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Contrasting Roles of Geothermal Energy and Fossil Fuels in Indonesia's Carbon Emissions

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Abstract

The transition toward renewable energy is essential for improving environmental quality and mitigating climate change, particularly in fossil fuel-dependent emerging economies. Indonesia has substantial geothermal energy potential, yet its energy mix remains heavily reliant on fossil fuels, highlighting the importance of assessing geothermal energy's contribution to carbon emission reduction. This study investigates the dynamic impacts of geothermal energy in comparison with coal, oil, and gas on environmental quality in Indonesia, proxied by CO_2 emissions from 1990Q1 to 2024Q4. The analysis employs the Autoregressive Distributed Lag (ARDL) and Bootstrap Quantile Regression (BQR). The ARDL long-run results indicate that geothermal energy significantly reduces CO_2 emissions in the long run. In contrast, coal and oil consumption significantly increase CO_2 emissions, while gas shows no significant long-run effect. Among the control variables, FDI and manufacturing value added contribute to CO_2 emission reductions in the long run. The BQR results further reveal pronounced heterogeneity, showing that the adverse effects of coal consumption are more pronounced at higher emission quantiles, while oil consumption increases CO_2 emissions across all quantiles. Meanwhile, the emission-reducing effect of geothermal energy becomes more evident at higher quantiles of the CO_2 emissions distribution. Overall, the results underscore the importance of expanding geothermal energy deployment while reducing reliance on coal and oil to achieve long-term environmental sustainability in Indonesia, providing strong empirical support for policies that promote renewable energy investment and a gradual transition toward cleaner energy systems.

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1. Introduction

Environmental degradation and climate change have emerged as some of the most pressing global challenges of the past decade, closely associated with patterns of energy production and consumption [1–4]. Energy use plays a central role in shaping environmental outcomes, particularly through its contribution to pollution and greenhouse gas emissions [5, 6]. Historically, fossil fuels such as coal, oil, and natural gas have dominated energy

systems due to their efficiency and reliability, but their extensive use has substantially intensified environmental degradation and exacerbated climate change [7–9]. Against this backdrop, recent global energy assessments provide important insights into how current energy demand trends and technological progress continue to shape emissions trajectories. Recent global energy assessments highlight the persistence of these challenges. The British Petroleum (BP) [10] indicates that the global energy system remains on a trajectory of rising demand and emissions despite substantial progress in low-carbon technologies. Between 2019 and 2024, global energy demand increased by approximately 1% per year, with all net growth originating from emerging economies driven by rising incomes and economic expansion. This slowdown has sustained the continued growth of fossil fuel consumption, even as low-carbon energy sources expanded rapidly [11, 12]. The climate crisis has intensified the need to accelerate the shift from fossil fuels to renewable and sustainable energy sources. By 2023, renewables accounted for about 30% of global electricity generation and are projected to increase to 46% by 2030 [13, 14].

According to Jiang et al. [15], from 2015 to 2024, global CO_2 emissions increased by 5.6%, or 0.6% annually, because GDP growth exceeded declines in carbon intensity. Nevertheless, the projected 2100 temperature rise fell only modestly from 2.6 °C to 2.4 °C, with only a 17% probability of staying below 2 °C. Under a scenario in which countries meet their initial Nationally Determined Contributions (NDCs) targets and continue reducing emissions beyond 2030, projected warming would be limited to approximately 2.1 °C, increasing the probability of remaining below 2 °C to 34% [16, 17]. If CO_2 emissions remain close to current levels, the carbon budget identified by the Intergovernmental Panel on Climate Change (IPCC) for a high probability of limiting global temperature increases to 2 °C is expected to be exhausted by the early 2040s [10, 18].

Against this backdrop, fossil fuels continue to dominate the global energy mix. According to the International Energy Agency (IEA) in its Global Energy Review 2026 [19], global energy-related CO_2 emissions increased by approximately 0.4% in 2025, reaching a record high of nearly 38.4 gigatonnes of CO_2 (Gt CO_2). Emissions from fuel combustion rose by nearly 0.5%, equivalent to 185 megatonnes of CO_2 (Mt CO_2), with natural gas accounting for the largest contribution to this increase (85 Mt CO_2), followed by oil (60 Mt CO_2) and coal (25 Mt CO_2). These findings underscore the continued contribution of fossil fuels to global CO_2 emissions despite the expansion of low-emission energy sources. Furthermore, empirical studies worldwide consistently find that non-renewable energy sources, particularly coal, oil, and gas, worsen environmental quality [20–22].

Renewable energy is widely regarded as a key solution for improving environmental quality and reducing CO_2 emissions in the long run [21–24]. These energy sources include hydropower, biomass, geothermal, solar, and wind, and they are generally considered more environmentally sustainable than fossil fuels [25–28]. Recognizing these challenges, the International Energy Agency emphasizes that achieving a 50% reduction in global emissions by 2050 will require a broad and coordinated energy transition, with renewable energy serving as a central pillar of this transformation [29]. At the same time, investment in clean energy has accelerated significantly. The International Energy Agency estimates that global clean energy investment will reach approximately USD 2.2 trillion in 2025, representing a 70% increase since 2000 [30]. Geothermal energy is widely recognized as a sustainable and clean energy source that generates substantially lower emissions than fossil fuels. Previous studies, including Hunt [31], Lund & Boyd [32], and Yousefi et al. [33], demonstrate that increased geothermal utilization reduces CO_2 emissions and improves environmental quality. Beyond electricity generation, geothermal energy provides a stable and continuous supply of low- and medium-temperature heat for space heating, industrial processes, and district heating systems. Unlike intermittent renewable sources, its constant availability enables geothermal energy to effectively replace fossil fuel–based heat and power across multiple sectors, reinforcing its role as a dispatchable, low-emission energy source in long-term energy transition strategies.

Indonesia has abundant renewable energy resources, including geothermal energy [14, 34]. The country showcases 331 potential geothermal sites scattered along the volcanic belt (Ring of Fire) from Sumatra, Java, Nusa Tenggara, Maluku, to Sulawesi, with an estimated geothermal energy potential of 23.7 gigawatts (GW) distributed across 30 provinces [14, 35, 36]. Indonesia's long-term energy outlook anticipates a substantial increase in renewable capacity by 2050, led by solar power at around 40 GW, followed by hydropower at 38.5 GW, biomass-based sources at approximately 24.5 GW, and geothermal energy at 10 GW. This expansion highlights the importance of renewable energy, especially geothermal power, in reducing reliance on fossil fuels and advancing national climate goals [37]. As the world's second-largest producer of geothermal energy, Indonesia holds the largest geothermal energy potential globally, accounting for approximately 40% of

total resources. Acknowledging its significance, the Indonesian government recognizes the geothermal sector as pivotal in achieving national energy sustainability goals [38]. Despite the government's target of 7,000 MW of installed geothermal capacity by 2025 [39], actual capacity reached only 2,744 MW by the end of 2025 [40], highlighting the gap between national targets and actual geothermal development.

The existing literature on the relationship between geothermal energy and environmental quality presents mixed findings. Several studies report emission-increasing or mixed effects of geothermal energy [41–43], whereas others demonstrate its potential to reduce CO_2 emissions and improve environmental quality [44–46]. Furthermore, Umar et al. [47] highlight variations in the environmental effects of geothermal energy across countries and emission levels. In Indonesia, empirical findings remain inconsistent, with Idroes et al. [48] reporting a small positive association between geothermal energy and CO_2 emissions, while Idroes et al. [49] identify an emission-reducing relationship.

Despite these contributions, further investigation is warranted to better understand the relationship between geothermal energy and CO_2 emissions alongside individual fossil fuel sources in Indonesia. Building on the existing literature, this study examines the relationships between geothermal energy, coal, oil, natural gas, and CO_2 emissions in Indonesia from 1990Q1 to 2024Q4. The analysis employs the Autoregressive Distributed Lag (ARDL) model to investigate short- and long-run relationships, complemented by Bootstrap Quantile Regression (BQR) to examine variations across different emission levels. FMOLS, CCR, and DOLS are further employed as robustness checks. By integrating a geothermal-specific perspective with disaggregated fossil fuel consumption and distributional analysis, this study seeks to provide a clearer understanding of the energy–environment nexus and offer empirical insights relevant to Indonesia's energy transition and emission reduction strategies.

2. Literature Review

2.1. Previous Studies

Previous studies examining the relationship between geothermal energy and environmental quality report mixed findings across countries, methodologies, and time horizons. Early evidence suggests that the environmental effects of geothermal energy are not uniform and may vary depending on country-specific energy structures and economic conditions. For instance, Bilgili et al. [41], using wavelet and partial wavelet coherence techniques for the United States over the period January 1980 to August 2019, find that geothermal energy exhibits both emission-increasing and emission-reducing effects in the short and long run, highlighting the dynamic and context-dependent nature of geothermal utilization.

Beyond single-country analyses, several panel studies have explored the role of geothermal energy within broader energy and growth frameworks. Zhang et al. [42], focusing on five emerging economies and employing GMM and FMOLS estimators, report that economic growth exacerbates environmental degradation, while increases in geothermal and hydropower production are also associated with higher emissions. In contrast, nuclear and wind energy are found to mitigate environmental degradation, underscoring the heterogeneous environmental impacts of different energy sources even within the renewable category.

A growing strand of the literature directly compares geothermal energy with fossil fuels, particularly coal. Shahzad et al. [43], analyzing the Philippine economy using the ARDL approach, find that geothermal energy and economic growth increase carbon emissions in the long run, whereas coal consumption unexpectedly reduces emissions, suggesting country-specific energy efficiency and substitution effects. Their causality analysis further reveals two-way causality between geothermal energy and emissions. In contrast, Adebayo et al. [44], examining ten newly industrialized countries using fixed-effects OLS, DOLS, FMOLS, and MMQR, document that coal consumption consistently increases emissions, while geothermal energy reduces emissions across all quantiles, indicating a more robust emission-mitigating role of geothermal energy in multi-country settings.

Consistent with these findings, Bashir et al. [45] show that coal consumption and economic growth worsen ecological footprints in both the short and long run, whereas geothermal energy improves environmental quality. Their Dumitrescu–Hurlin causality analysis confirms a unidirectional causal relationship running from geothermal energy to ecological footprint. Similarly, Alsaleh et al. [46], employing the ARDL framework for 27 European Union countries over the period 1990–2021, demonstrate that increased geothermal utilization significantly reduces long-run CO_2 emissions, while fossil fuel consumption intensifies environmental degradation. Extending the analysis to distributional effects, Umar et al. [47] apply the Quantile-on-Quantile (QQ) approach to the seven largest geothermal energy-consuming countries and find heterogeneous impacts: geothermal energy reduces emissions in Italy, Mexico, and New Zealand, but increases emissions in the Philippines, India,

Turkey, and the United States, reinforcing the importance of country-specific characteristics and emission levels.

Despite the growing international literature, empirical evidence focusing on Indonesia remains limited. Idroes et al. [48], using a Green Solow framework combined with ARDL modeling, find that geothermal energy exerts a positive but relatively small impact on CO_2 emissions in Indonesia, with biomass energy exhibiting a stronger effect. Their Granger causality results indicate a unidirectional causal relationship from geothermal energy to emissions. More recently, Idroes et al. [49], applying FMOLS with DOLS robustness checks for the period 1995–2020, report that geothermal energy and technological innovation significantly improve environmental quality by reducing CO_2 emissions, while non-renewable energy consumption deteriorates environmental quality in the long run. However, existing Indonesian studies largely rely on annual data and do not examine emission heterogeneity or explicitly compare geothermal energy with major fossil fuels across different emission levels.

2.2. Theoretical Framework

The theoretical foundation of this study is anchored in the energy–environment nexus and the Green Solow Model (GSM) developed by Brock & Taylor [50]. The GSM extends the traditional Solow growth framework by explicitly incorporating pollution and clean technology, arguing that long-run economic growth can be compatible with environmental improvement when technological progress and cleaner energy sources reduce emissions intensity. Within this framework, environmental quality is determined not only by the scale of economic activity but also by the structure of energy consumption and the adoption of low-emission technologies.

Energy sources differ substantially in their carbon intensity, making the composition of the energy mix a critical determinant of CO_2 emissions. Fossil fuels such as coal, oil, and natural gas are carbon-intensive and are theoretically associated with higher emissions through combustion-based energy production. In contrast, renewable energy sources, particularly geothermal energy, generate significantly lower lifecycle emissions and align with the GSM's prediction that clean energy adoption can offset the pollution effects of economic growth in the long run. Geothermal energy is especially relevant because it provides stable, dispatchable baseload power, enabling effective substitution away from fossil fuels and supporting sustained emission reductions over time.

In addition to energy structure, the framework incorporates key macroeconomic factors emphasized in the Green Solow Model. Capital accumulation, labor expansion, foreign direct investment, and manufacturing activity influence environmental quality through scale, composition, and technology channels. While economic expansion may initially increase emissions, investment-driven technological improvements and structural change can enhance energy efficiency and lower emissions in the long run. Given these dynamics, this study adopts a dynamic empirical framework using the ARDL approach to capture long-run equilibrium relationships and short-run adjustments, complemented by quantile regression to account for heterogeneous effects across different emission levels. Together, these methods provide a comprehensive framework for examining how geothermal energy and fossil fuels affect environmental quality in Indonesia.

2.3. Research Gap and Study Contribution

Existing empirical studies have extensively examined the relationship between renewable energy, fossil fuel consumption, and environmental quality, with particular attention to geothermal energy in both country-specific and cross-country contexts. While several studies report that geothermal energy reduces CO_2 emissions, others document mixed or even adverse effects, suggesting that its environmental implications may vary across countries and economic conditions. Moreover, existing research has provided relatively limited evidence on the relationships between geothermal energy and individual fossil fuel sources, particularly when considering their heterogeneous associations with CO_2 emissions across different emission levels.

In the context of Indonesia, empirical evidence remains limited and mixed. Previous studies, including Idroes et al. [48, 49], have examined the environmental implications of geothermal energy using different econometric approaches, predominantly relying on annual data. However, relatively little attention has been given to jointly examining geothermal installed capacity alongside coal, oil, and natural gas consumption while accounting for macroeconomic factors and variations across the emissions distribution. Consequently, further investigation is warranted to better understand how these energy sources are associated with CO_2 emissions in both the short and long run and across different emission quantiles.

Accordingly, the contribution of this study lies in examining whether the relationships between geothermal installed capacity, individual fossil fuel sources, and CO_2 emissions differ across time horizons

Table 1. Variable synopsis.

Symbol	Variable Name	Measurement	Source
CO_2	Carbon dioxide emissions per capita	Metric tons	OWID [51]
GEO	Geothermal energy capacity	Installed capacity (MW)	OWID [52]
COAL	Coal consumption	Terawatt-hours (TWh)	OWID [53]
OIL	Oil consumption	Terawatt-hours (TWh)	OWID [53]
GAS	Gas consumption	Terawatt-hours (TWh)	OWID [53]
FDI	Foreign direct investment	Net inflows (% of GDP)	WDI [54]
GDPPC	Gross domestic product per capita	Constant 2015 US dollars	WDI [54]
GFCF	Gross fixed capital formation	Constant 2015 US dollars	WDI [54]
LF	Labor force	Total labor force	WDI [54]
MANU	Manufacturing value added	Constant 2015 US dollars	WDI [54]

and emission levels. This distinction is important because conventional mean-based estimates may overlook heterogeneous relationships under different emission conditions. By considering geothermal energy alongside coal, oil, and natural gas within a unified empirical framework, the study provides a more differentiated assessment of the energy–environment nexus in Indonesia. Furthermore, examining the consistency of long-run estimates across alternative econometric approaches strengthens the assessment of these relationships and their relevance to energy transition policies.

3. Materials and Methods

3.1. Data Sources and Justification

The research uses secondary time-series data for Indonesia between 1990Q1 and 2024Q4. Our World in Data (OWID) provides data on CO_2 emissions, geothermal energy capacity, and fossil fuel consumption (coal, oil, and natural gas). Macroeconomic variables, including foreign direct investment, GDP per capita, gross fixed capital formation, labor force, and manufacturing value added, are sourced from the World Development Indicators (WDI) database of the World Bank. Detailed descriptions of all variables and their measurements are presented in Table 1.

In this study, CO_2 emissions per capita are employed as a proxy for environmental quality, as carbon emissions are widely recognized as a primary contributor to environmental degradation and climate change and are commonly used in the energy–environment literature to capture the environmental impacts of economic and energy activities. Geothermal energy is proxied by total installed geothermal capacity, which reflects the scale and intensity of geothermal energy deployment and is an appropriate indicator of long-term investment and utilization in the geothermal sector. Fossil fuel use is represented by coal, oil, and natural gas consumption, measured in energy terms, to capture the distinct environmental effects of different non-renewable energy sources. Additionally, foreign direct investment, GDP per capita, gross fixed capital formation, labor force, and manufacturing value added are included as control variables to account for macroeconomic activity, production capacity, and structural characteristics that may influence emissions. These proxies are chosen in line with empirical studies that have been conducted previously and enable the thorough evaluation of the dynamic connection between the patterns of energy consumption and the environmental quality in Indonesia.

This study uses geothermal installed capacity data for Indonesia covering 1990–2024. The observations for 1990 and 1995 were obtained from an archived version of the Our World in Data (OWID) dataset downloaded before later revisions, while data from 2000 onward were taken from the current OWID release. Historical studies by Huttrer [55] and Hochstein & Sudarman [56] provide additional evidence of Indonesia's geothermal installed capacity during 1990–2000, supporting the historical context of the early observations. The missing annual observations for 1991–1994 and 1996–1999 were estimated using linear interpolation between the observed benchmark years of 1990, 1995, and 2000. This approach was adopted to maintain continuity in the time series, considering that geothermal installed capacity reflects long-term infrastructure development through exploration, construction, and commissioning processes. Although actual capacity additions may occur at discrete intervals, the interpolated values are treated as approximations of the historical capacity trend rather than directly observed annual data.

All variables in the analysis, except FDI, were transformed from annual to quarterly frequency using interpolation to support the econometric analysis. The original annual dataset covers the period 1990 to 2024, comprising 35 observations, which may limit dynamic estimation, lag analysis, and long-run relationship testing. This approach is considered appropriate for Indonesia's geothermal sector because installed capacity follows long investment, construction, and commissioning cycles and

therefore evolves gradually and cumulatively rather than fluctuating sharply in the short term. Given the limited availability of long-term geothermal datasets and the relatively small number of econometric studies on geothermal energy compared with other renewable sources, quarterly interpolation provides a practical means of increasing the number of observations available for estimation while preserving the underlying trends in the original annual data.

3.2. Empirical Model and Estimation Technique

Based on the theoretical framework and existing empirical literature on the energy–environment nexus, this study specifies a functional relationship between environmental quality, energy consumption, and macroeconomic factors in Indonesia. Environmental quality is proxied by CO_2 emissions per capita, which are modeled as a function of geothermal energy, fossil fuel consumption, and a set of control variables. The baseline empirical function model employed in this study is given in Equation (1).

$$CO2_t = f\,(GEO_t + COAL_t + OIL_t + GAS_t + FDI_t + GDPPC_t + GFCF_t + LF_t + MANU_t) \quad (1)$$

where $CO2$ denotes carbon dioxide emissions per capita, GEO represents geothermal energy capacity, $COAL$, OIL, and GAS denote fossil fuel consumption, FDI refers to foreign direct investment, $GDPPC$ is GDP per capita, $GFCF$ represents gross fixed capital formation, LF denotes the labor force, and $MANU$ captures manufacturing value added. All variables, except FDI, were transformed into natural logarithms to help reduce heteroskedasticity, allowing the coefficients of log-transformed explanatory variables to be interpreted as elasticities, while the FDI coefficient is interpreted as a semi-elasticity.

To examine both long-run equilibrium relationships and short-run dynamics, this study employs the Autoregressive Distributed Lag (ARDL) modeling approach. The ARDL framework is particularly suitable because it allows variables with different orders of integration, provided none are integrated beyond the first difference, and performs well in finite samples. The ARDL bounds testing procedure is used to assess the existence of a long-run cointegration relationship among the variables [57–59]. Once cointegration is established, long-run coefficients and short-run adjustment dynamics are estimated through an Error Correction Model (ECM) representation. The ARDL model is widely applied to examine the environmental impacts, particularly CO_2 emissions, of various explanatory variables, as demonstrated in the studies by Hatmanu et al. [60], Guevara-Segarra et al. [61] and Xuan [62]. Based on our function in Equation (1), we transform it into the ARDL model in Equation (2).

$$\begin{aligned}\Delta lnCO2_t = {} & \psi_0 + \sum_{i=1}^{p}\psi_1\,\Delta lnCO2_{t-i} + \sum_{i=0}^{q}\psi_2\,\Delta lnGEO_{t-i} + \sum_{i=0}^{q}\psi_3\,\Delta lnCOAL_{t-i} + \sum_{i=0}^{q}\psi_4\,\Delta lnOIL_{t-i} + \\ & \sum_{i=0}^{q}\psi_5\,\Delta lnGAS_{t-i} + \sum_{i=0}^{q}\psi_6\,\Delta FDI_{t-i} + \sum_{i=0}^{q}\psi_7\,\Delta lnGDPPC_{t-i} + \sum_{i=0}^{q}\psi_8\,\Delta lnGFCF_{t-i} + \sum_{i=0}^{q}\psi_9\,\Delta lnLF_{t-i} + \\ & \sum_{i=0}^{q}\psi_{10}\,\Delta lnMANU_{t-i} + \lambda ECT_{t-1} + \delta_1 lnCO2_{t-1} + \delta_2 lnGEO_{t-1} + \delta_3 lnCOAL_{t-1} + \delta_4 lnOIL_{t-1} + \delta_5 lnGAS_{t-1} + \\ & \delta_6 FDI_{t-1} + \delta_7 lnGDPPC_{t-1} + \delta_8 lnGFCF_{t-1} + \delta_9 lnLF_{t-1} + \delta_{10} lnMANU_{t-1} + \varepsilon_t\end{aligned} \quad (2)$$

In Equation (2), $\Delta lnCO2_t$ denotes the natural logarithm of per capita carbon dioxide emissions, which proxies environmental quality in Indonesia at time t. The operator Δ represents the first-difference operator and captures short-run adjustments in the variables. The variables $\Delta lnGEO$, $\Delta lnCOAL$, $\Delta lnOIL$, and $\Delta lnGAS$ refer to the natural logarithms of geothermal installed capacity and fossil fuel consumption from coal, oil, and natural gas, respectively. The model also includes key macroeconomic control variables, namely foreign direct investment (ΔFDI), real GDP per capita ($\Delta lnGDPPC$), gross fixed capital formation ($\Delta lnGFCF$), labor force ($\Delta lnLF$), and manufacturing value added ($\Delta lnMANU$).

The coefficient ψ_0 is the intercept term, while the parameters ψ_1 to ψ_{10} capture the short-run dynamic effects of changes in the explanatory variables on CO_2 emissions. The summation terms with lag orders p and q represent the optimal lag structure selected for the ARDL model. The parameters δ_1 to δ_{10} correspond to the long-run coefficients associated with the lagged level variables, reflecting their equilibrium relationships with CO_2 emissions.

The term ECT_{t-1} denotes the Error Correction Term (ECT) derived from the long-run cointegrating relationship, and its coefficient λ measures the speed of adjustment toward long-run equilibrium following a short-run shock. A negative and statistically significant λ confirms the existence of cointegration and indicates how quickly deviations from equilibrium are corrected over time. Finally, ε_t is the stochastic error term, assumed to be white noise with zero mean and constant variance.

In addition to mean-based estimates, this study applies Bootstrap Quantile Regression (BQR) to capture potential heterogeneity in the impact of energy consumption across different levels of CO_2 emissions. Unlike conventional regression methods, quantile regression allows the effects of explanatory variables to vary across the conditional distribution of the dependent variable, providing deeper insights into how geothermal energy

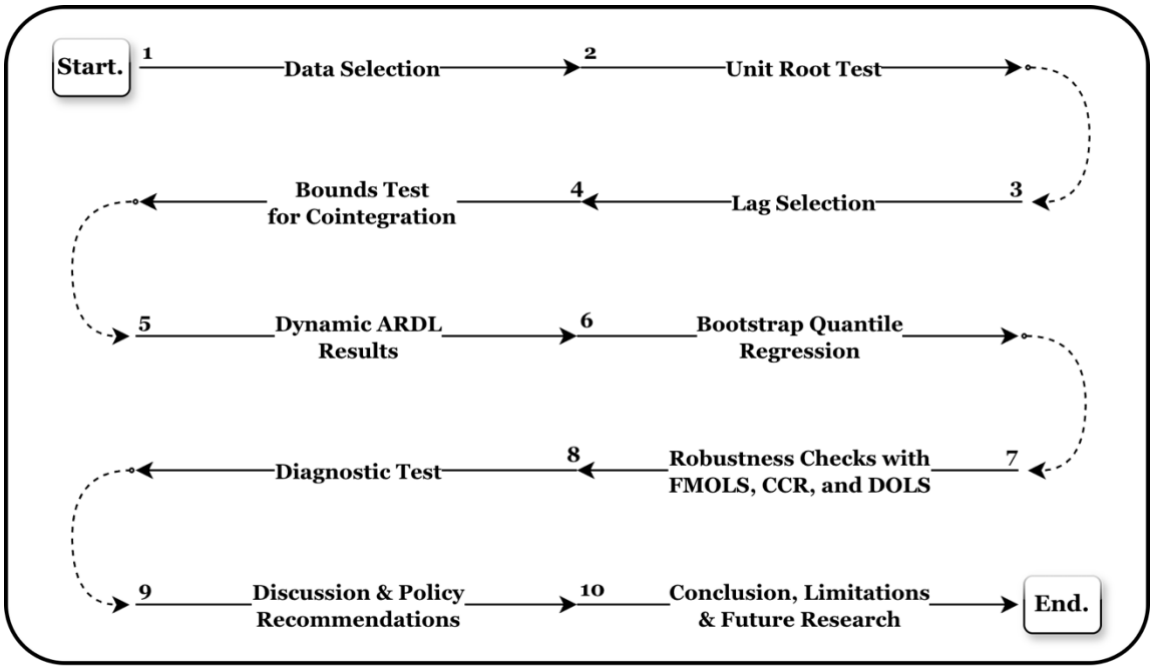


Figure 1. Workflow of the study.

and fossil fuels influence low, medium, and high emission regimes.

To ensure the robustness of the long-run results, alternative cointegration estimators are employed, including Fully Modified Ordinary Least Squares (FMOLS), Canonical Cointegrating Regression (CCR), and Dynamic Ordinary Least Squares (DOLS). These techniques correct for endogeneity and serial correlation and provide consistent long-run estimates [63, 64]. The consistency of results across ARDL, quantile regression, and robustness estimators strengthens the reliability of the empirical findings.

3.3. Flow Analysis of the Study

Figure 1 presents the sequential flow of the empirical strategy adopted in this study. The analysis begins with data selection, followed by unit root testing to examine the stationarity properties of the variables. An appropriate lag structure is then selected, followed by the bounds test for cointegration. Dynamic ARDL estimation subsequently captures both long-run and short-run relationships. To further explore distributional heterogeneity, the study applies BQR. Robustness of the findings is subsequently assessed using FMOLS, CCR, and DOLS estimations. Diagnostic tests are conducted to validate model adequacy and reliability, after which the empirical results are discussed and translated into policy recommendations. The analysis concludes with a summary of key findings and a discussion of study limitations and directions for future research.

4. Results

4.1. Preliminary Test Results

The descriptive statistics in Table 2, based on 140 quarterly observations, summarize the distributional properties of the variables used in the analysis, with all variables except FDI expressed in logarithmic form. Log CO_2 emissions have a mean of 0.4881 and a standard deviation of 0.3027, with values ranging from −0.1689 to 1.0526. GEO records a mean of 6.7257, while COAL, OIL, and GAS exhibit mean values of 5.5858, 6.5218, and 5.8814, respectively, with coal showing relatively higher dispersion compared to oil and gas. Foreign direct investment displays notable variability, with a mean of 1.3066 and values ranging from −2.7574 to 2.9161, expressed in its original units (% of GDP). GDPPC, GFCF, LF, and MANU present relatively narrow ranges and lower standard deviations, indicating less dispersion over the sample period.

As can be noted, the Phillips-Perron (P-P) unit root test results provided in Table 3 indicate that the variables have mixed stationarity. CO_2, GEO, COAL, FDI, GDP, GFCF, LF, and MANU are non-stationary at levels but stationary in first differences. On the other hand, stationarity is found in OIL and GAS at level. Significantly, no second differencing appears in any of the variables. These findings suggest that there was a mix of level-stationary and first-difference stationary variables, which is suitable for using the ARDL approach later in the analysis.

Table 2. Descriptive statistics.

Variable	Mean	Median	Max.	Min.	Std. Dev.	Obs.
CO2	0.4881	0.4383	1.0526	-0.1689	0.3027	140
GEO	6.7257	6.8876	7.8781	4.9754	0.8114	140
COAL	5.5858	5.9177	7.1788	3.6836	1.0001	140
OIL	6.5218	6.5954	6.7966	5.9034	0.2475	140
GAS	5.8814	5.9483	6.2138	5.1459	0.2442	140
FDI	1.3066	1.6588	2.9161	-2.7574	1.2414	140
GDPPC	7.8181	7.7644	8.3820	7.2936	0.3174	140
GFCF	25.9158	25.8272	26.6849	25.1596	0.4854	140
LF	18.5183	18.5353	18.7794	18.1733	0.1749	140
MANU	25.5426	25.5698	26.2227	24.6032	0.4369	140

Table 3. The results of the unit root test with P-P.

Variable	Level		First Difference	
	t-stat.	Prob.	t-stat.	Prob.
CO2	-1.1280	0.7036	-4.0660***	0.0015
GEO	-2.2553	0.1881	-3.4668**	0.0104
COAL	-1.2510	0.6510	-4.2724***	0.0007
OIL	-3.1994**	0.0221	-4.1434***	0.0012
GAS	-3.8267***	0.0034	-4.0578***	0.0016
FDI	-2.0657	0.2589	-3.9549***	0.0022
GDP	-0.0538	0.9511	-3.8729***	0.0029
GFCF	-0.5915	0.8676	-3.7436***	0.0044
LF	-2.7181	0.0735	-3.8447***	0.0032
MANU	-2.4036	0.1426	-3.6563***	0.0058

Note: *** and ** represent significance levels at the 1% and 5% levels, respectively.

Table 4 presents the lag length selection results based on multiple information criteria. All five criteria (LR, FPE, AIC, SC, and HQ) favor a lag order of two. In this study, the Akaike Information Criterion (AIC) was selected as the primary criterion for lag selection, which also identified lag two as optimal. Accordingly, a maximum lag length of two was adopted for the subsequent ARDL model selection procedure.

The findings of the ARDL bounds cointegration test, as shown in Table 5, reveal that the variables in the model are in a long-run relationship. The calculated F-statistic is 5.8703, which is greater than the upper bound critical values I(1) at the 10%, 5%, and 1% significance levels. Therefore, the null hypothesis of no cointegration is rejected, and the variables are cointegrated and behave in the long term.

4.2. Empirical Results and Econometric Analysis

4.2.1. ARDL Long Run and Short Run Results

The econometric analysis based on the ARDL estimation, as reported in Table 6 and illustrated in Figure 2, provides important insights into the long-run and short-run relationships between energy consumption, macroeconomic factors, and environmental quality in Indonesia, as proxied by CO_2 emissions. Focusing on the long-run estimates, GEO exhibits a statistically significant negative effect on CO_2 emissions. Specifically, a 1% increase in GEO leads to a 0.1567% reduction in CO_2 emissions. In contrast, fossil fuel consumption demonstrates a substantial and heterogeneous impact on environmental degradation. COAL shows a strong positive relationship with CO_2 emissions, whereby a 1% increase in COAL raises CO_2 emissions by 0.3405%. Similarly, OIL exerts a significant positive impact on emissions, with a 1% increase in OIL increasing CO_2 emissions by 0.3066%. Meanwhile, GAS displays a positive but statistically insignificant coefficient. Regarding the control variables, FDI is found to significantly reduce CO_2 emissions in the long run, as a one-percentage-point increase in FDI (% of GDP) is associated with an approximately 3.06% decline in emissions. MANU also exhibits a statistically significant negative effect on CO_2 emissions, with a 1% increase in MANU reducing CO_2 emissions by 0.4399%. In contrast, GDPPC, GFCF, and LF do not show statistically significant long-run effects on CO_2 emissions.

The short-run dynamics, however, reveal notable differences from the long-run results. The ECT is negative and highly significant, indicating adjustment toward the long-run equilibrium, with approximately 14.4% of the previous quarter's deviation from equilibrium corrected each quarter. In the short run, GEO shows a significant positive contemporaneous effect (0.1061) but a negative

Table 4. Optimal lag length selection.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1524.17	NA	6.12e-23	-22.77	-22.55	-22.68
1	4294.14	5081.75	2.25e-40	-62.92	-60.53	-61.95
2	4781.96	821.59*	6.74e-43*	-68.75*	-64.19*	-66.900*
3	4813.24	47.98	2.01e-42	-67.72	-60.98	-64.98
4	4873.46	83.31	4.13e-42	-67.12	-58.21	-63.50

Note: * indicates the lag order selected by the criterion.

Table 5. ARDL Bounds cointegration test results.

Test Statistic	Value	Significance Level	I(0) Lower Bound	I(1) Upper Bound
F-statistic	5.8703	10%	1.80	2.80
		5%	2.04	2.08
		1%	2.50	3.68

Note: The ARDL bounds test is conducted under Case II (restricted constant, no trend), with nine explanatory variables (k = 9) and an effective sample size of 135. Asymptotic critical values are reported.

lagged effect (−0.1101), contrasting with its emission-reducing relationship in the long run. Similarly, COAL exhibits a significant positive effect on CO_2 emissions (0.4173), followed by a negative lagged effect (−0.2029). FDI (0.0053) and MANU (1.6682) also exhibit significant positive short-run effects, despite their negative long-run coefficients. Meanwhile, lagged GDPPC (−1.0826) and contemporaneous LF (−0.6532) are negatively associated with emissions, whereas lagged GFCF (0.2232) shows a positive relationship. These findings highlight distinct short-run adjustment dynamics and differences from the long-run relationships between energy consumption, macroeconomic variables, and CO_2 emissions in Indonesia.

4.2.2. BQR Results

The quantile regression results reported in Table 7 and presented visually in Figure 3 reveal heterogeneous effects of energy consumption and macroeconomic variables on CO_2 emissions across different quantiles of the emission distribution. For renewable energy, GEO shows an increasingly negative effect at higher quantiles. While GEO is not statistically significant at lower and middle quantiles, it becomes negative and statistically significant at the upper quantiles, indicating that geothermal energy is associated with lower CO_2 emissions primarily in high-emission regimes.

Regarding fossil fuels, COAL exhibits a positive effect on CO_2 emissions that strengthens across higher quantiles. The coefficient of COAL is statistically insignificant at lower quantiles but becomes positive and significant at upper quantiles, suggesting that the emission-increasing effect of coal consumption is more pronounced when emission levels are high. In contrast, OIL displays a consistently positive and statistically significant effect across all quantiles, indicating a uniform relationship between oil consumption and CO_2 emissions throughout the emission distribution. GAS, however, does not show a statistically significant effect at most quantiles, suggesting the absence of a systematic relationship between gas consumption and CO_2 emissions across different emission regimes.

The control variables, FDI exhibits a negative and statistically significant effect from Q0.60 to Q0.90, while remaining insignificant at lower quantiles. GDPPC shows a positive and statistically significant relationship with CO_2 emissions across all quantiles, although the magnitude of the coefficient declines at higher quantiles. GFCF exhibits a negative and significant effect mainly at lower and middle quantiles, whereas its effect becomes statistically insignificant at upper quantiles. LF presents a negative and statistically significant relationship with emissions at lower and middle quantiles, with diminishing significance at higher quantiles. Finally, MANU displays a negative effect that becomes statistically significant only at the upper quantile, indicating a differentiated impact across the emission distribution.

4.2.3. Robustness Checks Based on FMOLS, DOLS, and CCR Estimations

The robustness estimations using FMOLS, CCR, and DOLS, as reported in Table 8, further confirm the long-run relationships between energy consumption, macroeconomic variables, and CO_2 emissions in Indonesia. Starting with renewable energy, GEO consistently exhibits a negative coefficient across all robustness estimators, with estimated effects ranging from approximately -0.03 to -0.10, indicating an inverse long-run relationship between geothermal energy and CO_2 emissions, although the statistical significance varies across models. Turning to fossil fuels, COAL shows a

Table 6. Long-run and short-run results of the ARDL model.

Variable	Coef.	Std. Er.	t-stat.	Prob.
Long run				
GEO	-0.1567***	0.0590	-2.6545	0.0090
COAL	0.3405***	0.0580	5.8701	0.0000
OIL	0.3066**	0.1420	2.1589	0.0328
GAS	0.1132	0.0947	1.1958	0.2340
FDI	-0.0306***	0.0091	-3.3684	0.0010
GDPPC	0.6468	0.3947	1.6385	0.1038
GFCF	0.2989	0.2091	1.4292	0.1554
LF	-0.5542	0.4115	-1.3469	0.1805
MANU	-0.4399***	0.1670	-2.6348	0.0095
C	5.6638	6.8117	0.8315	0.4073
Short run ARDL(2,2,2,1,0,1,2,2,1,1)				
ECT(-1)	-0.1441***	0.0172	-8.3899	0.0000
D(CO2(-1))	0.6299***	0.0490	12.8538	0.0000
D(GEO)	0.1061**	0.0411	2.5804	0.0111
D(GEO(-1))	-0.1101***	0.0403	-2.7353	0.0072
D(COAL)	0.4173***	0.0257	16.2078	0.0000
D(COAL(-1))	-0.2029***	0.0293	-6.9141	0.0000
D(OIL)	-0.0552	0.0513	-1.0752	0.2844
D(FDI)	0.0053**	0.0023	2.3041	0.0229
D(GDPPC)	-0.5363	0.3507	-1.5295	0.1288
D(GDPPC(-1))	-1.0826***	0.2118	-5.1124	0.0000
D(GFCF)	-0.1158	0.0767	-1.5098	0.1337
D(GFCF(-1))	0.2232***	0.0737	3.0272	0.0030
D(LF)	-0.6532***	0.1822	-3.5857	0.0005
D(MANU)	1.6682***	0.2346	7.1102	0.0000
R^2	0.9276			
Adj. R^2	0.9199			

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

robust and statistically significant positive effect on CO_2 emissions across all estimators, with coefficients ranging from about 0.10 to 0.26, confirming that higher coal consumption is associated with increased emissions in the long run. Similarly, OIL displays a strong and statistically significant positive relationship with emissions, with estimated coefficients ranging between 0.57 and 0.71, indicating a persistent emission-increasing effect of oil consumption across different robustness specifications. In contrast, GAS exhibits negative but statistically insignificant coefficients across the robustness estimations.

Regarding the control variables, FDI consistently shows a statistically significant negative association with CO_2 emissions, with coefficient estimates ranging from around -0.02 to -0.03. GDPPC demonstrates a positive and statistically significant relationship with emissions across all robustness models, with coefficients ranging from approximately 1.11 to 1.97. The effect of GFCF appears mixed, with estimated coefficients ranging from about -0.49 to 0.02, indicating sensitivity to model specification. LF exhibits a consistently negative and statistically significant relationship with CO_2 emissions, with coefficients ranging from approximately -0.82 to -1.17. Meanwhile, MANU displays negative coefficients across all estimators, with magnitudes ranging from about -0.19 to -0.36, although statistical significance is not uniform across models. Overall, the FMOLS, DOLS, and CCR estimations provide consistent and robust evidence supporting the long-run relationships identified in the ARDL model, reinforcing the stability of the estimated effects across alternative cointegration-based estimation techniques.

4.3. Diagnostic Test Results

The diagnostic test results reported in Table 9 confirm the adequacy, stability, and reliability of the estimated ARDL model. The CUSUM and CUSUMQ tests (displayed in Figure 4) indicate parameter stability over the sample period, confirming that the model does not suffer from structural instability. The Breusch–Godfrey LM test yields an F-statistic of 0.3720 with a probability value of 0.6328, indicating no evidence of serial correlation in the residuals, while the Ramsey RESET test reports an F-statistic of 2.6205 (p = 0.1084), suggesting that the model is correctly specified with no evidence of omitted variables or functional form misspecification. In terms of heteroscedasticity, the Breusch–Pagan–Godfrey, Harvey,

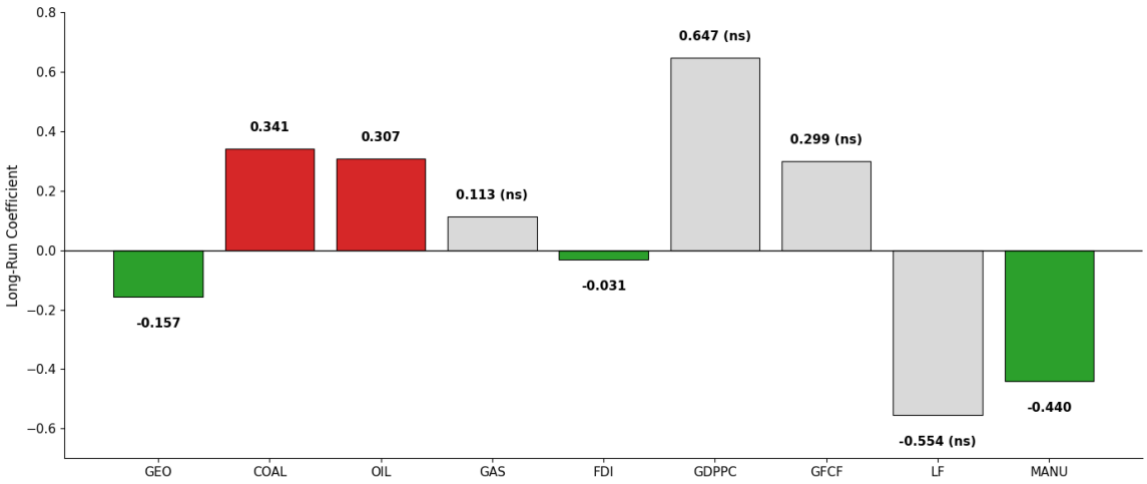


Figure 2. Graphical summary of long-run ARDL effects on CO_2 emissions.
Note: Red bars indicate emission-increasing effects, green bars indicate emission-reducing effects, and "ns" denotes statistically insignificant coefficients.

Table 7. BQR results.

Variable	Low			Middle			High		
	$Q^{0.10}$	$Q^{0.20}$	$Q^{0.30}$	$Q^{0.40}$	$Q^{0.50}$	$Q^{0.60}$	$Q^{0.70}$	$Q^{0.80}$	$Q^{0.90}$
GEO	0.107	0.040	0.028	-0.007	-0.011	-0.026	-0.068	-0.083*	-0.115***
	(0.157)	(0.598)	(0.662)	(0.890)	(0.793)	(0.537)	(0.118)	(0.052)	(0.009)
COAL	-0.007	0.029	0.045	0.057	0.058	0.101	0.140*	0.157**	0.184**
	(0.907)	(0.632)	(0.428)	(0.367)	(0.377)	(0.186)	(0.072)	(0.033)	(0.014)
OIL	0.543***	0.470***	0.588***	0.574***	0.704***	0.632***	0.525**	0.444**	0.467**
	(0.001)	(0.004)	(0.002)	(0.004)	(0.001)	(0.003)	(0.012)	(0.014)	(0.013)
GAS	-0.053	-0.048	-0.122	-0.060	-0.103	-0.112*	-0.074	-0.035	-0.056
	(0.586)	(0.612)	(0.243)	(0.524)	(0.175)	(0.078)	(0.222)	(0.564)	(0.472)
FDI	-0.001	0.001	-0.007	-0.005	-0.012	-0.019**	-0.020***	-0.021***	-0.024***
	(0.917)	(0.956)	(0.530)	(0.690)	(0.285)	(0.040)	(0.008)	(0.001)	(0.001)
GDPPC	2.772***	2.591***	2.395***	2.194***	2.085***	1.681***	1.345***	1.173***	1.181***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)	(0.005)	(0.004)
GFCF	-1.121***	-1.069***	-0.929***	-0.781***	-0.655***	-0.410*	-0.213	-0.119	-0.097
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.099)	(0.378)	(0.589)	(0.656)
LF	-1.344**	-1.409**	-1.650***	-1.245**	-1.310**	-1.153***	-0.700*	-0.489	-0.369
	(0.038)	(0.014)	(0.003)	(0.030)	(0.011)	(0.008)	(0.065)	(0.106)	(0.151)
MANU	-0.004	0.178	0.230	0.070	0.004	-0.051	-0.178	-0.229*	-0.323***
	(0.984)	(0.424)	(0.301)	(0.770)	(0.984)	(0.779)	(0.238)	(0.077)	(0.007)
C	28.917***	26.229***	26.941***	21.202***	21.083***	16.798***	9.732*	6.348	5.956
	(0.003)	(0.000)	(0.000)	(0.001)	(0.000)	(0.006)	(0.087)	(0.158)	(0.156)

Note: Coeff. (Prob.) denotes coefficients with corresponding probabilities, while ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

and ARCH tests consistently fail to reject the null hypothesis of homoscedasticity, with probability values of 0.0891, 0.0666, and 0.4792, respectively, indicating no significant evidence of heteroscedasticity at the 5% level. Overall, these diagnostic results suggest that the ARDL model satisfies the key econometric assumptions and is suitable for inference and policy interpretation.

5. Discussion and Policy Recommendations

The empirical results of this study demonstrate that geothermal energy contributes significantly to reducing CO_2 emissions in Indonesia over the long run. The negative and statistically significant long-run coefficient of geothermal installed capacity indicates that increasing geothermal deployment effectively lowers emissions by displacing carbon-intensive electricity generation, particularly from coal-fired power plants. This finding is supported by Adebayo et al. [44], Bashir et al. [45], Alsaleh et al. [46], Idroes et al. [49] and Umar et al. [47]. It is particularly important for Indonesia, where geothermal resources are abundant but remain underutilized relative to their estimated potential. As a renewable energy source that provides stable and continuous baseload power, geothermal energy enables sustained

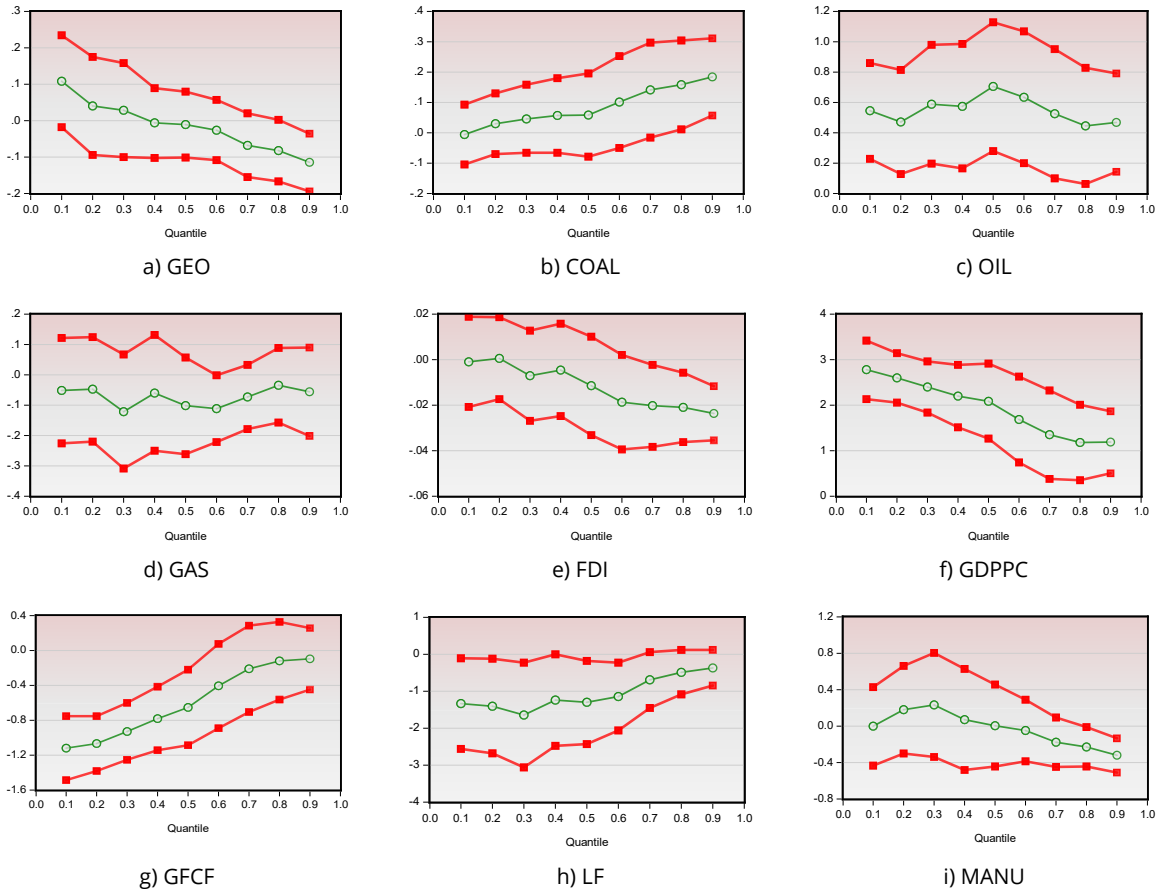


Figure 3. BQR estimates of the effects of explanatory variables across CO_2 emission quantiles.

Table 8. Robustness results from FMOLS, CCR, and DOLS estimations.

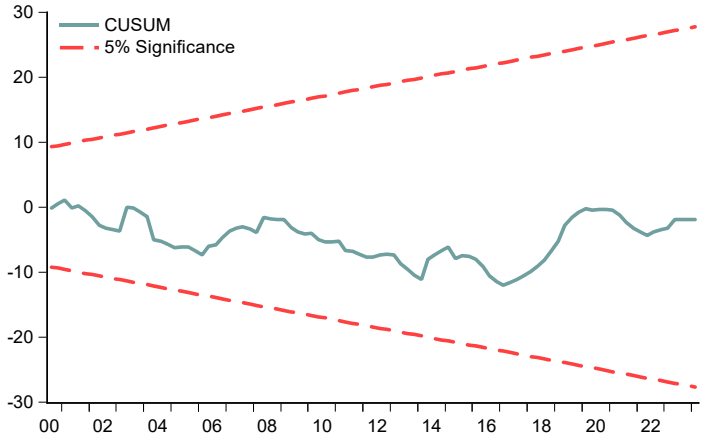
Variable	FMOLS		CCR		DOLS	
	Coef.	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**
GEO	-0.0331	0.4634	-0.0369	0.4205	-0.1003*	0.0659
COAL	0.1024**	0.0326	0.1075**	0.0240	0.2566***	0.0000
OIL	0.7073***	0.0000	0.6939***	0.0000	0.5677***	0.0003
GAS	-0.0780	0.4224	-0.0662	0.4950	-0.0425	0.6872
FDI	-0.0189**	0.0229	-0.0191**	0.0187	-0.0290***	0.0018
GDPPC	1.9615***	0.0000	1.9677***	0.0000	1.1101***	0.0014
GFCF	-0.4930***	0.0024	-0.4921***	0.0013	0.0173	0.9220
LF	-1.1672***	0.0068	-1.1551***	0.0056	-0.8222**	0.0229
MANU	-0.1899	0.2407	-0.2016	0.2001	-0.3570**	0.0104
C	19.9183***	0.0031	19.9344***	0.0025	11.5130**	0.0437
R^2	0.9900		0.9899		0.9973	
Adj. R^2	0.9893		0.9891		0.9963	

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

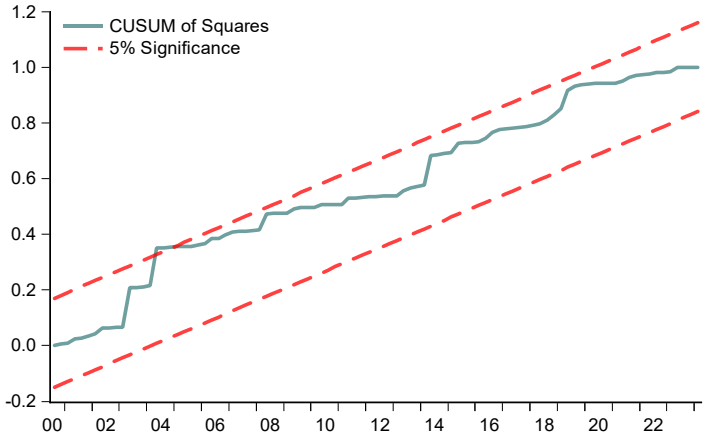
substitution away from fossil fuels and supports long-term emission reductions across the power sector [47, 49]. These results reinforce the role of geothermal energy as a key component of Indonesia's low-carbon energy transition and highlight its capacity to deliver meaningful environmental benefits beyond those offered by intermittent renewable sources. From a policy perspective, the findings suggest that accelerating geothermal development should be a strategic priority within Indonesia's energy transition agenda. Indonesia's long-term energy planning envisions a substantial expansion of renewable capacity by mid-century, with geothermal energy expected to play an increasingly important role alongside solar and hydropower. To realize this potential, policy interventions should focus on reducing institutional and financial barriers that have constrained geothermal deployment. Streamlining permitting procedures, strengthening risk-sharing

Table 9. The results of the diagnostic tests.

Diagnostic tests	F-stat.	Prob.	Decision
CUSUM & CUSUMQ	-	-	Stable at the 5% significance level
Breusch-Godfrey LM test	0.3720	0.6328	No evidence of serial correlation
Ramsey test	2.6205	0.1084	No evidence of model misspecification
Breusch-Pagan-Godfrey test	1.5339	0.0891	No evidence of heteroscedasticity
Harvey test	1.6182	0.0666	No evidence of heteroscedasticity
ARCH test	0.5037	0.4792	No evidence of heteroscedasticity



a)



b)

Figure 4. Stability tests based on CUSUM (a) and CUSUMQ (b).

mechanisms for exploration, and enhancing fiscal incentives can improve project viability and attract private investment. In addition, improving grid integration and expanding public–private partnerships would facilitate large-scale geothermal deployment and reinforce its contribution to long-term CO_2 emission reductions. Overall, the results indicate that sustained policy support for geothermal energy can significantly advance Indonesia's environmental sustainability goals while enhancing energy security and system reliability.

The empirical results clearly indicate that coal consumption significantly increases CO_2 emissions, confirming coal as the most environmentally damaging energy source in Indonesia. This finding is consistent with Indonesia's heavy reliance on coal for electricity generation, which has been driven by abundant domestic reserves, established infrastructure, and historically low production costs. This finding aligns with the empirical evidence reported by Sharma & Kautish [65], Jiang & Sun [66], and Kartal et al. [67]. Coal has remained the backbone of Indonesia's power sector, contributing a substantial share of total electricity generation and accounting for a large proportion of energy-related emissions. However, coal combustion is highly carbon-intensive and generates considerable local

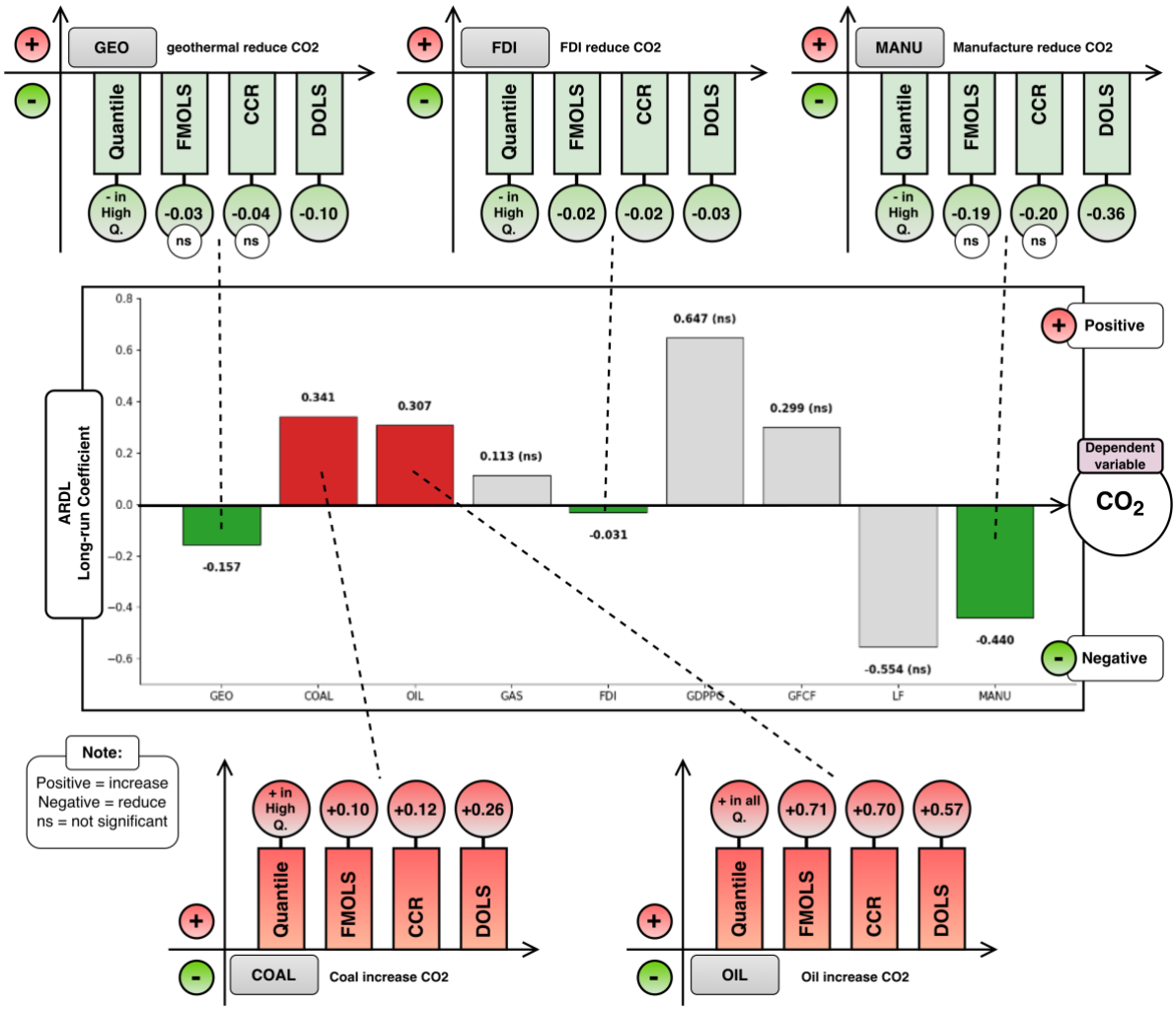


Figure 5. Graphical results of the impact of the independent variable on CO_2 emissions.

environmental and health externalities, including air pollution and associated public health risks. The results underscore that continued dependence on coal is fundamentally incompatible with Indonesia's long-term environmental sustainability and climate commitments. From a policy standpoint, these findings highlight the urgency of implementing a structured coal phase-down strategy. Key measures include revising coal pricing and subsidy policies that currently favor coal use, enforcing stricter emission standards for coal-fired power plants, and accelerating the retirement of aging and inefficient coal facilities. The introduction of carbon pricing mechanisms, such as carbon taxes or emissions trading schemes, could further internalize the environmental costs of coal consumption and discourage its use. Redirecting fiscal support from coal toward renewable energy investments, particularly geothermal energy, would help facilitate a cleaner energy transition while maintaining energy security.

Oil consumption is also found to have a statistically significant positive impact on CO_2 emissions, reflecting Indonesia's continued dependence on oil, particularly in the transportation and industrial sectors. Despite policy efforts aimed at diversifying the energy mix, oil remains a dominant energy source for road transport, freight, and industrial activities, contributing substantially to national emissions. The results indicate that without targeted interventions, rising transport demand and industrial expansion will continue to drive oil-related emissions growth. This finding is in line with the conclusions drawn by Apergis et al. [68], Sharma & Kautish [65], and Kartal et al. [67]. Addressing this challenge requires a comprehensive policy approach that goes beyond energy supply diversification. Strengthening fuel efficiency standards, promoting the adoption of cleaner vehicle technologies, and expanding public transportation infrastructure are essential steps to reduce oil demand and associated emissions. Moreover, accelerating the electrification of the transport sector, supported by electricity generated from low-carbon sources such as geothermal energy, can significantly reduce oil dependence and decouple economic growth from

emission increases. Complementary measures, including incentives for electric vehicles, investments in charging infrastructure, and integrated urban transport planning, would further enhance the effectiveness of these policies. Together, these actions can reduce oil-driven emissions while supporting Indonesia's broader energy transition and environmental objectives.

Unlike coal and oil, natural gas does not exhibit a statistically significant long-run relationship with CO_2 emissions. This finding is consistent with the predominantly insignificant BQR results and alternative long-run estimators. One possible explanation is that the environmental implications of natural gas consumption depend on its sectoral use and whether it substitutes for more carbon-intensive fuels such as coal. In Indonesia, natural gas is utilized across industrial and electricity generation sectors, while the country also remains a significant exporter of natural gas, particularly liquefied natural gas (LNG) [69, 70]. This diverse utilization pattern may contribute to the absence of a consistent aggregate relationship between natural gas consumption and CO_2 emissions. Nevertheless, this interpretation remains tentative, as sectoral gas use and fuel substitution are not directly examined in this study.

Finally, among the control variables, only FDI and MANU are statistically significant in the long run, while GDPPC, GFCF, and LF show no significant effects on CO_2 emissions. The negative effect of FDI suggests that foreign investment in Indonesia has increasingly supported cleaner production through technology transfer, improved management practices, and compliance with environmental regulations applied to large and foreign-invested projects, particularly in the energy and manufacturing sectors. This finding is consistent with the evidence reported by Mert & Caglar [71], Yilanci et al. [72], Ahmad et al. [73], and Saqib et al. [74]. At the same time, the negative coefficient of manufacturing value added indicates gradual structural upgrading within Indonesia's industrial sector, where efficiency improvements, technological modernization, and the adoption of less energy-intensive production processes have contributed to reducing emissions intensity rather than expanding pollution in the long run. This finding contrasts with Idroes et al. [75], Zahoor et al. [76], and Prastiyo et al. [77], who report that manufacturing value added increases CO_2 emissions and deteriorates environmental quality. The difference in results may reflect Indonesia's recent shift toward cleaner industrial practices, stricter environmental regulations, and increased adoption of energy-efficient technologies, particularly in export-oriented and large-scale manufacturing sectors. Over the long run, these structural and technological adjustments appear to have offset the emission-increasing effects traditionally associated with manufacturing expansion, leading to an overall reduction in CO_2 emissions.

The empirical findings can also be interpreted in relation to the GSM proposed by Brock and Taylor [50], which emphasizes the role of technological progress in mitigating the environmental pressures associated with economic growth. Consistent with this broader theoretical perspective, the negative long-run relationship between geothermal installed capacity and CO_2 emissions, contrasted with the positive effects of coal and oil consumption, suggests that the composition of energy sources plays an important role in environmental outcomes. The stronger emission-reducing association of geothermal energy at higher emission quantiles further highlights the potential relevance of cleaner energy deployment under high-emission conditions. Moreover, the negative long-run coefficients of FDI and manufacturing value added are consistent with potential improvements in production efficiency and technological development, although these mechanisms are not directly measured. Meanwhile, the positive relationship between GDP per capita and emissions across quantiles indicates that economic growth may continue to exert environmental pressures. Taken together, these findings are broadly consistent with the GSM perspective that environmental improvement alongside economic development requires mechanisms that reduce pollution intensity, although the present analysis does not constitute a direct empirical test of the model.

Overall, Figure 5 supports the discussion by clearly depicting the direction and magnitude of the ARDL results, thereby confirming the consistency and robustness of the estimated relationships.

6. Conclusion, Limitations and Future Research

In this study, we investigated the dynamic impact of geothermal energy, coal, oil, and gas on CO_2 emissions in Indonesia from 1990 to 2024. By employing robust econometric methodologies, including ARDL and BQR, complemented by FMOLS, CCR and DOLS as robustness checks, we uncovered significant findings regarding the environmental consequences of energy consumption patterns. Our results highlight the crucial role of geothermal energy in reducing CO_2 emissions and improving environmental quality in Indonesia, as evidenced by its long-term negative coefficient impact on emissions. In contrast, the persistent positive coefficients associated with coal and oil consumption underscore the detrimental effects of reliance on non-renewable energy sources on environmental quality.

Based on these findings, we strongly recommend that policymakers prioritize the expansion of geothermal energy infrastructure as a key component of Indonesia's environmental sustainability strategy. This involves creating incentives for private investment in geothermal projects, promoting technological advancements in geothermal energy production, and gradually reducing dependence on environmentally harmful non-renewable energy sources. Additionally, policies should be designed to encourage energy efficiency measures and support sustainable development practices across various economic sectors.

Although our study provides valuable insights, it is important to acknowledge its limitations. The use of aggregate data may obscure regional variations, and the focus on CO_2 emissions alone does not capture other aspects of environmental impact. Furthermore, the use of interpolated quarterly data, particularly for historical geothermal installed capacity, may smooth short-term fluctuations and introduce additional uncertainty into the estimates. The study also does not explicitly account for potential structural breaks associated with major economic disruptions, such as the 1998 Asian financial crisis and the COVID-19 pandemic in 2020, which may affect the estimated relationships over the study period. To address these limitations, future research should utilize more granular data, incorporate observed quarterly data where available, account for potential structural breaks, and consider a wider range of environmental indicators. Moreover, future studies could explore the socio-economic implications of transitioning to renewable energy sources, evaluate the effectiveness of government policies in promoting renewable energy adoption, and assess the environmental impact of alternative renewable energy sources such as solar and wind power. Addressing these limitations could improve the robustness of future empirical findings and provide more reliable evidence to support energy transition strategies and environmental policymaking in Indonesia.

Abbreviations:

AIC	: Akaike Information Criterion
ARDL	: Autoregressive Distributed Lag
BP	: British Petroleum
BQR	: Bootstrap Quantile Regression
CCR	: Canonical Cointegrating Regression
CO_2	: Carbon dioxide emissions
COAL	: Coal Consumption
COVID-19	: Corona Virus Disease 2019
CUSUM	: Cumulative sum of recursive residuals
CUSUMQ	: Cumulative sum of squares of recursive residuals
DOLS	: Dynamic Ordinary Least Squares
ECM	: Error Correction Model
ECT	: Error Correction Term
FDI	: Foreign Direct Investment
FMOLS	: Fully Modified Ordinary Least Squares
FPE	: Final Prediction Error
GAS	: Gas Consumption
GDP	: Gross domestic product
GFCF	: Gross Fixed Capital Formation
GMM	: Generalized Method of Moments
GSM	: Green Solow Model
GW	: Gigawatt
HQ	: Hannan–Quinn
IEA	: International Energy Agency
IPCC	: Intergovernmental Panel on Climate Change
LF	: Labor force
LR	: Likelihood Ratio test
MANU	: Manufacturing Value Added
Max.	: Maximum
Min.	: Minimum
MMQR	: Method of Moments Quantile Regression
NDC	: Nationally Determined Contributions
Obs.	: Observation
OIL	: Oil Consumption
OLS	: Ordinary Least Squares
OWID	: Our World in Data
P-P	: Phillips-Perron
QR	: Quantile Regression
QQ	: Quantile-on-Quantile
SC	: Schwarz Criterion
TWh	: Terawatt-hour
USD	: United States dollar
WDI	: World Development Indicator

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