deficit across developing Asian economies. In addition, none of the study variables follow the normal symmetric distribution, evident by the skewness and kurtosis values. Furthermore, the Ho of the JB test is that the variables are normally distributed. The p-value associated with JB further validates the non-normal distribution of all variables, including dependent and explanatory variables. In addition, Quantile-quantile plots were used to visually evaluate normality. The Q-Q plot should ideally resemble a diagonal line in a dataset that is normally distributed. Non-normality is shown by the points' substantial deviation from this linearity, as shown in Figure 2.

Table 1: Statistical Insights

Stats	LCF	Y	REC	FFuel	NRR	FDI	POP
Mean	0.6538324	25.84336	46.31363	42.58801	4.319145	2.40546	1.420441
SD	0.3753175	1.731765	24.53059	32.2482	4.928323	2.757624	0.9701667
Min	0.2112314	22.28112	2	0	0.0648341	-4.541592	-2.799683
Max	2.355494	30.59636	95.1	99.38349	29.3686	23.53729	8.098189
Skewness	2.212311	0.3072725	0.1485623	-0.039916	1.98783	2.131321	2.297668
Kurtosis	8.922324	3.052455	2.155413	1.624895	7.464394	11.21415	16.24989
Jarque-Bera	1685	7.828	30.82	51.27	5050	441.7	2756
Probability(jb)	0.000	0.02	0.000	0.000	0.000	0.000	0.000

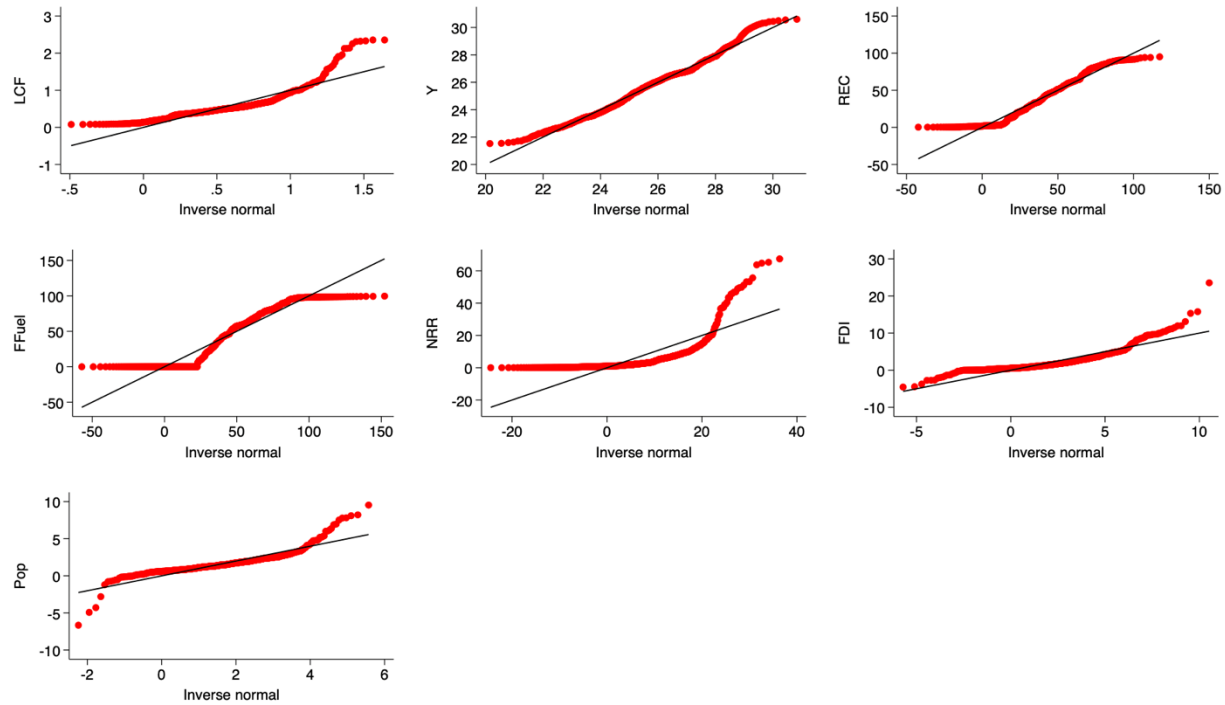


Figure 2: Q-Q plot

Table 2 and Figure 3 reveal the correlation among study variables. Correlation stats and visual graphs indicate a positive correlation between REC, NRR, FDI and LCF. in other words, these variables are associated with increase EQ. While FFuel and pop are negatively correlated with LCF. In addition, the VIF indicates that multicollinearity is not present among explanatory variables.

Table 2: Correlation Plot

	LCF	Y	REC	FFuel	NRR	FDI	POP	VIF		
LCF	1							REC	1.84	0.543069
Y	-0.2416	1						Y	1.65	0.604538
REC	0.5523	-0.433	1					FFuel	1.40	0.715171
FFuel	-0.1846	0.1615	-0.5071	1				POP	1.39	0.720133
NRR	0.1908	-0.0404	-0.18	0.1219	1			NRR	1.06	0.946689
FDI	0.1902	-0.1696	0.0045	0.0441	-0.025	1		FDI	1.04	0.960731
POP	-0.1536	-0.329	-0.2053	0.2615	0.0825	0.1102	1	Mean VIF	1.40	

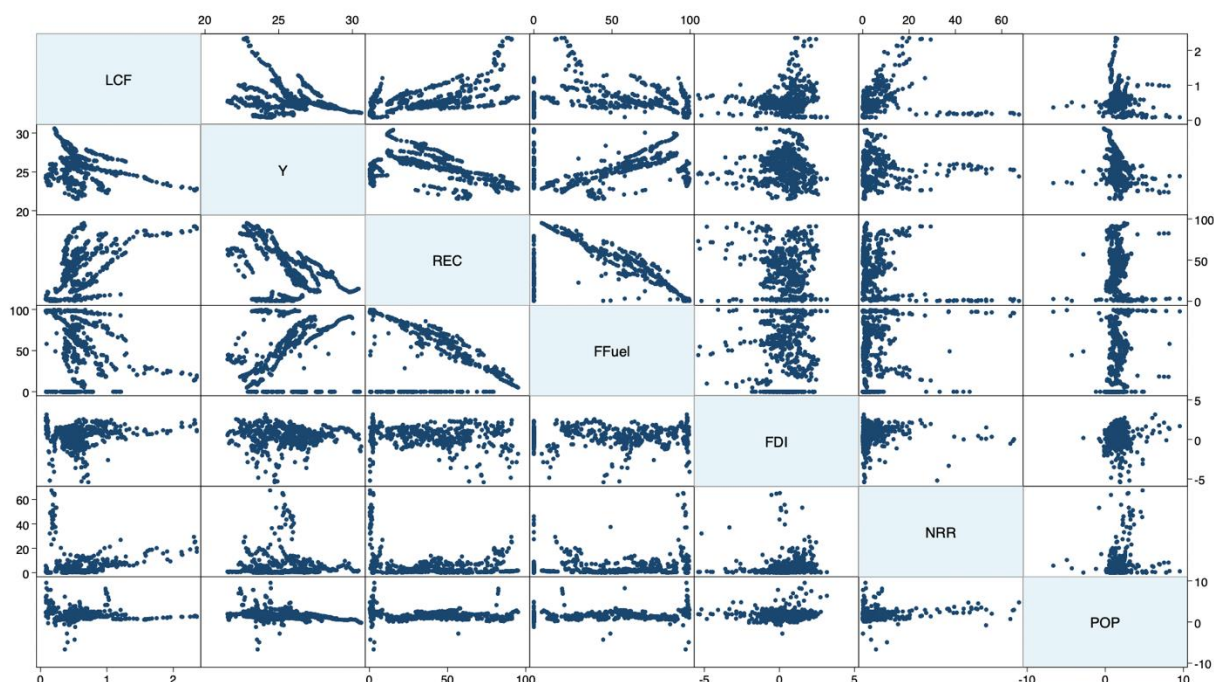


Figure 3: Correlation plot

The findings of the CSD are reported in Table 3. The results indicate the presence of cross section dependence. Therefore, interdependence of all the cross-section in the data set cannot be disregarded. Table 4 provides evidence of SH, indicating that the coefficients vary significantly between groups or time periods. This suggests that the consequences of the factors under study vary considerably, supporting the necessity for differential tactics in modeling or policy-making. Presence of CSD and SH suggests moving to move for second generation unit root tests.

Table 3: Cross-section Dependence test

Variable	CD-test	p- value	corr	abs(corr)
LCF_{it}	41.49	0.000	0.604	0.617
Y_{it}	59.19	0.000	0.883	0.893
REC_{it}	30.78	0.000	0.448	0.595
$FFuel_{it}$	61.25	0.000	0.915	0.915
NRR_{it}	15.60	0.000	0.227	0.403
FDI_{it}	5.41	0.000	0.07	0.234
Pop_{it}	28.03	0.000	0.406	0.546

Table 4: Slope heterogeneity test

	Statistics	Prob
$\tilde{\Delta}$	16.682***	0.000
$\tilde{\Delta}_{adjusted}$	19.487***	0.000
Conclusion	Slope coefficient are heterogenous	

Table 5 shows the outcome of the unit root tests of CIPS and CADF. The results show that the variables are of mixed order of integration. Some variables are stationary at level while some are stationary at first difference. Based on the findings, the study applies cointegration to check the long-run association among the dependent variables and their covariates.

Table 5: Unit root tests

Variables	CIPS		CADF	
	I(0)	I(1)	I(0)	I(1)
LCF_{it}	-2.881	-5.681***	-2.826	-12.259***
Y_{it}	-2.251**	-----	-2.193**	-----
REC_{it}	-1.578	-4.437***	-0.171	-6.858***
$FFuel_{it}$	-1.494	-5.187***	2.141	-3.490***
NRR_{it}	-2.840	-----	-1.609*	-----
FDI_{it}	-2.909	-----	-4.004	-----
Pop_{it}	-1.781	-3.890***	-2.755***	-----

Table 6 reveals the stats of Kao, Pedroni and Westerlund cointegration. The statistics of all these tests confirm that there is long-term cointegration among LCF, Y, REC, FFuel, NRR, FDI and pop.

Table 6: Cointegration analysis.

Cointegration Tests		Statistic	p-value
Kao	Modified Dickey–Fuller t	-2.0815	0.0187
	Dickey–Fuller t	-2.6831	0.0036
	Augmented Dickey–Fuller t	-1.1498	0.1251
	Unadjusted modified Dickey–Fuller t	-2.5643	0.0052
	Unadjusted Dickey–Fuller t	-2.9102	0.0018

Pedroni	Modified Phillips–Perron t	1.0174	0.1545
	Phillips–Perron t	-9.6763	0.0000
	Augmented Dickey–Fuller t	-7.6244	0.0000
Westerlund	Variance ratio	-2.7719	0.0028

Finally, this study employs MMQR to assess the long-run relationship between LCF and Y, Y2, REC, FFuel, NRR, FDI and pop. The findings of MMQR are reported in Table 7. The coefficient of Y is significantly positive and significant across all levels of LCF. The harmful impact of Y becomes more intensify at higher quantiles. While the square term of Y shows a negative and significant impact on all distributions of EQ. The findings align with well know EKC hypothesis that, at early stages of development, an increase in Y has a detrimental effect on ecological quality due to increase resource and energy consumption. However, when income further grows, the environment quality improves. The positive sign of Y and the negative sign of Y2 confirm that the load capacity curve is valid for developing Asia countries. In the perceptive of LCF, this negative relationship between Y and LCF and positive relationship between Y2 and LCF confirm the load capacity curve. This suggests that although initial economic expansion exacerbates ecological degradation by expanding human footprints relative to biocapacity, but eventually further rise in Y leads to foster environmental recovery. The findings are supported with earlier studies of Pata & Kartal, (2022), Pata & Samour, (2022), Sun et al., (2023), and Pata & Kartal, (2023).

The coefficient of REC is statistically significant and positive irrespective of the distribution of LCF. REC contribute to LCF more at the lowest quantile compared to higher quantiles. This beneficial impact of REC shows a monotonic decline as move towards higher quantiles. The decreasing positive impact can be explained by the law of diminishing marginal returns to ecological restoration. Countries with a low level of LCF, where ecosystem is under critical capacity deficits, find that clean energy eliminates critical environmental constraints. While nations with high LCF, additional clean energy can only deliver smaller additional gains to ecological sustainability. Conversely, the FFuel coefficient is negative and significant across all quantiles of LCF. The harmful impact of FFuel on LCF intensity increases as we move from lower to higher levels of LCF. Increased FFuel raises carbon emissions, intensifies extraction pressure and leads to increased ecosystem degradation, thus expanding the EF while reducing the regenerative capacity of natural systems. Therefore, the transition from fossil fuels to renewable

solutions is essential for environmental sustainability (Cui et al., 2022). Unlike fossil fuels, clean energy sources like renewables have longer lifespans and are always available. For instance, solar energy production produces no waste and prevents water contamination, whereas wind energy has the smallest water footprint (Chen et al., 2021). Renewable energy sources do not cause local harm, in contrast to coal and traditional biomass (Omri & Belaïd, 2021). With these benefits, a variety of renewable energy sources can actively support the achievement of the Sustainable Development Goals (SDGs) and the general increase in LCF. The results that REC enhances environmental quality are also consistent with Dogan & Pata, (2022), and Lu et al., (2023).

As for the other variables, FDI and NRR significantly contribute to environmental sustainability. Population growth is negatively associated with LCF. Efficient resource extraction and the application of modern and efficient technologies to lower greenhouse gas emissions are becoming increasingly important in developing nations. One measure that is strongly related to the health of the economy is NRR (Khan et al., 2020). These results are aligned with earlier studies of Zafar et al., (2019) and Wang et al., (2023). The positive relationship between FDI and LCF supports the pollution Halo hypothesis. These findings indicate that FDI contribute to LCF in developing Asian countries through technology transfer, efficiency gains, and improved production processes. Foreign firms usually bring advance technologies, clean production and higher environmental standards, which can enhance resource efficiency and reduce environmental pressure in host countries. The graphical presentation of MMQR is also presented in Figure 4.

Although the MMQR provide robust and reliable estimates, in order to further validate the results, we utilized Driscoll-Kraay standard errors. The findings of DK is provided in Table 8. The coefficients and magnitudes of the variables are close to the MMQR findings, thus validating the results of our baseline model.

Table 7: MMQR regression analysis

	Location	Scale	Q10	Q20	Q20	Q20	Q50	Q60	Q70	Q80	Q90
Y_{it}	- 0.5040 ***	- 0.1277 **	- 0.3179 **	- 0.3712 ***	- 0.4113 ***	- 0.4497 ***	- 0.4931 ***	- 0.5479 ***	- 0.5954 ***	- 0.6399 ***	- 0.7146 ***
	(0.125 3)	(0.06 51)	(0.134 3)	(0.119 6)	(0.114 3)	(0.115 2)	(0.122 9)	(0.140 0)	(0.1599)	(0.1818)	(0.2235)
Y_{it}^2	0.0064 ***	0.0021 ***	0.0034	0.0042 **	0.0049 **	0.0055 ***	0.0063 ***	0.0072 ***	0.0080 ***	0.0087 ***	0.0100 **

	(0.002 2)	(0.000 5)	(0.002 4)	(0.002 1)	(0.002 0)	(0.002 1)	(0.002 2)	(0.002 5)	(0.0028)	(0.0032)	(0.0040)
<i>REC_{it}</i>	0.0049 ***	- 0.006* **	0.0057 ***	0.0055 ***	0.0053 ***	0.0051 ***	0.0049 ***	0.0047 ***	0.0045 ***	0.0043 ***	0.0039 **
	(0.000 9)	(0.002 2)	(0.000 9)	(0.000 8)	(0.000 8)	(0.000 8)	(0.000 8)	(0.001 0)	(0.0011)	(0.0013)	(0.0015)
<i>FFuel_{it}</i>	- 0.0008 ***	- 0.0003 **	- 0.0005 **	- 0.0006 ***	- 0.0007 ***	- 0.0007 ***	- 0.0008 ***	- 0.0009 ***	- 0.0010 ***	- 0.0011 ***	- 0.0013 ***
	(0.000 2)	(0.000 1)	(0.000 2)	(0.000 2)	(0.000 2)	(0.000 2)	(0.000 2)	(0.000 2)	(0.0002)	(0.0002)	(0.0003)
<i>NRR_{it}</i>	0.0143 ***	0.0011	0.0127 ***	0.0131 ***	0.0135 ***	0.0138 ***	0.0142 ***	0.0147 ***	0.0151 ***	0.0154 ***	0.0161 ***
	(0.002 5)	(0.001 7)	(0.002 7)	(0.002 4)	(0.002 3)	(0.002 3)	(0.002 4)	(0.002 8)	(0.0032)	(0.0036)	(0.0045)
<i>FDI_{it}</i>	0.0137 ***	- 0.0022	0.0169 ***	0.0160 ***	0.0153 ***	0.0147 ***	0.0139 ***	0.0130 **	0.0122 **	0.0114 *	0.0101
	(0.004 5)	(0.003 1)	(0.004 9)	(0.004 3)	(0.004 2)	(0.004 2)	(0.004 4)	(0.005 1)	(0.0058)	(0.0066)	(0.0081)
<i>Pop_{it}</i>	- 0.0112	0.0067	- 0.0209 ***	- 0.0181 **	- 0.0160 **	- 0.0140 **	- 0.0117	- 0.0089	-0.0064	-0.0040	-0.0001
	(0.007 4)	(0.005 1)	(0.008 0)	(0.007 1)	(0.006 8)	(0.006 8)	(0.007 3)	(0.008 3)	(0.0095)	(0.0108)	(0.0133)
<i>cons</i>	9.0421 ***	1.9425	6.2107 ***	7.0217 ***	7.6315 ***	8.2160 ***	8.8760 ***	9.7102 ***	10.433 5***	11.110 1***	12.246 7***
	(1.774 7)	(1.205 3)	(1.901 8)	(1.694 5)	(1.619 5)	(1.631 4)	(1.741 4)	(1.982 7)	(2.2638)	(2.5739)	(3.1662)

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

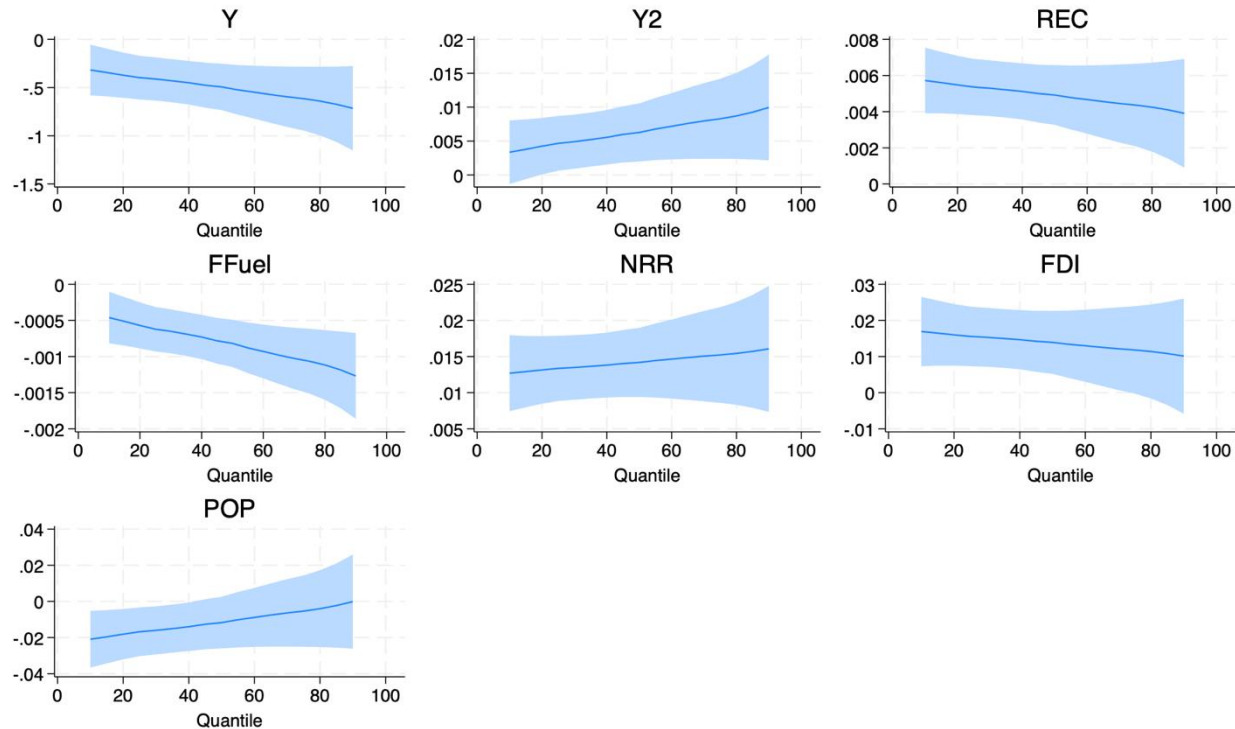


Figure 4: Graphical representation of MMQR

Table 8: Regression with Driscoll-Kraay standard errors

LCF	Coefficient	Drisc/Kraay std. err.	t	P>t	[95% conf. interval]
Y	-.5039933	.0944972	-5.33	0.000	-.6967216 - .3112649
Y2	.0064479	.0018319	3.52	0.001	.0027117 .0101842
REC	.0048725	.0004259	11.44	0.000	.0040039 .0057412
FFuel	-.0008399	.00017	-4.94	0.000	-.0011866 -.0004932
NRR	.014277	.0041884	3.41	0.002	.0057348 .0228192
FDI	.0137314	.0051441	2.67	0.012	.00324 .0242228
POP	-.0111611	.0077063	-1.45	0.158	-.0268782 .004556
cons	9.042068	1.242244	7.28	0.000	6.508493 11.57564

6. Conclusion and Policy Implications

This study explores the impact of Y, Y square, renewable vs fossil fuel energy consumption, natural resource rents, foreign direct investment and population growth on environment quality. Instead of using CO₂ and other GHG emissions, the current study utilized LCF as a measure of environmental quality. To this end, MMQR is utilized on the sample of developing Asian countries spanning from 1990-2024. Based on the findings, Y has a negative impact, while Y square positively contributes to LCF. The findings of Y and Y2 validate the LCC for Asian economies.

In addition, REC, NRR, FDI contribute to environmental quality, evident by their positive coefficient. While FFuel and POP deteriorate the environment by decreasing LCF.

In light of the study findings, the study suggests some policy implications. As LCC is valid for the sample countries, developing countries should concentrate on their economic growth over the coming years on investments that support environmental preservation. Investments in carbon capture technologies and renewable energy should take precedence over rising income levels. Fishing operations should be coordinated, industrial trash that is dumped into waterways should have its toxins removed using advanced technology, and fresh trees should be planted to stop land degradation in order to eradicate water pollution. Regarding energy dynamics, countries that have low LCF can get greater benefit by adopting energy transition; therefore, these countries should focus on tax breaks and off-grid clean energy projects. At the same time, governments should remove subsidies from fossil fuels and redirect their funds towards grid modernization therefore can prevent the damage associated with fossil fuels. To ensure long-term sustainability, governments must also align fiscal policies, foreign capital, and urban planning with natural resource limits. Revenues generated from natural resource extraction should be channeled directly into dedicated green funds that finance reforestation, land recovery, and soil conservation projects. Furthermore, to capitalize on positive spillovers from foreign investment, promotion agencies should offer tax incentives and fast-tracked permits specifically to foreign companies that bring energy-efficient technologies and eco-friendly standards. Finally, in countries where population growth places severe strain on local ecosystems, urban planners must enforce smarter land-use rules, compact city designs, and green public transit systems to prevent demographic expansion from overwhelming local natural resources.

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Appendix A: List of countries

Bangladesh	Malaysia
China	Nepal
Indonesia	Pakistan
India	Philippines
Iraq	Syrian Arab Republic
Jordan	Thailand
Cambodia	Tajikistan
Sri Lanka	Türkiye
Myanmar	Viet Nam