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Economic Activities and Carbon Dioxide Emissions in Thailand: A Quantile Regression Analysis

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ABSTRACT

This study examines the heterogeneous determinants of carbon dioxide (CO_2) emissions in Thailand using quantile regression to capture variation across the emission distribution. Monthly data from 2015 to 2024 were analyzed, incorporating economic, energy, and demographic indicators such as crude oil production, power consumption, the Leading Economic Index (LEI), Cost, Insurance, and Freight (CIF), tourism, unemployment, population, and the Private Consumption Index (PCI). The analysis reveals significant cross-quantile asymmetry, indicating that emission drivers differ based on intensity. At the lower quantiles, tourism and unemployment are statistically significant, suggesting that low-emission periods are more sensitive to service-sector activity and labor market conditions. At the median and higher quantiles, energy-related variables dominate; power consumption is consistently significant across all quantiles, while crude oil production becomes increasingly important at upper quantiles. Economic indicators such as LEI, CIF, and PCI show weak or inconsistent effects, while population and CIF are not significant at any quantile. These findings highlight the need to enhance energy efficiency, promote renewable energy adoption, and encourage sustainable tourism to support Thailand's low-carbon transition.

Keywords: Carbon Dioxide Emissions, Quantile Regression, Economic Activities
JEL Classifications: C21, Q43, Q56

1. INTRODUCTION

Carbon dioxide (CO_2) emissions pose a significant threat to environmental sustainability and are a major contributor to global climate change. Emissions are strongly linked to economic and industrial activities, making it essential to understand how economic development influences environmental outcomes. Although carbon credit mechanisms can promote cleaner technologies and emission reduction, identifying the underlying relationship between economic activity and emissions remains fundamental for designing effective policies. Empirical evidence shows that factors such as production and consumption levels, energy use, investment, urbanization, and population dynamics are closely related to emission outcomes. For Thailand, where economic expansion depends on energy-intensive sectors, understanding these linkages is crucial for policymakers aiming to balance economic growth with environmental protection.

Statistical modeling provides an effective analytical framework for examining the relationship between carbon emissions and economic factors. Regression-based methods are broadly used to quantify how economic variables influence emissions. Traditional multiple linear regression, also known as ordinary least squares (OLS) regression, however, focuses on estimating mean effects and may not adequately capture the distributional heterogeneity of CO_2 emissions. In practice, economic activities can influence low and high emission regimes differently. Another practical limitation of OLS regression is its sensitivity to multicollinearity among explanatory variables, as indicated by the variance inflation factor (VIF) values. Such collinearity can reduce the reliability of coefficient estimates, particularly when assessing how correlated economic indicators influence emissions. Quantile regression (QR), introduced by Koenker and Bassett (1978) offers a flexible extension to OLS by estimating conditional quantiles rather than only the conditional mean. QR is therefore well suited for environmental studies in which the impacts of economic drivers may be heterogeneous and nonlinear across the emission distribution. This makes QR more robust in the presence of correlated predictors and allows for more stable estimation of heterogeneous effects across emission levels. Together, these considerations strengthen the case for applying quantile regression rather than traditional mean-based models in this study.

To address these complexities, the present study employs quantile regression with monthly data to provide the first comprehensive assessment of how Thailand's economic activities affect CO_2 emissions across the emission distribution. The analysis incorporates key economic indicators, including crude oil production, power consumption, Leading Economic Index (LEI), Cost, Insurance, and Freight (CIF), Private Consumption Index (PCI), unemployment, tourism, and population to examine their heterogeneous effects across quantiles. Using monthly data enhances the analysis by improving estimate precision and capturing seasonal dynamics such as tourism cycles, energy-demand peaks, and production-related fluctuations that are not observable in annual data.

2. LITERATURE REVIEW

CO_2 emission data frequently exhibit asymmetric behavior, and volatility, caused by mainly economic-related factors such as changes in production activity, energy usage patterns, and trade dynamics (Aydogan and Vardar, 2020; Genc et al., 2022; Udeagha and Breitenbach, 2023). Many studies have examined how economic activity is connected to carbon emissions using a variety of modeling approaches. In this study, we focus specifically on statistical modeling to explain the relationship between economic activity and carbon emissions in Thailand; therefore, the literature review is narrowed to research that aligns with this context. For example, Khobai and Le Roux (2017) identified a long-run relationship among energy consumption, economic growth, CO_2 emissions, trade openness, and urbanization in South Africa, showing that rising energy demand increases CO_2 emissions. Similarly, Ardakani and Seyedaliakbar (2019) examined seven oil-rich countries and found that GDP growth and energy consumption significantly influence CO_2 emissions within the Environmental Kuznets Curve (EKC) framework, highlighting a nonlinear relationship between economic growth and environmental degradation.

In the Thai context, empirical evidence remains limited, although some studies have examined related aspects of emission behavior. For example, Bamrungwong et al. (2020) applied multiple linear regression to estimate CO_2 emission coefficients for medium- and heavy-duty vehicles across varying terrain conditions, highlighting the importance of context-specific factors in assessing emission patterns. Mata et al. (2021) reported that CO_2 emissions, urbanization, energy consumption, and agricultural activity are key drivers of Thailand's long-term economic growth. Raihan et al. (2023) found that economic growth, urbanization, industrialization, and tourism increase emissions, while renewable energy use, agricultural productivity, and forest expansion reduce them. More recently, Xuan et al. (2024) showed that population growth increases emissions, renewable energy mitigates them, and foreign direct investment (FDI) has sector-specific effects.

Alongside these developments, recent literature highlights the importance of quantile-based modeling for capturing heterogeneous emission responses. Mean-based methods such as OLS regression provide a single estimate of the conditional mean and are therefore unable to reflect variations across the emission distribution. For instance, economic growth or changes in energy demand may have stronger effects during high-emission periods than during low-emission periods. In response to these limitations, an increasing number of studies have applied quantile regression–based approaches to examine differential effects across the distribution. For instance, Zhou et al. (2018) employed panel quantile regression for ten major emitting countries and found that energy consumption consistently increases emissions across the emission distribution. Khan et al. (2020) found that renewable energy consumption reduces emissions, whereas financial development intensifies them across quantiles in a global sample. Voumik et al. (2022) demonstrated that coal and gas use raise emissions in ASEAN countries, while renewable and hydroelectric power reduce them. Awan et al. (2022) emphasized the heterogeneous long-run effects of energy efficiency and renewable energy across quantiles, and Yu et al. (2024) showed that economic policy uncertainty influences emission efficiency differently across quantiles using multivariate quantile-on-quantile regression.

Collectively, these studies underscore the importance of flexible modeling frameworks capable of capturing distributional heterogeneity. However, existing research on Thailand largely relies on mean-based approaches, or random-effects panel models, which assume uniform effects across emission levels. Such methods overlook variations in how different economic activities influence emissions under low, medium, and high emission conditions. Moreover, the predominant use of annual or quarterly data limits the ability to detect short-term and seasonal dynamics. These gaps motivate the use of quantile regression with monthly data in the present study to provide a more comprehensive understanding of emission behavior in Thailand.

3. METHODOLOGY

3.1. Conceptual Rationale for Variable Selection

CO_2 emissions are influenced by a complex interplay of energy consumption, economic activity, demographic characteristics, and consumption behavior. In this study, the selection of explanatory variables is guided by both theoretical foundations and empirical evidence from environmental economics and energy research (e.g., Poumanyvong and Kaneko, 2010; Sadorsky, 2013; Wang et al. 2014), together with the availability of relevant data. Accordingly, the model incorporates nine key variables presenting these dimensions, which are organized into three main groups to capture the relationship between economic activity and carbon emissions from multiple perspectives.

The first group represents energy and industrial use. In Thailand, the main contributors to national CO_2 emissions primarily from both uses fossil fuels for both electricity generation and transportation. As a result, we include crude oil production and power consumption, which directly reflect the level of industrial activity and energy demand. These variables represent crucial drivers of CO_2 emissions. The second group, economic and trade activity, comprises the LEI, CIF, PCI, and unemployment rate. These variables represent various aspects of economic performance, trade intensity, and consumption behavior that collectively influence industrial output and energy demand. Specifically, CIF reflects trade-related logistics and transportation activities that are closely associated with freight-induced CO_2 emissions, while LEI provides insights into business cycles and prospective economic growth. PCI captures domestic consumption and spending patterns that drive production and energy use, whereas unemployment serves as an inverse indicator of economic performance and labor market efficiency, indirectly affecting energy demand through reduced income and consumption levels. The third group, demographic and mobility factor, includes population and tourism, which account for the impacts of population growth, travel-related energy consumption, and transportation intensity on emission levels. Together, these nine variables offer a multidimensional framework for examining how energy use, economic dynamics, and demographic trends interact to shape carbon emissions in the Thai economy. By structuring the variables in this manner, the study aims to explore how energy, industrial, and economic dynamics, along with demographic pressures, interact to influence carbon emissions in Thailand. This categorization facilitates a clearer interpretation of causal pathways and helps identify which sectors contribute most significantly to environmental change.

3.2. Data and Description of Variables

The variables and its description along with source of data are presented in Table 1.

3.3. Quantile Regression

Quantile Regression (QR), introduced by Koenker and Bassett (1978), offers a more comprehensive framework by modeling conditional quantiles of the dependent variable, thus allowing the assessment of how explanatory variables influence different parts of the emission distribution. This is particularly relevant in environmental and energy economics, where policy interventions may have asymmetric impacts across emission levels (Koenker, 2005). QR extends the classical linear regression model by estimating conditional quantiles rather than the conditional mean. Let denote the dependent variable representing CO_2 emissions, and $X_t = (x_{1t}, x_{2t}, \ldots, x_{pt})$ a vector of explanatory variables. The τ-th conditional quantile of Y_t given X_t can be expressed as

$$Q_{Y_t}(\tau | X_t) = X_t^T \beta(\tau), 0 < \tau < 1$$

Where $\beta(\tau)$ is a vector of quantile -specific parameters describing the relationship between at quantile τ. The quantile regression estimator minimizes an asymmetric loss function defined as

$$\hat{\beta}(\tau) = \arg\min \rho_t \left(Y_t - X_t^T \beta \right)$$

Where $\rho_\tau(u)$ is the check function given by $\rho^\tau(u) = u(\tau\text{-}1\,(u<0))$. This function assigns asymmetric weights to positive and negative residuals, enabling the estimation of different quantiles across the distribution. For example, $\tau = 0.5$ corresponds to the conditional median, while $\tau = 0.1$ and, $\tau = 0.9$ represent the lower and upper quantiles, respectively. By estimating a set of coefficients $\beta(\tau)$ for multiple quantiles, the model captures how the influence of each explanatory variable varies across the emission distribution. In the context of this study, the quantile regression framework enables the identification of whether variables such as energy use, trade activity, or population have stronger effects during high emission periods than during low-emission periods.

We also provide confidence intervals for each estimate; however, QR does not assume normally distributed errors. Therefore, the traditional confidence intervals using standard errors do not work properly. As a result, bootstrap confidence intervals are commonly used in QR. Bootstrap intervals are obtained by repeatedly resampling the dataset, re-estimating the model for each resample, and using the distribution of bootstrap coefficients to compute standard errors and confidence limits. This approach provides robust inference without relying on normality assumptions and is particularly appropriate for QR, where the sampling distribution of the estimators is typically non-normal.

3.4. Packages and Programming

In R programming, there is the *rq* function available from the quantreg package. We then use this function to perform quantile regression analysis for various quantiles of the dependent variable, providing a more comprehensive picture for the heterogeneous effects of explanatory variables across the emission distribution. Before estimation, all variables are transformed into their natural logarithmic forms to improve the model's interpretability and to reduce variability in magnitude for each variable. Besides, the log transformation mitigates the influence of extreme values and improves robustness, leading to more reliable estimates.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1. Data Summary

The dataset consists of monthly observations from January 2015 to December 2024. Because the unemployment series contains missing values, these gaps were filled using date-based linear interpolation to ensure continuity in the analysis. The descriptive statistics of all variables used in this study are shown in Table 2.

The amount of CO_2 emissions range from 18,730.77 to 23,677.01 with a mean of 20,997.97, indicating moderate variation. Crude oil and power consumption display higher values with means of 115,556.98 and 15,972.99, respectively. LEI and PCI show stable economic activity, averaging 153.69 and 132.55. CIF values vary widely, reflecting fluctuations in trade, while unemployment ranges from 254.67 to 830.95 with a mean of 418.94. Tourist arrivals show extreme variability, with values dropping to zero during the COVID-19 pandemic and travel restrictions, and an overall average of 2,149.83, reflecting the sector's sensitivity to global

Table 1: Data description and source

No.	Variables	Description	Source
1	CO_2	The amount of carbon dioxide emissions (in thousand tons)	Energy Policy and Planning office (EPPO) under the Ministry of Energy
2	Crude oil	Volume of crude oil production (barrels per day, bpd), reflecting fossil fuel use in transportation and industry.	Energy Policy and Planning office (EPPO) under the Ministry of Energy
3	Power	Electricity consumption (Gigawatt-hour, GWh) across industrial, commercial, and residential sectors, indicating energy demand.	Energy Policy and Planning office (EPPO) under the Ministry of Energy
4	LEI	Leading Economic Index (LEI), a composite indicator summarizing key signals of future economic activity, including production and investment trends.	Bank of Thailand
5	CIF	Cost, Insurance, and Freight (CIF), representing the total value of imported goods, including cost, insurance, and freight charges to the destination port. Reflects trade intensity and logistics activity. Unit: Thai Baht (THB).	The Customs Department operates under the Ministry of Finance
6	Unemployed	Number of unemployed persons (thousand persons), reflecting labor market conditions and economic performance.	Bank of Thailand
7	PCI	Private Consumption Index (PCI), indicating household spending on goods and services, reflecting domestic demand and consumption behavior.	Bank of Thailand
8	Tourism	Number of international tourist arrivals (thousand persons), capturing travel-related and service-sector economic activity.	Bank of Thailand
9	Population	Total population of Thailand (persons), reflecting population size and associated demand for energy and resources.	Registration Administration (BORA), Department of Provincial Administration (DOPA), Ministry of Interior

Table 2: Descriptive statistics

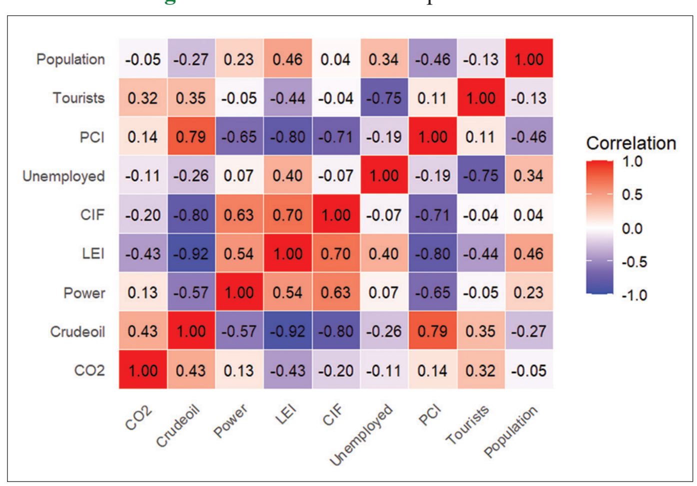
Variables	Min	Q1	Median	Mean	SD	Q3	Max
CO_2	18,730.77	20,368.33	21,049.82	20,997.97	950.89	21,666.85	23,677.01
Crude oil	61,724	82,310	121,916.50	115,556.98	31,893.50	139,911.75	172,572
Power	12,689.02	15,138.15	15,957.86	15,972.99	1,320.58	16,664.77	20,241.39
LEI	141.73	149.82	153.34	153.68	5.96	159.44	162.40
CIF	4.44e+11	5.86e+11	6.51e+11	6.95e+11	1.38e+11	8.19e+11	1.01e+12
Unemployed	254.67	361.12	397.16	418.94	100.78	443.94	830.95
PCI	104.70	122.34	131.11	132.55	13.61	141.78	165.38
Tourists	0	1,241.51	2,600.45	2,149.83	1,236.46	3,043.85	3,947.34
Population	65,144,936	65,970,114.50	66,106,271.50	66,081,482.75	326,025.27	66,222,738.25	66,586,964

disruptions. Population remains steady at around 66 million with minimal variation.

To explore the relationships among variables and assess potential correlations prior to estimation, a correlation heatmap was constructed. The visualization provides an initial overview of how the economic, energy, and population variables relate to one another before undertaking the quantile regression analysis. The heatmap in Figure 1 illustrates the pairwise Pearson for all variables included in the study, with the color scale ranging from blue (negative correlation) to red (positive correlation), and white indicating weak or no association. From the figure, CO_2 emissions show a moderately positive correlation with crude oil (0.43) and international tourist arrivals (0.32), but only a weak association with power consumption (0.13). CO_2 is negatively correlated with LEI (–0.43) and CIF (–0.20). In contrast, several economic variables exhibit strong interrelationships, such as crude oil with LEI (–0.92) and CIF (–0.80), and power consumption with LEI (0.54) and CIF (0.63). Overall, CO_2 shows limited linear relationships, suggesting that more complex or heterogeneous effects may emerge beyond simple correlations.

The heatmap also highlights notable associations among several explanatory variables, which could lead to misleading

Figure 1: Correlation heatmap of variables



interpretations if OLS regression were applied. A subsequent VIF check confirms that all variables except LEI exceed the common threshold of 10, indicating substantial multicollinearity. However, this issue is less problematic in the context of quantile regression, where VIF diagnostics are not required in the same way as in OLS.

4.2. Quantile Regression Analysis

In this work, we use τ = (0.10,0.25,0.50,0.75,0.90) to represent low-emission periods (10th quantile) to high-emission periods (90th quantile). The results show that the magnitude and significance of coefficients vary across quantiles, meaning that the drivers of emissions are not uniform across all emission levels as shown in Table 3. Note that the variables we used are all transformed to the natural logarithm.

Figure 2: Significance map across quantities

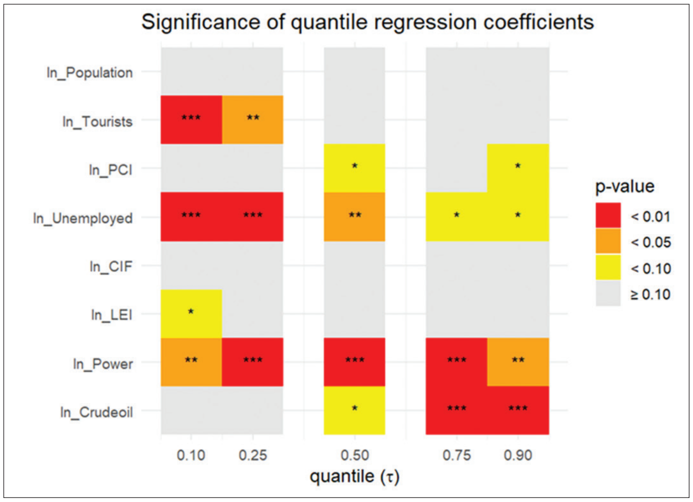


Table 3 and Figure 2 reveal that the factors influencing CO_2 emissions vary across quantiles, reflecting heterogeneity across the conditional distribution. At the lower quantile (τ = 0.10), tourism and unemployment are highly significant (p-value < 0.01), while power consumption is moderately significant and LEI are marginally significant, suggesting that economic and service-sector activities influence emissions during low emission periods. At τ = 0.25, unemployment remains highly significant, alongside power consumption, while tourism is significant at the 5% level, reflecting continued sensitivity of emissions to energy and labor-related factors.

At the median quantile (τ = 0.50), power consumption remains highly significant, whereas crude oil production and PCI exhibit marginal significance, implying that energy and economic

Figure 3: Coefficients of quantile regression with 95% confidence intervals

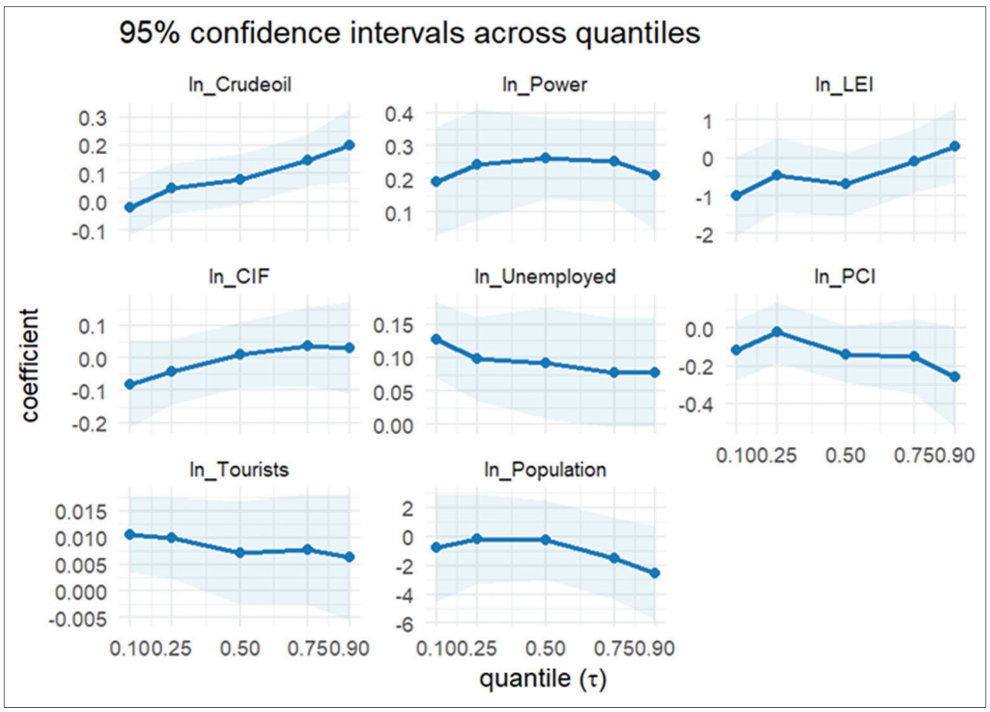


Table 3: Quantile regression estimates for ln_CO_2

Variables	Quantiles				
	0.1	0.25	0.5	0.75	0.9
(Intercept)	29.14940 (0.38825)	13.19075 (0.63798)	14.31435 (0.55477)	32.09660 (0.19563)	49.65398 (0.07871)*
ln_Crudeoil	−0.02076 (0.67558)	0.04762 (0.29733)	0.07892 (0.08839)*	0.14782 (0.00202)***	0.19909 (0.00283)***
ln_Power	0.19295 (0.02196)**	0.24196 (0.00565)***	0.26335 (0.00006)***	0.25332 (0.00010)***	0.21024 (0.01394)**
ln_LEI	−0.99636 (0.06530)*	−0.45047 (0.36383)	−0.69964 (0.10262)	−0.07928 (0.85130)	0.31365 (0.52651)
ln_CIF	−0.08160 (0.23615)	−0.04427 (0.39274)	0.00844 (0.87039)	0.03511 (0.56926)	0.03113 (0.66560)
ln_Unemployed	0.12651 (0.00003)***	0.09812 (0.00245)***	0.09188 (0.03241)**	0.07724 (0.06857)*	0.07715 (0.06706)*
ln_PCI	−0.11702 (0.14861)	−0.02109 (0.79750)	−0.13686 (0.07857)*	−0.14932 (0.14235)	−0.25831 (0.06265)*
ln_Tourists	0.01063 (0.00403)***	0.00991 (0.01141)**	0.00714 (0.15071)	0.00780 (0.14119)	0.00626 (0.29997)
ln_Population	−0.77151 (0.68254)	−0.18004 (0.90998)	−0.24846 (0.85923)	−1.47950 (0.30673)	−2.53692 (0.13225)

Coefficients are reported with p-values in parentheses. Significance levels: 0.10 (*), 0.05 (**), 0.01 (***)

performance play a joint role under normal emission conditions. At higher quantiles ($\tau = 0.75$ and 0.90), the influence of energy-related variables becomes dominant. Crude oil generation, power consumption, and unemployment all remain significant and positively associated with emissions, with crude oil showing particularly strong significance at the extreme quantile (0.90). PCI also shows weak significance at the highest quantile, again with a negative coefficient. In contrast, tourism, LEI, CIF, and population remain insignificant across both upper quantiles. Overall, population and CIF show no statistically significant effects across any estimated quantile.

The confidence interval plots in Figure 3 show that power consumption has a consistently positive and precise effect across all quantiles, while crude oil becomes increasingly influential at higher emission levels. Unemployment matters mainly at lower quantiles, whereas tourism, PCI, LEI, CIF, and population show wide intervals crossing zero, indicating weak or insignificant effects. Overall, the results highlight stronger energy-related impacts in high-emission regimes.

5. CONCLUSION AND DISCUSSION

The results from quantile regression analysis provide crucial evidence suggesting that CO_2 emissions in Thailand are not uniform across the emission distribution, reflecting substantial heterogeneity in their effects. They demonstrate that the influence of economic, energy, and social factors varies significantly between low and high emission periods.

At the lower quantiles, tourism and unemployment emerge as key contributors to emissions, suggesting that during low-emission periods, fluctuations in service-sector activity and labor dynamics directly influence the level of CO_2 emission. This pattern aligns with the findings of Wei and Ullah (2022) and Daga et al. (2025), who reported that tourism-related activities significantly affect emissions at lower and middle quantiles, particularly in developing economies dependent on the tourism sector. Similarly, Mehmood and Kaewsaeng-on (2024) and Kuldasheva et al. (2023) that tourism development tends to increase carbon emissions, whereas greater use of renewable energy helps mitigate them in tourism-dependent economies.

As emission levels rise toward the median and upper quantiles, the role of energy consumption becomes increasingly dominant. Power consumption is consistently significant across all quantiles, confirming that electricity demand is the most stable and influential determinant of CO_2 emissions in Thailand. Crude oil generation gains significance at higher quantiles, indicating that fossil fuel use becomes a critical driver under conditions of intensified industrial and transportation activity. These results are in line with Majumder et al. (2023), who found that energy consumption exerts a stronger and more persistent effect on emissions at higher quantiles, underscoring the central role of the energy sector in shaping carbon intensity.

The marginal significance of LEI and PCI suggests that these broader economic indicators have only limited and indirect influence on CO_2 emissions, likely working through trade, production, and demand-related channels rather than directly affecting emission levels. This weak relationship raises concerns about how well such macroeconomic indices capture short-term emission changes. Nevertheless, the pattern is partly consistent with Sobirov et al. (2024), who found that trade and financial development increase emissions mainly by stimulating industrial activity and energy use.

In general, the findings indicate that quantile-based analysis effectively captures the asymmetric and context-dependent behavior of CO_2 emissions in Thailand. Energy use, particularly electricity consumption and crude oil, emerges as the primary and consistently significant driver across all emission levels. In contrast, the influence of tourism, employment, and private consumption becomes more prominent during low to moderate emission phases. Population and CIF, however, are not significant at any quantile. One likely explanation is that population is a long-run demographic factor that changes only gradually over time; therefore, when monthly data are used, it exhibits little short-term variation and contributes minimally to changes in emissions. Surprisingly, CIF also lacks significance at any quantile, which may be due to its broad aggregation of trade-related costs that obscures the more direct freight and transport activities typically associated with CO_2 emissions. When considered together, these findings suggest several possible policy directions for supporting Thailand's low-carbon transition. Since energy use is the most persistent and influential driver of emissions, strengthening energy efficiency and accelerating the shift toward renewable energy should remain central to mitigation strategies. At the same time, the quantile-specific influence of tourism, employment, and private consumption suggests that targeted interventions such as promoting sustainable tourism practices, improving labor-market resilience, and encouraging low-carbon consumer behavior can help reduce emissions during low to moderate emission periods. The limited explanatory role of population and CIF calls for caution, suggesting that policies may need to prioritize short and medium term economic and energy dynamics.

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