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Does renewable energy reduce energy intensity? A matter of income inequality

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This study investigates the complex relationships between income inequality, renewable energy utilization, and energy efficiency across 104 countries from 2010 to 2020. By employing the Panel Threshold Model and Unconditional Quantile Regression based on the Re-centered Influence Function, the analysis focuses on the moderating role of income inequality in shaping the impact of renewable energy consumption on energy intensity. The results indicate a nonlinear relationship, driven by a single-threshold effect of income inequality. In contexts with low income inequality, renewable energy consumption significantly reduces energy intensity, demonstrating its potential to enhance energy efficiency. However, as income inequality increases, this positive association weakens, suggesting that income inequality can act as a barrier to achieving energy-efficient economies. The study further highlights substantial variations across regions and income levels. In high-income economies, greater financial resources enable more widespread adoption of renewable energy, mitigating the adverse effects of income inequality on energy efficiency. By contrast, in middle-income countries, severe income disparities erode the ability of renewable energy to contribute meaningfully to reducing energy intensity. These findings suggest that by incorporating equity considerations into energy strategies, nations can strengthen the synergy between renewable energy adoption and energy efficiency, fostering progress across diverse economies.

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Introduction

With the escalating global environmental concerns, the need to curb energy intensity while promoting economic growth has emerged as a pivotal discussion point. By promoting the United Nations Sustainable Development Goals (SDGs), countries can achieve sustainable development, especially in the area of environmental sustainability (Caglar et al., 2024g). Goals 6 (Clean Water and Sanitation), 7 (Affordable and Clean Energy), and 13 (Climate Action) all emphasize the importance of environmental protection and resource management (Caglar et al., 2024i). In the face of worsening environmental degradation, the achievement of SDG targets needs to be accelerated (Caglar et al., 2024e). Governments around the world are increasingly focusing on SDGs and formulating corresponding sustainable energy policies (Caglar et al., 2024a). Policymakers globally are advocating for the amplification of renewable energy deployment as a crucial solution to these environmental challenges (Caglar et al., 2024d). However, despite robust global efforts, the correlation between the increased prevalence of renewable energy and heightened energy efficiency remains an empirical question. This situation arises amidst the complexities of globalization where the intricate interplay among macroeconomic factors poses multifaceted challenges. These challenges exert diverse influences on renewable energy intensity and sustainable development (Adebayo and Ullah, 2023; Elavarasan et al., 2023; Rahman et al., 2022).

In this complex landscape, income inequality has emerged as a significant factor that correlates with energy efficiency and creates asymmetry in the promotion of renewable energy consumption. This fact underscores the necessity for a comprehensive reassessment and exploration of the strategies to optimize energy intensity while ensuring socio-economic equilibrium. To address this gap, our study aims to reassess the threshold effects of income inequality on the capacity of renewable energy consumption to correlate with reductions in energy intensity. We employ empirical analysis on balanced panel data from 104 countries over the period of 2010 to 2020. In our quest to examine the relationship between renewable energy consumption and energy intensity, we have constructed a fixed-effects panel data model. Additionally, to probe the influence of income inequality on this relationship, we established a linear interaction term model. Our analysis places particular emphasis on the nonlinear association between renewable energy consumption and energy intensity across varying income inequality levels. In this context, we use income inequality as the threshold variable and renewable energy consumption as the institutional variable. We develop a panel threshold model that identifies breakpoints for structural shifts and heterogeneity in renewable energy consumption and energy intensity within distinct income inequality intervals. Through this study, we aim to contribute to the literature by elucidating the inherent mechanism of income inequality's threshold effects on the correlation between renewable energy consumption and reductions in energy intensity. Our findings will provide valuable insights for the formulation of pertinent policies.

The rest of the paper is structured as follows: The literature review section revisits prior research on renewable energy consumption, energy intensity, and income inequality. It summarizes existing findings and scrutinizes research limitations. Following this, the data and methodology section expounds on data sources, sample selection, and the research methodologies employed for empirical analysis. Subsequently, the empirical results and discussion section unveils the findings of the analysis and provides a comprehensive interpretation and discussion. Finally, the conclusions and policy recommendations section summarizes key discoveries and proposes policy directives rooted in the research findings.

Literature review

A review of the impact of renewable energy consumption on energy intensity.

The consumption of renewable energy and energy intensity represent two pivotal components within the dialog on energy utilization and sustainability. They offer significant perspectives for comprehending the patterns of energy use and their environmental implications comprehensively. The consumption of renewable energy refers to the utilization of energy derived from resources that naturally replenish on a human timescale, encompassing sunlight, wind, rain, tides, waves, and geothermal heat (Jacobson and Delucchi, 2011). This mode of energy usage aims to mitigate the impact of conventional energy on the environment, as traditional energy sources are often finite and emit harmful pollutants during utilization (Sovacool, 2012). Conversely, energy intensity serves as a metric for gauging the energy efficiency of a nation's economy. It is calculated as units of energy per unit GDP (Gross Domestic Product). A lower figure implies a more cost-effective conversion of energy into economic output (Stern, 2004). Consequently, this metric bears substantial relevance in understanding a nation's energy usage efficiency and potential for improvements in energy conservation (Steinberger and Roberts, 2010). Overall, through the concepts of renewable energy consumption and energy intensity, we can comprehensively scrutinize energy usage and sustainability. These concepts underscore the importance of transitioning to renewable energy and enhancing energy efficiency to mitigate environmental degradation and promote sustainable development.

The interrelation between renewable energy consumption and energy intensity has been the subject of extensive investigation, encompassing various theories and models to address this mutual influence. The Energy Efficiency Hypothesis and the Jevons Paradox are two theories that have been given considerable attention. The former posits that an augmentation in renewable energy consumption could potentially result in a diminution of energy intensity is primarily attributed to the high efficiency of renewable energy systems in transforming energy into actual effectiveness (Patterson, 1996). Renewable energy technologies like wind turbines and solar panels, for instance, typically outperform traditional energy in converting energy into useful work. In a competitive industrial environment, renewable energy, due to its strong performance in energy efficiency, enhances industrial performance, thereby promoting environmental sustainability(Caglar et al., 2024c). Consequently, escalating consumption of renewable energy might lead to a decrease in energy intensity (Al-Mulali and Ozturk, 2015). However, the Jevons Paradox may counteract this effect, suggesting that enhancements in energy efficiency could inadvertently lead to an overall increment in energy consumption, thereby augmenting energy intensity. The "rebound effect" is the driving force behind this paradox that efficiency improvements reduce the cost of energy services, leading to an increase in demand (Sorrell et al., 2009). A study focusing on Russia found that although the consumption of natural resources per unit has a positive impact on environmental sustainability, the excessive consumption of natural resources harms environmental well-being (Caglar et al., 2024b). Evidence from the European Union also indicates that the consumption of renewable energy enhances environmental carrying capacity, thereby promoting improvements in environmental quality (Caglar et al., 2024h). In terms of models, the Environmental Kuznets Curve (EKC) has been utilized to analyze the relation between renewable energy consumption and energy intensity. The EKC model purports that with economic development, energy intensity will initially increase, peak, and then decline (Stern, 2004). However, the applicability of the EKC model in the

context of renewable energy consumption remains a contentious issue in academia (Fodha and Zaghdoud, 2010). In summary, the relationship between renewable energy consumption and energy intensity remains intricate and complex. To reconcile the discrepancies among various theories and gain a comprehensive understanding of the nuances of this relationship, further investigation is requisite.

The degree to which renewable energy consumption influences energy intensity is contingent upon the specific milieu. Factors such as the amalgamation of renewable energies utilized, the level of technological advancement, prevailing policy frameworks, and socioeconomic conditions play pivotal roles in determining this influence (Amri, 2017). For instance, nations possessing comprehensive renewable energy policies and advanced technologies are likely to witness a conspicuous reduction in energy intensity concomitant with the augmentation of renewable energy consumption (Popp et al., 2010). A study focusing on Turkey found that increasing investment in research and development for renewable energy significantly reduces energy intensity and promotes the low-carbon transition of the economy (Emre Caglar et al., 2024). The implementation of renewable energy policies alleviates the conflict between employment and preventing environmental degradation, which may be achieved through improved energy efficiency (Yavuz et al., 2024). Similar results have also been found in studies in European countries (Caglar et al., 2024f). Renewable energy consumption is deemed a critical determinant of energy intensity, the relationship between these variables is not only significant but intricate, mediated by numerous mechanisms and varying in degree across different environments. A primary mechanism through which renewable energy consumption influences energy intensity is via substitution for conventional energy. Studies indicate that the adoption of renewable energy technologies can curtail reliance on traditional energy sources such as coal and petroleum, thereby diminishing energy intensity (Apergis and Payne, 2010). However, the degree of this impact could vary depending on the extent of renewable energy utilization and the efficiency of the deployed renewable energy technologies. Another cardinal mechanism is through the enhancement of energy efficiency. Renewable energy technologies, particularly those associated with solar and wind energy, are typically more energy-efficient than their conventional counterparts. As such, renewable energy consumption can engender an improvement in overall energy efficiency, thereby reducing energy intensity (Bhattacharya et al., 2016). The extent of this effect could be influenced by a plethora of factors, including the type of renewable energy used and the specific conditions of the energy market. Nonetheless, it is important to note that the impact of renewable energy consumption on energy intensity could also be constrained by several other factors. For example, the level of economic development, industrial structure, and governmental policies could all play a role in shaping the relationship between these two variables (Sadorsky, 2009). Other exogenous shocks, such as natural disasters, political turmoil, war, and racial division, can also impact energy intensity. Natural disasters can damage energy infrastructure, leading to interruptions or reductions in energy supply, causing energy intensity to rise in the short term (Paudel, 2022). Natural disasters can disrupt production activities, affecting GDP and energy consumption. During the post-disaster reconstruction process, energy demand may increase sharply, temporarily raising energy intensity (Paudel, 2023). Frequent natural disasters may prompt governments and enterprises to invest in more energy-efficient and sustainable infrastructure, which could help reduce energy intensity in the long term (Chan and Delina, 2023). Political turmoil and war can lead to instability in energy supply, especially in regions rich in energy resources but politically unstable (Tol,

2023). Political turmoil may trigger drastic changes in energy consumption. For example, governments may prioritize energy security over sustainable development, affecting the long-term trend of energy intensity. Racial division may cause unjust energy consumption patterns in society (Paudel, 2021). Fluctuations in energy prices will influence energy consumption patterns and energy intensity. In sum, the consumption of renewable energy holds immense potential to lower energy intensity through the substitution of traditional energy and the enhancement of energy efficiency. However, the specific impact can vary widely based on a multitude of factors, underscoring the complexity of this relationship.

The relationship between renewable energy consumption and energy intensity exhibits a multifaceted nature, influenced by various factors, necessitating a plethora of empirical studies to elucidate the nuances of this interaction and its implications for sustainable energy policies. According to extant empirical research, the impact of renewable energy consumption on energy intensity is manifested in linear, spatial econometric, and nonlinear outcomes. In linear studies, Yu et al. (2022) ascertained that renewable energy development significantly diminishes energy intensity, with the degree of impact varying relative to the level of development. Similarly, the studies by Alola et al. (2023) and Chen et al. (2022a) also underscored the substantial contribution of energy efficiency improvement, energy intensity reduction, and expenditures on renewable energy research and development to the proliferation of renewable energy. From a spatial econometric model perspective, research by Quito et al. (2023) revealed that the utilization of renewable energy positively influences the energy efficiency of neighboring economies. Additionally, Ge et al. (2023) demonstrated that the establishment of energy intensity targets significantly influences renewable energy consumption, with this impact exhibiting heterogeneity across different regions. In nonlinear outcomes, research by Liu et al. (2022) revealed significant heterogeneity in the impact of renewable energy development on energy intensity, influenced by the level of economic development. Concurrently, Bashir et al. (2021) indicated that the implementation of environmental taxes and improvements in energy efficiency significantly influence renewable energy consumption. From a causality perspective, Shahbaz et al. (2022) discerned a bidirectional causal relationship between energy intensity and production-based CO2 emissions, per capita income and consumption-based CO2 emissions, and population size and renewable energy usage. In terms of operational mechanisms, Jin (2022) unveiled the role of heat and electricity consumption in influencing energy intensity; although they augment energy intensity, the utilization of renewable energy mitigates energy intensity by fostering new markets. However, some studies found the impact of renewable energy on energy intensity to be inconsequential, such as the analysis by Rafiq et al. (2016), which found the role of renewable energy in influencing energy intensity in emerging economies to be insignificant.

The potential impact of income inequality on the relationship between renewable energy consumption and energy intensity. As a unique concept, income inequality predominantly delineates the asymmetrical distribution of income within a community. This constitutes a socio-economic metric, principally employed to measure the disparities in the allocation of economic resources among individuals or households in an economy (Atkinson and Bourguignon, 2000). The Gini coefficient is frequently utilized in the quantification process of income inequality. The range of this indicator is from 0 to 1, signifying all possible scenarios from absolute equality, where everyone's income is identical, to

absolute inequality, where all income belongs to one person, and others have none (Gastwirth, 1972; Gini, 1921). Nonetheless, the concept of income inequality is not strictly confined to the measurement of economic disparities; it encompasses broader social implications. Income inequality is intimately linked with numerous socio-economic issues such as poverty, social mobility, economic stability, and socio-political turbulence (Stiglitz, 2015). Consequently, the impact and measurement methodologies of income inequality have become a crucial research direction within the realms of economics and social sciences.

In recent years, the intricate and multidimensional interrelations among income inequality, renewable energy consumption, and energy intensity have instigated copious scholarly investigations. Primarily, pronounced income disparity is often correlated with a lower level of public goods provision, such as the establishment and utilization of renewable energy infrastructure (Birdsall and Londono, 1997). The affluent classes are likely to have easier access to renewable energy technologies, while the impoverished classes may still rely on conventional energy sources (Ravallion, 2001). Secondly, individuals with stronger purchasing power may exhibit a greater propensity to invest in renewable energy technologies, thereby stimulating an augmentation in renewable energy consumption (Uzar, 2020; Wang et al., 2024a). However, for energy intensity, the impact of income inequality may be more indirect. High-income disparity could lead to an increase in energy consumption, particularly among the wealthy classes, due to their lifestyle choices, which may trigger higher energy intensity (York, 2007).

Under the thematic umbrella of "Renewable Energy Consumption–Energy Intensity–Income Inequality," numerous studies proffer valuable perspectives. Initially, Wang et al. (2025a) posited that the impact of renewable energy on carbon efficiency is most pronounced in nations with moderate income levels. They underscored the necessity for countries to contemplate the interplay between renewable energy consumption and income levels in their pursuit of sustainable development. Within the Pan-Third Pole area, Sun et al.'s (2021b) scrutiny discerned that the household head's educational level, non-agricultural status, and income are pivotal factors influencing stable energy usage. They highlighted that inequality is more severe in economically underdeveloped areas, and delivering commercialized energy to households can effectively mitigate energy inequality. Additionally, Bardazzi et al. (2021), in their exploration of energy poverty in Italy, identified a significant correlation between income inequality and energy poverty indicators. Regarding the impact of renewable energy consumption on income inequality, Topcu and Tugcu's (2020) investigation revealed that from 1990 to 2014, an increase in renewable energy consumption led to a reduction in income inequality. Similarly, Yang et al.'s (2022) research corroborated the existence of a bidirectional causal relationship between income inequality and renewable energy consumption. On the other hand, McGee and Greiner (2019)s study unveiled how national income inequality modulated the relationship between renewable energy consumption and per capita carbon dioxide emissions. They found a substantial decline in the consumption of renewable energy and emissions when inequality escalated. Moreover, Muhammad et al.'s (2023) research divulged that as income inequality diminishes, the utilization of renewable energy will ascend. Lastly, Tan and Uprasen (2021) scrutinized the asymmetrical influence of income inequality on renewable energy consumption. They discovered that the alleviation of income inequality fosters renewable energy consumption, but the positive impact of income inequality has a more significant effect on renewable energy consumption than the negative impact. In Upham et al.'s (2022) study, they indicated that in nations with high-income levels and low inequality, inequality issues caused by

energy transition could still potentially exist. In summary, these research endeavors illustrate the multifaceted impacts of income inequality on renewable energy consumption, providing us with beneficial vistas for a deeper understanding of this topic.

The literature review distinctly underscores that renewable energy consumption has the potential to decrease energy intensity, a notion that has been corroborated by numerous studies. However, while the influence of income inequality on renewable energy consumption is acknowledged, its exact impact remains ambiguous. Specifically, no existing research has yet investigated the threshold effect of income inequality on the capacity of renewable energy consumption to reduce energy intensity. Moreover, despite the emphasis placed on policy intervention in addressing income inequality in the literature, it remains unclear how redistributive policies can positively mitigate the adverse impact of income inequality on the reduction of energy intensity through renewable energy consumption. Similarly, the literature acknowledges the heterogeneity of income and regional groups on research outcomes, yet the manner in which such heterogeneity affects the effectiveness of renewable energy consumption in reducing energy intensity and whether a threshold effect exists constitutes an ongoing research gap. Consequently, the potential contribution of this paper lies in its empirical analysis on a global scale, investigating the threshold effect of income inequality on the reduction of energy intensity through renewable energy consumption, and elucidating the indirect impact of income inequality and the role of redistributive policies. This paper will delve into the impact of heterogeneity in income and regional groups on energy intensity, as well as the asymmetry of energy intensity. These potential contributions offer significant policy recommendations for addressing income inequality, promoting renewable energy consumption, and reducing energy intensity, and provide a fresh perspective in understanding the formation mechanism of energy intensity.

Data and methods

Data and preliminary analysis. The theoretical foundation of this study primarily derives from literature related to energy economics and development economics. According to existing research, factors such as per capita GDP, foreign direct investment, industrial structure, energy prices, urbanization level, and population density are widely regarded as significant influencers of energy intensity (Li et al., 2022b; Su et al., 2022). These theoretical frameworks provide us with the basis for selecting research variables and constructing models. In particular, energy intensity, as a measure of energy efficiency, is influenced by multiple factors including the level of economic development, the transformation of industrial structures, and the process of urbanization (Li et al., 2022a). The selection of the sample dataset is based on an understanding of the theoretical foundation and the guidance of existing literature. We chose representative countries as samples to ensure the universality and representativeness of the research results. The data used in this study encompasses balanced panel data from 104 countries worldwide, spanning the decade from 2010 to 2020. A comprehensive list of the countries included can be found in Table A6 in the appendix. Energy intensity, a measure of energy consumption relative to output, serves as a gauge of energy efficiency across various economies and reveals the degree of reliance on energy in their economic development (Ang and Goh, 2018). Harnessing renewable energy is a significant strategy to enhance energy efficiency and diminish dependency on conventional fossil fuels. Moreover, it aids in mitigating environmental pollution and greenhouse gas emissions (Liu et al., 2023).

Income disparity represents the extent of income inequality within a country or region. To facilitate a global analysis and

comparison of income disparity, this study employs the Gini index from the Standardized World Income Inequality Database (SWIID), compiled by Solt (2020). The Gini index, ranging from 0 to 100, indicates the level of income inequality—the higher the value, the greater the inequality, and vice versa. SWIID provides high-quality comparable data, widely utilized in inequality research.

In addition to these core indicators, per capita GDP, foreign direct investment (Doytch and Narayan, 2016), industrial structure (Chen et al., 2022b), energy prices (Chen et al., 2023), urbanization level, and population density (Rafiq et al., 2016) were selected as control variables to account for other potentially influential factors on energy intensity. Incorporating these indicators, commonly employed in the empirical literature, into the model aids in circumventing potential omitted variable bias. Energy intensity may be influenced by more exogenous shocks beyond those considered in this article. Exogenous shock variables such as natural disasters, political turmoil, technological innovations, global economic fluctuations, and environmental policies can all have a significant impact on energy intensity. However, considering that these variables are not the focus of this study, adding too many exogenous shock variables when constructing the regression model may lead to an overly complex model, increasing multicollinearity issues and identification difficulties, thereby reducing the explanatory power and pre-dictive power of the model. In the existing literature, the roles of these factors are relatively indirect and uncertain, and data availability is limited. Therefore, we choose to focus on the main influencing factors to ensure the simplicity of the model and the reliability of the results. While this approach ensures the accuracy of the study's findings, it also brings limitations. Future research can further explore the specific impacts of these exogenous shock factors to supplement and expand the findings of this study. Besides the Gini index, data for all other indicators were sourced from the World Development Indicators (WDI) of the World Bank. For individuals with partially missing values, an imputation method was employed. The selection and processing of the data strictly followed the guidance of relevant theories and literature to ensure the reliability and validity of the data. During the data processing phase, we cleaned and treated the raw data. First, we removed observations with more than 2 missing values. Subsequently, for individuals that still had some missing values, we used linear interpolation to handle them. To reduce the potential impact of outliers and to meet the assumptions of the statistical models, we logarithmically transformed variables such as energy intensity, renewable energy consumption, Gini index, per capita GDP, foreign direct investment, industrial structure, and population density. These treatments help to ensure the accuracy of data analysis and the credibility of the results. Table 1 provides descriptions of each variable and their data sources.

Table 2 enumerates the descriptive statistical outcomes for each variable. lnEI possesses an average value of 1.395, with the minimum and maximum values being 0.199 and 2.845, respectively. lnRNEW, on the other hand, has an average value of 2.875, with a minimum and maximum value of −4.605 and 4.544, respectively. The mean value of lngini_disp is 3.598, with extreme values being 3.011 and 4.160. Figure 1 provides a visual representation of the numerical disparity between the 2020 lnEI, lnRNEW, and lngini_disp for various nations. This is congruent with the findings from the descriptive statistics, highlighting significant differences in lnEI and lnRNEW across nations. Although the disparity in lngini_disp is less than that of lnEI and lnRNEW, it remains significant. Descriptive analysis results indicate noteworthy differ-ences between variables across nations, suggesting that the data sample represents the population more comprehensively. The scattered data can more effectively reveal the variance among variables, averting potential bias and enabling more precise estimation and forecasting, thus enhancing the reliability and generalizability of the results. Figure 2 visually depicts the

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Table 1 Variables description.

Variables	Description	Source
lngini_disp	Inequality in disposable (post-tax, post-transfer) income	Standardized World Income Inequality Database (https://fsolt.org/swiid/)
lngini_mkt	Inequality in market (pre-tax, pre-transfer) income	
lnEI	Energy intensity level of primary energy (MJ/$2017 PPP GDP)	World Bank (http://data.worldbank.org/indicator)
lnRNEW	Renewable energy consumption (% of total final energy consumption)	
lnpgdp	GDP per capita, PPP (constant 2017 international $)	
lnfdi	Foreign direct investment, net inflows (% of GDP)	
urb	Urban population (% of total population)	
lnIS	Industry (including construction), value added (% of GDP)	
pri	Pump price for gasoline (US$ per liter)	
lnden	Population density (people per sq. Km of land area)	

Table 2 Descriptive statistics of variables.

|	N	Mean	SD	Min.	Max.	Median	Skew.	Kurtosis
lnEI	1144	1.395	0.461	0.199	2.845	1.366	0.249	3.158
lnRNEW	1144	2.875	1.424	−4.605	4.544	3.194	−2.190	10.343
lngini_disp	1144	3.598	0.217	3.100	4.160	3.618	0.042	2.516
lngini_mkt	1144	3.818	0.141	3.450	4.278	3.842	−0.075	3.759
lnpgdp	1144	9.625	1.101	6.918	11.664	9.784	−0.538	2.399
lnfdi	1144	1.036	1.409	−6.394	9.752	1.049	−0.040	7.680
urb	1144	63.376	21.374	16.208	100.000	67.340	−0.410	2.246
lnIS	1144	3.215	0.358	1.488	4.146	3.232	−0.937	5.745
pri	1144	1.062	0.535	−0.560	2.540	1.057	0.019	2.609
lnden	1144	4.284	1.455	0.551	8.983	4.428	0.146	4.150
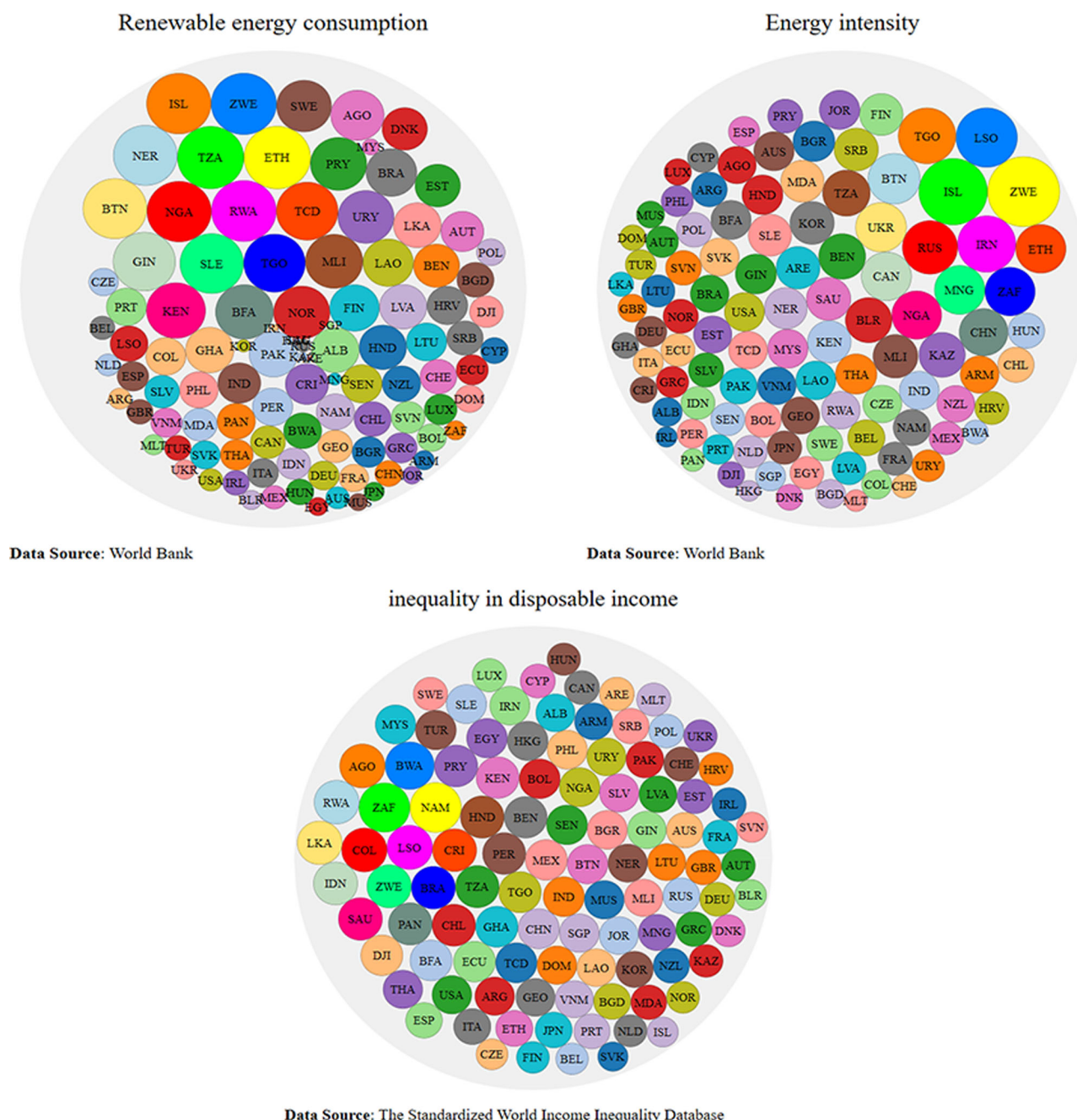
Fig. 1 Comparison of the differences in renewable energy consumption, energy intensity, and income inequality levels in the sample countries for the year 2020 (reflected in the relative size of the bubbles). The country names are represented by the Alpha-3 codes of ISO 3166-1. Figure 1 indicates that there are significant differences in lnEI, lnRNEW, and lngini_disp among various countries.

correlation between the variables in this paper. lnRNEW and lnIS are significantly positively correlated with lnEI, with correlation coefficients of 0.063 and 0.186 respectively. lnpgdp, lnfdi, urb, pri, and lnden are significantly negatively correlated with lnEI, with correlation coefficients ranging between −0.388 and −0.127. The correlation between lngini_disp and lnEI is not significant, while lngini_disp and lnRNEW exhibit a significant correlation, with a correlation coefficient of 0.154. Preliminary results from the correlation analysis suggest that income inequality may indirectly impact energy intensity by affecting the level of renewable energy consumption. Although we have a preliminary and seemingly reasonable hypothesis, further empirical testing is necessary through more in-depth econometric model analysis.

Model construction. This investigation aims to explore the impact of renewable energy consumption on energy intensity, and the potential moderating role of income inequality therein. Since per capita GDP, one of the right-hand side control variables, is also a component of the left-hand side dependent variable, this could lead to endogeneity issues and biased estimation results in the regression analysis. Therefore, following the approach of existing literature(Wang et al., 2024b; Wang et al., 2024c), this paper first constructs a baseline model using only fixed effects (Eq. 1) and performs a regression on the baseline model, with renewable energy consumption as the explanatory variable and energy intensity as the dependent variable. This approach avoids the direct issue of having GDP simultaneously
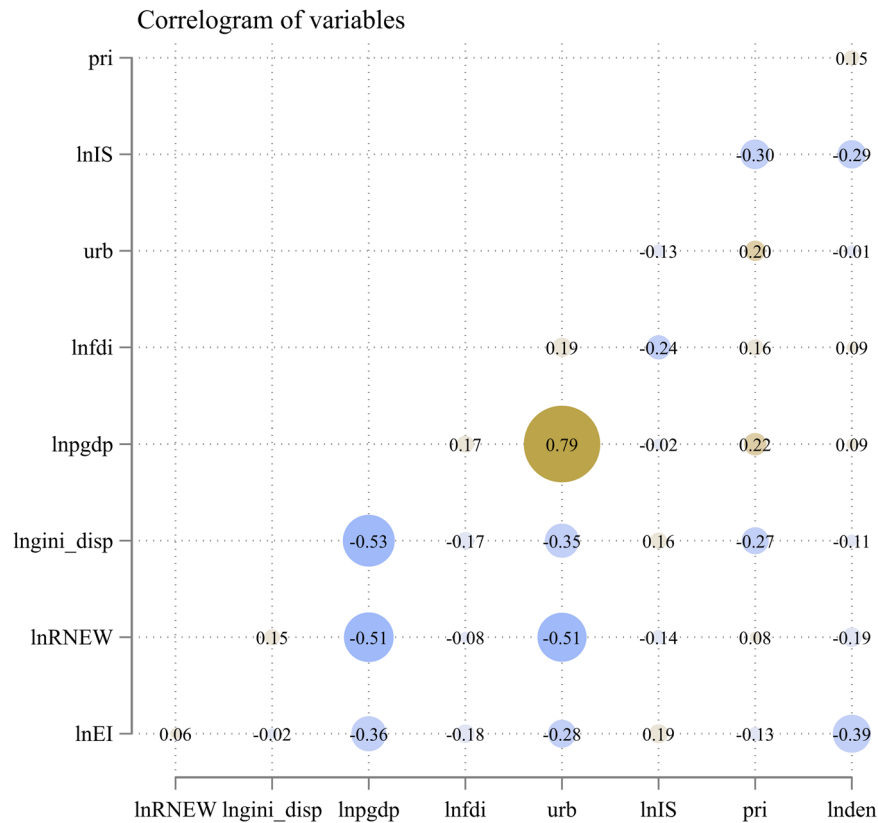
Fig. 2 Diagram showing the correlation coefficients between variables. The correlation coefficient data are sourced from Table A.1.

appear in both the dependent and explanatory variables. In this way, we initially establish the relationship between renewable energy consumption and energy intensity, without involving per capita GDP, thereby avoiding direct endogeneity problems. Subsequently, we gradually introduce control variables into the baseline model to construct Eq. 2, incrementally controlling for other factors that may affect energy intensity. This method helps us verify the robustness of the baseline results.

$$\ln EI_{it} = \alpha_0 + \alpha_1 X_{it} + \lambda_t + \mu_i + \varepsilon_{it} \qquad (1)$$

$$\begin{aligned} \ln EI_{it} = {} & \alpha_0 + \alpha_1 X_{it} + \alpha_2 lnpgdp_{it} \\ & + \alpha_3 lnfdi_{it} + \alpha_4 urb_{it} + \alpha_5 \ln IS_{it} + \alpha_6 pri_{it} \\ & + \alpha_7 lnden_{it} + \lambda_t + \mu_i + \varepsilon_{it} \end{aligned} \qquad (2)$$

Herein, $\ln EI_{it}$ denotes the logarithm of energy intensity for country i in year t, with similar interpretations for other variables. X represents the primary explanatory variable, signifying the logarithm of renewable energy consumption or the first-order lag of the logarithm of renewable energy consumption. $\alpha_1 - \alpha_7$ symbolize the coefficients of each variable, α_0 signifies the intercept term, whereas λ_t and μ_i respectively represent time-fixed effects and country-fixed effects, employed to absorb heterogeneity that does not vary with time or individuals, ε_{it} denotes the random disturbance term. The utilization of renewable energy typically possesses a higher energy conversion efficiency. Compared to traditional energy sources such as coal and oil, renewable energy has a lower energy intensity. Increasing renewable energy consumption might enhance the overall energy utilization efficiency and reduce energy intensity. Hence, we anticipate that the coefficient α_1 in Eqs. 1 and 2 is less than 0.

For the purpose of investigating the impact of income inequality on the relationship between renewable energy consumption and energy intensity, following existing research

(Wang et al., 2025b), we subsequently established a linear interaction term model (Eq. 3):

$$\begin{aligned} \ln EI_{it} = {} & \alpha_0 + \alpha_1 X_{it} + \beta_1 X_{it} \cdot lngini\_disp_{it} \\ & + \alpha_2 lngini\_disp_{it} + \alpha_3 lnpgdp_{it} + \alpha_4 lnfdi_{it} \& + \alpha_5 urb_{it} \\ & + \alpha_6 \ln IS_{it} + \alpha_7 pri_{it} + \alpha_8 lnden_{it} + \lambda_t + \mu_i + \varepsilon_{it} \end{aligned}$$

$$(3)$$

Wherein, X denotes the logarithm of renewable energy consumption or the first-order lag of the logarithm of renewable energy consumption. β_1 signifies the interaction term coefficient between X_{it} and $lngini disp_{it}$. To alleviate the potential multicollinearity between main effects and interaction terms that may destabilize the model, and to facilitate the interpretation and understanding of the coefficients, we have centralized $lngini disp$. In Eq. 3, α_1 can be interpreted as the main effect of X on lnEI, and the meaning of β_1 can be understood as the marginal effect of X on lnEI at different levels of $lngini disp$. The meanings of other symbols in Eq. 3 are the same as in Eq. 2. Income inequality exhibits extensive negative externalities. Disparities in income may lead to inequalities in energy policies and energy consumption, thereby offsetting the effect of renewable energy in reducing energy intensity. As the level of income inequality rises, the marginal effect of renewable energy consumption on income inequality diminishes and may even reverse. Therefore, in Eq. 3, we expect the coefficients of α_1 and β_1 to be opposite, with $\alpha_1 < 0$ and $\beta_1 > 0$.

The primary focus of this article is the nonlinear relationship between renewable energy consumption and energy intensity under varying levels of income inequality. To pinpoint the turning points of structural mutation, and the heterogeneity of renewable energy consumption and energy intensity within different income inequality segments, this paper utilizes the

method proposed by (Hansen, 1999), adopting *lnginidisp* as the threshold variable and lnRNEW as the institutional variable, to construct a panel threshold model (Eqs. 4,5):

$$
\begin{aligned}
\ln EI_{it} = {} & \alpha_0 + \beta_1 \ln RNEW_{it} \cdot \mathbf{1}\left(lngini\_disp_{it} \leq \gamma\right) \\
& + \beta_2 \ln RNEW_{it} \cdot \mathbf{1}\left(lngini\_disp_{it} > \gamma\right) \\
& + \alpha_i Z_{it} + \mu_i + \varepsilon_{it}
\end{aligned}
\tag{4}
$$

$$
\begin{aligned}
\ln EI_{it} = {} & \alpha_0 + \beta_1 \ln RNEW_{it} \cdot \mathbf{1}\left(lngini\_disp_{it} \leq \gamma\right) \\
& + \beta_2 \ln RNEW_{it} \cdot \mathbf{1}\left(lngini\_disp_{it} > \gamma\right) \\
& + \alpha_i Z_{it} + \lambda_t + \mu_i + \varepsilon_{it}
\end{aligned}
\tag{5}
$$

In Eqs. 4 and 5, γ denotes the threshold value, intrinsically determined within the model. $\mathbf{1}(\cdot)$ represents the indicator function, which returns a value of 1 when the condition within its brackets is true, otherwise, it returns a value of 0. By determining the threshold value endogenously and dividing the threshold interval through the indicator function, Eqs. 4 and 5 can effectively capture the heterogeneity in the impact of renewable energy consumption on energy intensity at different levels of income inequality. β_1 and β_2, respectively, signify the marginal effects of lnRNEW on lnEI within distinct income inequality intervals. Z_{it} denotes the control variables in Eq. 3, excluding X_{it} and interaction terms, while α_i represents the coefficients of each control variable and the rest of the symbols share the same meanings as in Eq. 3. Income inequality might suppress or even counterbalance the role of renewable energy consumption in reducing energy intensity, hence we anticipate that, in Eqs. 4 and 5, $\beta_1 < \beta_2$. In higher income inequality intervals, the effect of renewable energy consumption in reducing energy intensity is expected to be less than the effect in lower income inequality intervals.

Methods. The Panel Threshold Model is widely acknowledged as one of the optimal methodologies for modeling nonlinear relationships. When conducting regression analysis on the correlation between renewable energy consumption and energy intensity, it is imperative to ascertain the stability of the estimated coefficients for renewable energy consumption. However, the relationship between renewable energy consumption and energy intensity may be subject to structural changes caused by other factors. Utilizing conventional regression methods necessitates pinpointing these structural breakpoints, followed by segmented regression. If one were to employ conventional methods for estimating nonlinear relationships, such as introducing quadratic terms, indicator variables, or interaction terms into the regression, it could potentially precipitate multicollinearity issues and possibly result in biased estimates. In contrast, the Panel Threshold Model is adept at addressing these issues more effectively. Additionally, the Panel Threshold Model is exceptionally suited for investigating groups segmented by intrinsic factors. In this study, we hypothesize that income inequality inherently influences the relationship between renewable energy consumption and energy intensity, thereby segmenting their relationship into distinct intervals. The Panel Threshold Model, through threshold variables, segregates the sample into one or numerous threshold intervals, rendering the method of interval segmentation more rational than subjectively determining threshold intervals.

The article by Hansen (1996) introduced the estimation and testing methods for Time Series Threshold Autoregressive Model (TAR). For the first time, Hansen (1999) proposed the econometric analysis method for a panel threshold model with individual effects. This method determines the threshold value by minimizing the sum of residual squares and tests its significance, successfully overcoming the bias of subjectively setting structural breakpoints.

Following the ideas of Hansen (1999), income inequality was initially selected as the threshold variable. Subsequently, based on the discovered threshold value, the regression model was segmented into multiple intervals, with each interval's regression equation potentially differing. Thereafter, the other sample values were categorized according to the threshold-divided intervals. Ultimately, variations in coefficients across different intervals were compared through regression analysis.

In order to decipher Eqs. 4 and 5, we initially eliminate individual fixed effects by subtracting the time-averaged equation, adopting the panel threshold model econometric analysis methods expounded in Hansen (2000) and Hansen and Caner (2004). Subsequently, we estimate coefficients utilizing the Ordinary Least Squares (OLS) method. Given the limited sample size, we employ bootstrapping to repeatedly extract samples, thus enhancing the significance of the threshold effect and testing efficiency.

Consider the basic form of the panel threshold model (Eq. 6):

$$
y_{it} = \mu_i + \boldsymbol{\beta}_1' \mathbf{x}_{it} \cdot \mathbf{1}\left(q_{it} \leq \gamma\right) + \boldsymbol{\beta}_2' \mathbf{x}_{it} \cdot \mathbf{1}\left(q_{it} > \gamma\right) + \varepsilon_{it}
\tag{6}
$$

Herewith, y_{it} stands as the dependent variable, $\mathbf{x}_{it}$ signifies the explanatory variable affected by the threshold variable, q_{it} denotes the threshold variable, γ is the threshold value, μ_i is the intercept term indicating individual effects, and ε_{it} is the error term unrelated to $\mathbf{x}_{it}$.

In Eq. 6, we initially ascertain the estimated threshold by minimizing the sum of squared residuals, followed by examining the threshold effect via a likelihood ratio test. Precisely, given a certain threshold value γ, Eq. 6 is transformed into a linear model, with the coefficients consistently estimated via the Ordinary Least Squares (OLS) method obtaining $\hat{\beta}(\gamma)$ and the sum of squared residuals $S_1(\gamma) = \hat{\mathbf{e}}^*(\gamma)' \hat{\mathbf{e}}^*(\gamma)$. Minimizing the sum of squared residuals leads to the estimated threshold value $\hat{\gamma} = \min_\gamma S_1(\gamma)$, along with the estimated coefficients $\hat{\beta} = \hat{\beta}(\hat{\gamma})$. After estimating the threshold value, we need to test the threshold effect, where the null hypothesis is the absence of a threshold effect ($\beta_1 = \beta_2$), Eq. 6 is then converted into a simple linear model. Adopting the Ordinary Least Squares method for estimation, we obtain the sum of squared residuals S_0, then construct the likelihood ratio statistic $F_1 = \frac{S_0 - S_1(\hat{\gamma})}{S_1(\hat{\gamma})/n(T-1)}$ to test the threshold effect, and construct empirical *p*-values using the bootstrap method. Once the threshold effect is ascertained, we utilize the likelihood ratio test statistic proposed by Hansen (1999) to determine the confidence interval of the threshold value. The asymptotic distribution of this statistic satisfies $\mathrm{LR}_1(\gamma) \xrightarrow{d} \xi(n \to \infty)$, where $p(\xi \leq x) = \left(1 - e^{-x/2}\right)^2$. By constructing the inverse function $f(\alpha) = -2\ln\left(1 - \sqrt{1-\alpha}\right)$ of $p(\xi \leq x)$, we can obtain the confidence interval of γ at the significance level α. This comprehensive method provides important theoretical tools for our research.

Empirical analysis and discussion

Results of the preliminary econometric tests. Prior to analyzing the impact of income inequality on energy intensity in the consumption of renewable energy, we initially scrutinize the multicollinearity among the explanatory variables. Multicollinearity refers to the correlation among the explanatory variables in the linear regression model, which can result in inaccurate estimation outcomes. Appendix A.1 enumerates the correlation coefficients and the Variance Inflation Factors (VIF) between each variable. The correlation coefficients among each variable are predominantly below 0.5, with the VIF ranging between 1.11 and 3.83. All values of 1/VIF are less than 1, indicating that there is no

substantial multicollinearity among the variables, hence it will not influence the results of parameter estimation.

The initial step in the estimation of linear models and non-linear panel threshold models is to ascertain the stationarity of panel data. If non-stationary data are employed in the modeling of panel fixed effects and panel threshold models, it might lead to spurious regression phenomena. Unit root tests are a prevalent method for assessing panel data stationarity. To apply panel threshold models, each variable should be I(0) or I(1). Depending on whether a contemporaneous cross-sectional correlation exists in panel data, it can be divided into first and second-generation panel unit root tests. The second generation panel unit root test considers the situation of contemporaneous cross-sectional correlation based on the first generation. We initially conducted the CD test (Pesaran, 2004), and the results in Table 3 unanimously reject the null hypothesis of no cross-sectional correlation, indicating the presence of contemporaneous cross-sectional correlation in our data. To mitigate the impact of cross-sectional correlation on the validity of the first-generation panel unit root test, we centralized each variable to alleviate cross-sectional correlation, followed by IPS (Im et al., 2003) and llc (Levin et al., 2002) unit tests. To verify the robustness of the results, we also employed a second-generation panel unit root test method, namely the Breitung test (Breitung and Das, 2005). The results of all three panel unit root tests under the conditions of trend term (Table 4.) and intercept term (Table A.2) suggest that all variables are stationary at their own level or at the first difference level. In this scenario, we can continue the analysis of linear models and panel threshold models.

Model results

Linear interaction term model estimation. The preliminary analysis suggests a negative correlation between renewable energy consumption and energy intensity, with income inequality possibly exerting an indirect influence on this relationship. To substantiate this further, we initially established two linear models to explore the general relations among renewable energy consumption, energy intensity, and income inequality. Column (1) of Table 5 shows the regression results of the baseline model. The regression results of the baseline model indicate that the coefficient of lnRNEW is −0.091, which is significant at the 1% confidence level. This implies that renewable energy consumption reduces energy intensity. Column (2) in Table 5 exhibits the outcome of the panel fixed effects model, which scrutinizes the impact of renewable energy consumption on energy intensity. The coefficient of lnRNEW is −0.127, significant at the 1% level, indicating that with every 1% increase in renewable energy consumption, energy intensity reduces by 0.127%. This finding corroborates the preliminary analysis and aligns with Keynesian economic theory, suggesting that increases in renewable energy consumption foster technological innovation and development, hence enhancing energy efficiency (Huang et al., 2022). Concurrently, numerous theoretical studies reveal that utilizing renewable energy can curtail the energy required per unit of output, attributable to the lower energy used in their supply process and the relatively reduced heat generated by their combustion (Acquaye and Duffy, 2010).

Nevertheless, rudimentary linear regression is incapable of dissecting the disparities in renewable energy consumption's impact on energy intensity under varying levels of income inequality. Consequently, we further incorporated income inequality variables and the interaction between income inequality and renewable energy consumption. Column (3) in Table 5 presents the results of the interaction model, with coefficients of −0.081 and −0.322 for lnRNEW and *lnginidisp*, respectively, both significantly at the 1% level. The coefficient of *lnginidisp* denotes the primary effect of income inequality level on energy intensity; when income inequality is at the mean level, a 1% increase in the level of income inequality results in a 0.322% reduction in energy intensity. In the interaction model, our focus is primarily on the interaction term, that is, the significance of the marginal effect. The coefficient of lnRNEW · *lnginidisp* is positively significant at the 1% level, more precisely, for each 1% increase in the level of income inequality, the impact of renewable energy consumption on reducing energy intensity decreases by 0.084%. The results of the interaction model indicate that the effect of renewable energy consumption on reducing energy intensity varies with changes in the level of income inequality, and income inequality influences energy intensity through both direct and indirect routes.

To more precisely investigate the marginal impact of renewable energy consumption on energy intensity under various levels of

Table 3 Cross-sectional correlation test.					
Variable	CD-test	*p*-value	Average joint T	mean ρ	mean abs (ρ)
lnEI	92.980	0.000	11.00	0.38	0.64
lnRNEW	7.918	0.000	11.00	0.03	0.57
lngini disp	21.610	0.000	11.00	0.09	0.67
lnpgdp	136.200	0.000	11.00	0.56	0.72
lnfdi	4.923	0.000	11.00	0.02	0.34
urb	164.400	0.000	11.00	0.68	0.92
lnIS	33.160	0.000	11.00	0.14	0.50
pri	177.300	0.000	11.00	0.73	0.95
lnden	108.500	0.000	11.00	0.45	0.92

Table 4 Unit root test (trend term case).						
Variables	**IPS**		**llc**		**Breitung**	
	Level	**First Diff.**	**Level**	**First Diff.**	**Level**	**First Diff.**
lnEI	−2.888[a]	-	−19.554[a]	-	−0.765	−5.167[a]
lnRNEW	−2.477[a]	-	−8.311[a]	-	−1.299[c]	
lngini_disp	−34.164[a]	-	−61.010[a]	-	−5.732[a]	-
lnpgdp	−12.999[a]	-	−37.542[a]	-	−4.661[a]	-
lnfdi	−24.532[a]	-	−51.716[a]	-	2.462	−4.617[a]
urb	−51.932[a]	-	−61.888[a]	-	−13.403[a]	-
lnIS	−21.406[a]	-	−49.436[a]	-	−0.799	−3.001[a]
pri	−6.971[a]	-	−79000.000[a]	-	−15.633[a]	-
lnden	−40.645[a]	-	−40.685[a]	-	−9.508[a]	-

[a]Value at 1% significance level.
[c]Value at 10% significance level.

Table 5 Regression results of fixed effects model and interaction term model.

	(1) FE_BASE	(2) FE_lag_BASE	(3) FE_1	(4) FE_2	(5) FE_lag_1	(6) FE_lag_2
lnRNEW	−0.091*** (−4.58)		−0.127*** (−6.60)	−0.081*** (−4.32)		
L.lnRNEW		−0.086*** (−3.87)			−0.110*** (−5.33)	−0.066*** (−3.35)
lngini_disp				−0.322*** (−6.94)		−0.280*** (−5.06)
lnRNEW#lngini_disp				0.084*** (5.81)		
L.lnRNEW# lngini_disp						0.081*** (4.60)
lnpgdp			−0.446*** (−8.96)	−0.451*** (−9.22)	−0.452*** (−8.08)	−0.448*** (−8.10)
lnfdi			0.005 (1.58)	0.005 (1.52)	0.004 (1.23)	0.004 (1.20)
urb			0.005* (1.70)	0.004* (1.66)	0.004 (1.38)	0.004 (1.42)
lnIS			−0.103*** (−4.30)	−0.109*** (−4.62)	−0.082*** (−3.25)	−0.091*** (−3.70)
pri			0.037** (2.46)	0.018 (1.18)	0.032** (2.04)	0.016 (1.05)
lnden			−0.097 (−1.30)	−0.040 (−0.58)	−0.118 (−1.36)	−0.058 (−0.72)
_cons	1.523*** (15.71)	1.498*** (14.16)	5.956*** (10.85)	5.679*** (10.40)	5.938*** (9.42)	5.537*** (8.77)
Country_FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1144	1040	1144	1144	1040	1040
Adj. R-sq	0.970	0.972	0.976	0.977	0.977	0.978

Notes: *t*-statistics in parentheses *$p < 0.1$; ** $p < 0.05$; ***$p < 0.01$.
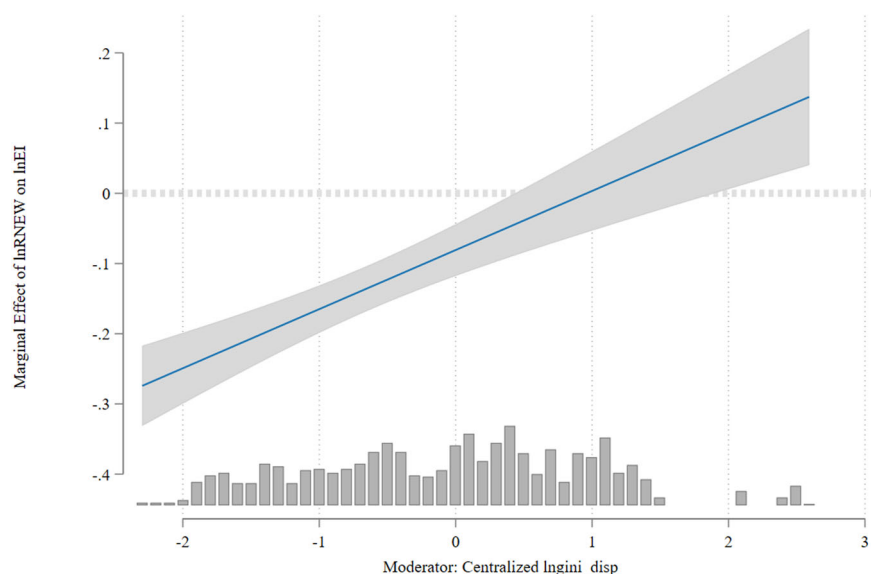
Fig. 3 Marginal effect of lnRNEW on lnEI. As the level of income inequality increases, the marginal effect of lnRNEW on lnEI gradually changes from a negative value to a positive value.

income inequality, we visually demonstrate the marginal effects of renewable energy consumption on energy intensity, drawing inspiration from the research of Hainmueller et al. (2019). Figure 3 reveals that as the level of income inequality escalates, the marginal effect of lnRNEW on lnEI successively shifts from a negative value towards zero. When income inequality enters a higher bracket, the marginal effect of lnRNEW on lnEI may even turn positive.

Considering potential endogeneity issues, we re-estimate Model 1 and Model 2 using the first lag of lnRNEW. The results are presented in columns (4),(5), and (6) of Table 5, with the marginal effects of the first lag of lnRNEW on lnEI depicted in Fig. 4. The results using lnRNEW and the first-order lag of lnRNEW do not show significant differences. Furthermore, the results of the regression with control variables are consistent with the results of the baseline model regression, indicating that the
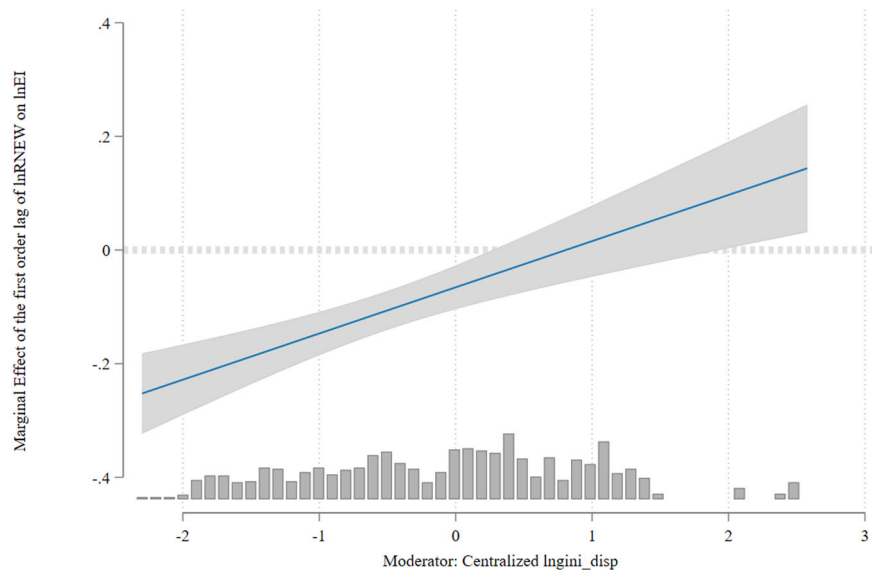
Fig. 4 Marginal effect of L.lnRNEW on lnEI. There are no significant differences between the results using the L.lnRNEW and the results estimated using lnRNEW.

Table 6 Results of the threshold effect test.									
	H0	**H1**	**RSS**	**MSE**	**Fstat**	**Prob**	**Crit10**	**Crit5**	**Crit1**
lngini_disp	None	Single	4.897	0.004	91.020	0.043	67.170	76.980	205.400
	Single	Double	4.818	0.004	18.560	0.747	46.360	56.290	79.300
	Double	Triple	4.753	0.004	15.520	0.737	71.230	88.940	143.300

conclusions of this paper are not affected by the specific model settings. This demonstrates that our results are robust. Concerning the control variables, it is noteworthy that the coefficients of *lnpgdp* and lnIS are significantly negative at the 1% level in columns (1)–(6) of Table 5. This implies that economic growth and industrial structure adjustments can reduce energy intensity, a conclusion that is robust and aligns with the relationship between economic growth, industrial structure, and energy intensity. Similar conclusions were drawn in the research by Tenaw (2021).

The estimations derived from the fixed effects model of the panel and the linear interaction model suggest that the consumption of renewable energy can diminish energy intensity, a finding consistent with research outcomes by Chien et al. (2023). However, the effectiveness of renewable energy consumption in reducing energy intensity is indirectly impacted by income inequality; as income disparity escalates, the inhibitory effect of renewable energy consumption on energy intensity gradually wanes. When income inequality reaches a certain threshold, an increase in renewable energy consumption may even exacerbate energy intensity. These outcomes reveal the transmission mechanism among energy intensity, renewable energy consumption, and income inequality from a linear model perspective. Nonetheless, the presence of interaction terms may induce multicollinearity among variables, thereby affecting the accuracy of the estimation results. To circumvent potential issues, we construct a panel threshold model to continue examining the relationship among energy intensity, renewable energy consumption, and income inequality from a nonlinear perspective.

Panel threshold model estimation. To ascertain the form of the panel threshold model, it is imperative initially to establish the existence or non-existence of a threshold effect and, if present, the

number of threshold intervals into which the panel threshold model should be subdivided. Table 6 exhibits the outcomes of the threshold effect examination when three, two, and one threshold values are present, respectively. When the null hypothesis assumes at least two or one threshold values, the threshold effect test cannot be validated, at this juncture, the probability value corresponding to the test statistic exceeds 0.1, signifying the existence of a minimum of one threshold value. Continuing with the null hypothesis that there is no threshold effect and the alternative hypothesis that at least one threshold value exists, at a significance level of 5%, the null hypothesis of no threshold effect is rejected. Consequently, it can be deduced that the impact of income inequality on energy intensity with respect to renewable energy consumption exhibits a singular threshold effect.

Upon the affirmation of a single-threshold effect existence, we construct a confidence interval for the threshold value γ by constructing a likelihood ratio statistic (LR statistic). Figure 5 demonstrates how to establish a confidence interval for the threshold value γ at a 95% confidence level. The blue curve indicates the likelihood ratio statistic corresponding to the null hypothesis $\gamma = \gamma_0$ at different threshold values γ, and the horizontal dashed line represents the critical value of the likelihood ratio statistic at a 5% statistical significance level. Therefore, the horizontal coordinates where the horizontal dashed line intersects with the LR curve are the upper and lower bounds of the confidence interval for the threshold value γ at a 95% confidence level.

The endogenously determined threshold model identifies the optimal value of *lnginidisp* as 3.597, significantly so at a 95% confidence level. Based on the single threshold of income inequality, we segregate the entire sample into high and low income inequality levels. Table 7 exhibits the results estimated by the single threshold model. After controlling for country-fixed effects, the marginal effect of renewable energy consumption on energy intensity is

Notes: Country fixed effects

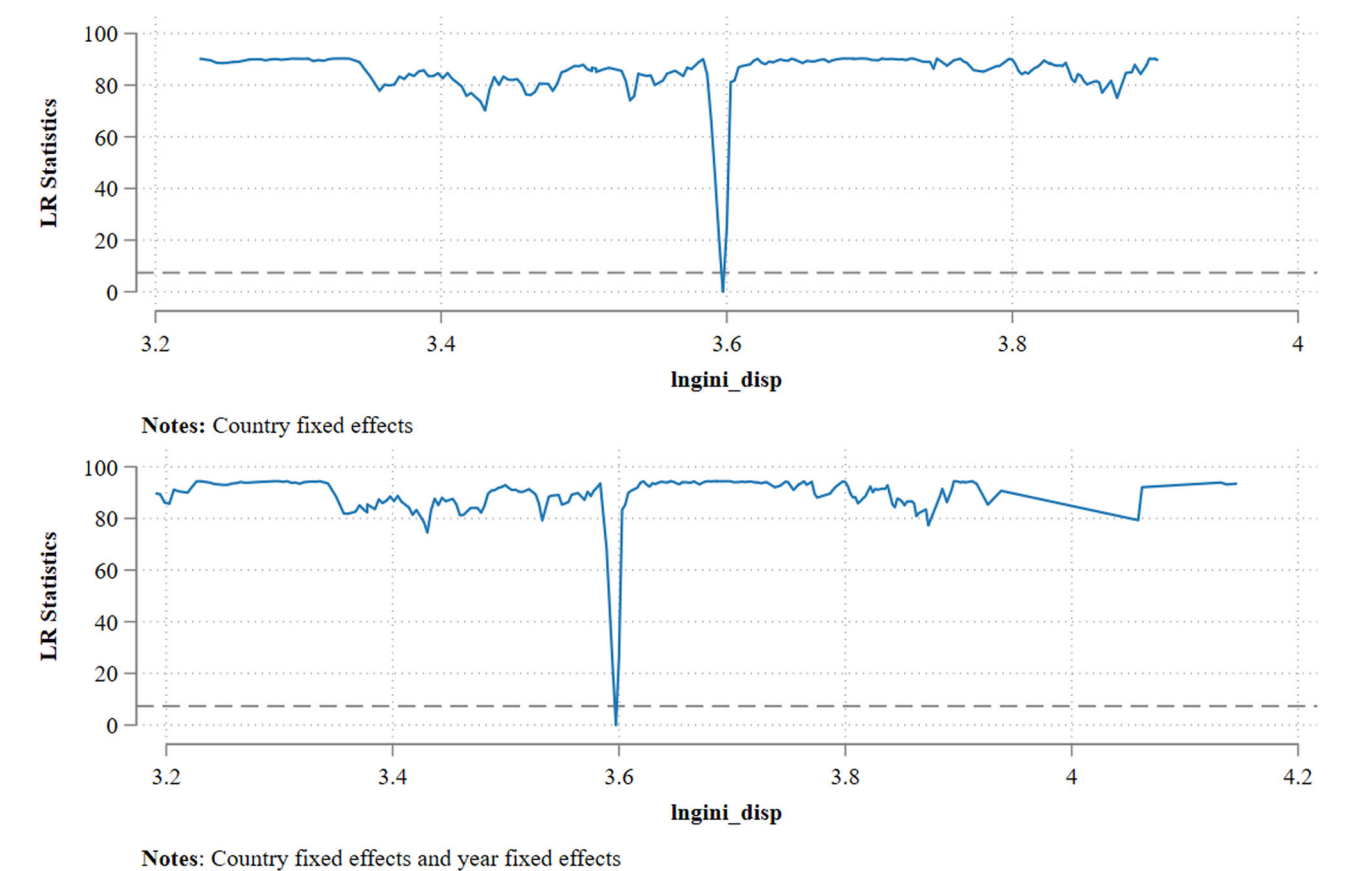**Notes:** Country fixed effects and year fixed effects

Fig. 5 Using disposable income inequality as the threshold variable, the likelihood ratio statistic for threshold value testing when the threshold value γ takes different values, and the critical value of the threshold value γ at a 5% significance level (marked with a horizontal short line). The panel threshold model endogenously determines the optimal threshold value of lngini_disp to be 3.597, and this result is significant at the 95% confidence level.

Table 7 Regression results of panel threshold model.		
	(1)	**(2)**
lnRNEW(Regime1)	−0.156***	−0.135***
	(−3.95)	(−3.31)
lnRNEW(Regime2)	−0.112***	−0.091**
	(−2.99)	(−2.22)
lngini_disp	−0.545**	−0.617***
	(−2.48)	(−2.70)
lnpgdp	−0.567***	−0.485***
	(−6.80)	(−4.94)
lnfdi	0.004	0.005
	−0.87	−0.97
urb	0.001	0.005
	−0.23	−0.86
lnIS	−0.057	−0.088*
	(−1.42)	(−1.98)
pri	0.038***	0.026
	−2.98	−0.9
lnden	−0.14	−0.01
	(−1.21)	(−0.06)
_cons	9.861***	8.643***
	−7.23	−5.34
N	1144	1144
Adj. R-sq	0.545	0.554
Threshold	3.597	3.597
Threshold C.I.	[3.595,3.600]	[3.595,3.600]
Country_FE	Yes	Yes
Year_FE	No	Yes

Notes: *t*-statistics in parentheses; *p < 0.1; **p < 0.05; ***p < 0.01.

negative, and significant at a 1% statistical level. However, the marginal effect of renewable energy consumption on energy intensity varies within two distinct income inequality intervals. In the first threshold interval corresponding to low-income inequality ($lnginidisp < 3.597$), under ceteris paribus, a 1% increase in renewable energy consumption leads to a 0.156% reduction in energy intensity. Conversely, in the second threshold interval corresponding to high-income inequality, under ceteris paribus, a 1% increase in renewable energy consumption results in a 0.112% decrease in energy intensity. Under ceteris paribus, compared to the samples in the low income inequality interval, the effect of renewable energy consumption in reducing energy intensity in the high income inequality interval decreases by 28.205%. Table 7, column (2) illustrates the results estimated by the panel single threshold model after controlling for country-fixed effects and year-fixed effects, where the marginal effects of renewable energy consumption on energy intensity are −0.135 and −0.091 in the low and high-income inequality threshold intervals, respectively, and are significant at 1% and 5% statistical thresholds. In the high-income inequality interval, the role of renewable energy in reducing energy intensity has diminished by 32.593%. This result, similar to the situation controlling only for country-fixed effects, provides preliminary evidence of the robustness of our findings. In Table 7, the coefficient of $lnginidisp$ is significantly negative, consistent with some research findings that income inequality impacts energy intensity. In societies with high-income inequality, the affluent tend to use more conventional energy, which may lead to an increase in energy intensity (Oswald et al., 2020). GDP has a significant negative impact on energy intensity, an intuitive result aligning with economic growth theory (Agovino et al., 2019). The results of the

Table 8 The number of countries in different regimes.											
Regime	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
lngini_disp < 3.597	48	48	49	49	49	48	47	47	48	49	49
lngini_disp > 3.597	56	56	55	55	55	56	57	57	56	55	55

panel threshold model validate our hypothesis, and this finding aligns with the research of Gyamfi et al. (2022) and others, demonstrating that clean energy and income reduce energy intensity, and the interaction between renewable energy and income level further diminishes energy intensity. This result also corroborates the conclusion of McGee and Greiner (2019) and others, indicating that lower levels of income inequality enhance the contribution of renewable energy consumption to reducing energy intensity. However, this finding contrasts with some existing studies, such as Rafiq et al. (2016)s research on 22 emerging economies, which did not find a significant impact of renewable energy consumption on reducing energy intensity.

The outcomes of a panel threshold regression indicate that an augmentation in the proportion of renewable energy consumption serves to mitigate energy intensity. However, these findings reflect correlation rather than causation, as all right-hand side variables, including income inequality, are endogenous. Varying levels of income disparity may instigate structural modifications to this function. Specifically, when levels of income inequality are modest, the consumption of renewable energy engenders a more pronounced effect on the reduction of energy intensity. This plausibility may be attributed to the fact that lower-income disparity signifies more individuals have access to and can utilize renewable energy, thereby diminishing overall energy intensity. Certain studies have ascertained that income inequality impacts the consumption of renewable energy. Specifically, when income distribution is more equitable, the consumption of renewable energy escalates owing to more people possessing the capacity to purchase and utilize these energy sources. Nonetheless, once levels of income inequality reach a state of high-income disparity, the correlation between renewable energy consumption and the reduction in energy intensity significantly depreciates. This likelihood may be due to the fact that under conditions of extreme income disparity, a minority of affluent individuals appropriate a larger share of resources and power, possibly favoring the use of conventional energy sources over renewable ones. Consequently, within an environment of high-income inequality, an increase in renewable energy consumption may not significantly reduce energy intensity.

Different levels of income inequality can lead to significant structural changes in the effect of reducing energy intensity from renewable energy consumption, making it critical to determine whether the level of income inequality has crossed a threshold. This section divides the 104 countries in the sample into two groups, high-income inequality, and low-income inequality, based on the threshold value estimated by the single panel threshold model. Table 8 shows the changes in the number of countries in different threshold intervals from 2010 to 2020. The number of countries with low-income inequality fluctuates between 47 and 49, and the corresponding number of countries with high-income inequality fluctuates between 57 and 55. Overall, the number of countries in the high-income inequality group has always been higher than that in the low-income inequality group, which means that for most countries, the correlation of reducing energy intensity from renewable energy consumption is always significantly negatively affected by income inequality.

Robustness analysis. Market income inequality measures pre-tax, pre-transfer payment income disparity. We substitute market

Table 9 Regression results of panel threshold model (lngini_mkt).		
	(1)	(2)
lnRNEW(Regime1)	−0.161***	−0.144***
	(−3.55)	(−3.09)
lnRNEW(Regime1)	−0.136***	−0.119***
	(−3.50)	(−2.86)
lngini_mkt	−0.546*	−0.574*
	(−1.94)	(−1.97)
lnpgdp	−0.544***	−0.473***
	(−6.09)	(−4.46)
lnfdi	0.005	0.006
	(1.12)	(1.18)
urb	0.002	0.005
	(0.36)	(0.84)
lnIS	−0.072*	−0.097**
	(−1.73)	(−2.07)
pri	0.039***	0.038
	(3.10)	(1.34)
lnden	−0.189	−0.100
	(−1.54)	(−0.64)
_cons	9.996***	8.933***
	(6.07)	(4.70)
N	1144	1144
Adj. R-sq	0.526	0.533
Threshold	3.635	3.635
Threshold C.I.	[3.630,3.638]	[3.630,3.638]
Country_FE	Yes	Yes
Year_FE	No	Yes

Notes: *t*-statistics in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

income inequality for disposable income inequality to re-estimate Models 4 and 5 (Eqs. 4, 5). The estimated results are presented in Table 9 and Fig. 6, suggesting that renewable energy consumption significantly diminishes energy intensity, and a single-threshold effect of market income inequality exists. The signs and significance of other control variables' coefficients do not markedly differ from the baseline regression, indicating the robustness of the baseline regression results. For Models 3 and 4, compared to lower levels of market income inequality, the role of renewable energy consumption in reducing energy intensity decreases by 15.528% and 17.361%, respectively, within higher market income inequality intervals, slightly less than the baseline regression results, a difference that is justifiable. In high-income inequality intervals, the effect of renewable energy consumption in reducing energy intensity, measured by disposable income inequality, is larger (decreasing 28.205–32.593%), potentially influenced by tax and transfer payment policies. High-income individuals may decrease their use of renewable energy due to increased tax burdens, while low-income individuals may increase their use of renewable energy due to increased income. However, due to the existence of income inequality, there may be more low-income individuals, and their actions could have a greater impact on overall renewable energy consumption, resulting in a larger effect when measured by disposable income inequality. When measuring with market income inequality, the decreasing effect is smaller (15.528–17.361%), potentially because market income inequality reflects more on an
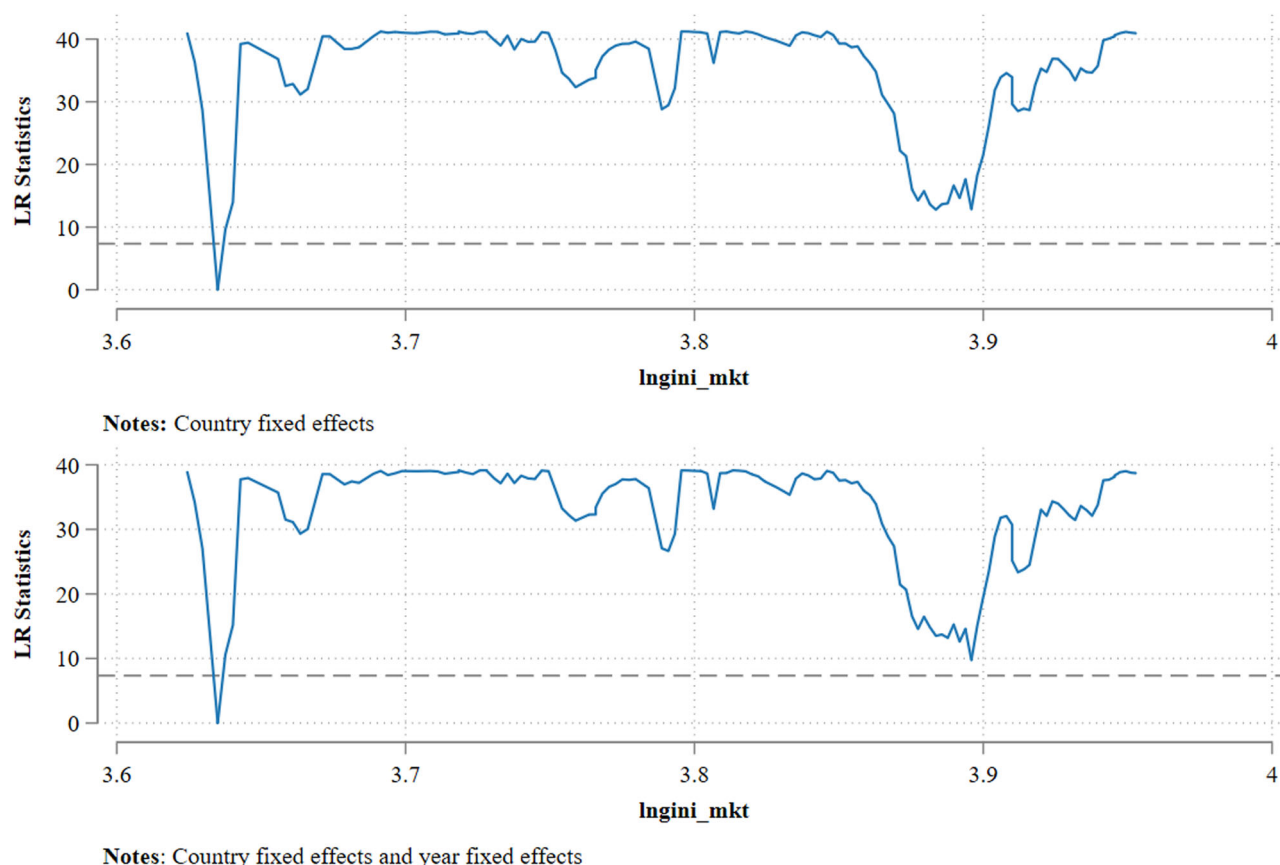
Fig. 6 Using market income inequality as the threshold variable, the likelihood ratio statistic for threshold value testing when the threshold value γ takes different values, and the critical value of the threshold value γ at a 5% significance level (marked with a horizontal short line). The results of the threshold effect test indicate that there is a single threshold effect of lngini_mkt on the impact of lnRNEW on lnEI.

individual's production ability and the outcome of economic activities rather than policy intervention. High-income individuals, due to their strong production ability, may obtain more market income and choose to use more renewable energy. Conversely, low-income individuals, due to their weaker production ability and less market income, may choose to use less renewable energy. Therefore, market income inequality may have a smaller impact on renewable energy consumption.

This outcome underscores the significance of policy intervention. Primarily, policymakers must ensure the equity of tax and transfer payment policies to avert exacerbating income inequality, which could subsequently influence the consumption of renewable energy. Secondly, contemplate augmenting subsidies for renewable energy to decrease its price, making it more appealing to all income levels, thereby elevating the consumption of renewable energy and reducing consumption disparities caused by income inequality. Furthermore, public awareness of renewable energy can be enhanced through education and publicity, boosting their consumption inclination. Lastly, addressing income inequality fundamentally, such as elevating the income levels of the lower-income population and enhancing their employment opportunities and labor skills to achieve a more equitable income distribution. By amalgamating these policy measures, we can anticipate not only an increase in the consumption of renewable energy but also a reduction in the negative impacts caused by income inequality.

Further discussion

The heterogeneity checks of income level. The World Bank categorizes countries and regions worldwide into high-income, upper-middle-income, lower-middle-income, and low-income groups based on the level of income disparity. Figure 7 illustrates the inter-country variations in energy intensity, renewable energy consumption, and disposable income inequality within our sample, segmented by income groups. The high-income group has the highest sample size, with the most significant differences in energy intensity and renewable energy consumption among countries. The upper-middle-income and lower-middle-income groups follow similar degrees of inter-country variations in energy intensity and renewable energy consumption. The low-income group has the smallest sample size, and the differences among countries in the three variables are not prominent. Given the characteristics of our sample data, we group the upper-middle-income and lower-middle-income countries into a median-income group and exclude the low-income countries from the sample scope. We then proceed with the panel threshold model estimation by the revised income group classification.

The results of income group regression are displayed in Table 10, and Fig. 8 illustrates the confidence intervals of threshold estimates at a 5% statistical critical value under varying income levels. Columns (1) and (3) of Table 10 present the outcomes of the estimation for Eq. 4 from high and middle-income groups. For the high-income group, the results of the threshold effect test can be found in Table A.3 in the appendix. The impact of renewable energy consumption on energy intensity possesses a significant single threshold effect. The threshold estimate for $lnginidisp$ is 3.584, and the marginal effect of renewable energy consumption on energy intensity is negative, significant at both 5% and 10% statistical critical values. Within the first threshold interval ($lnginidisp < 3.584$), a 1% increase in
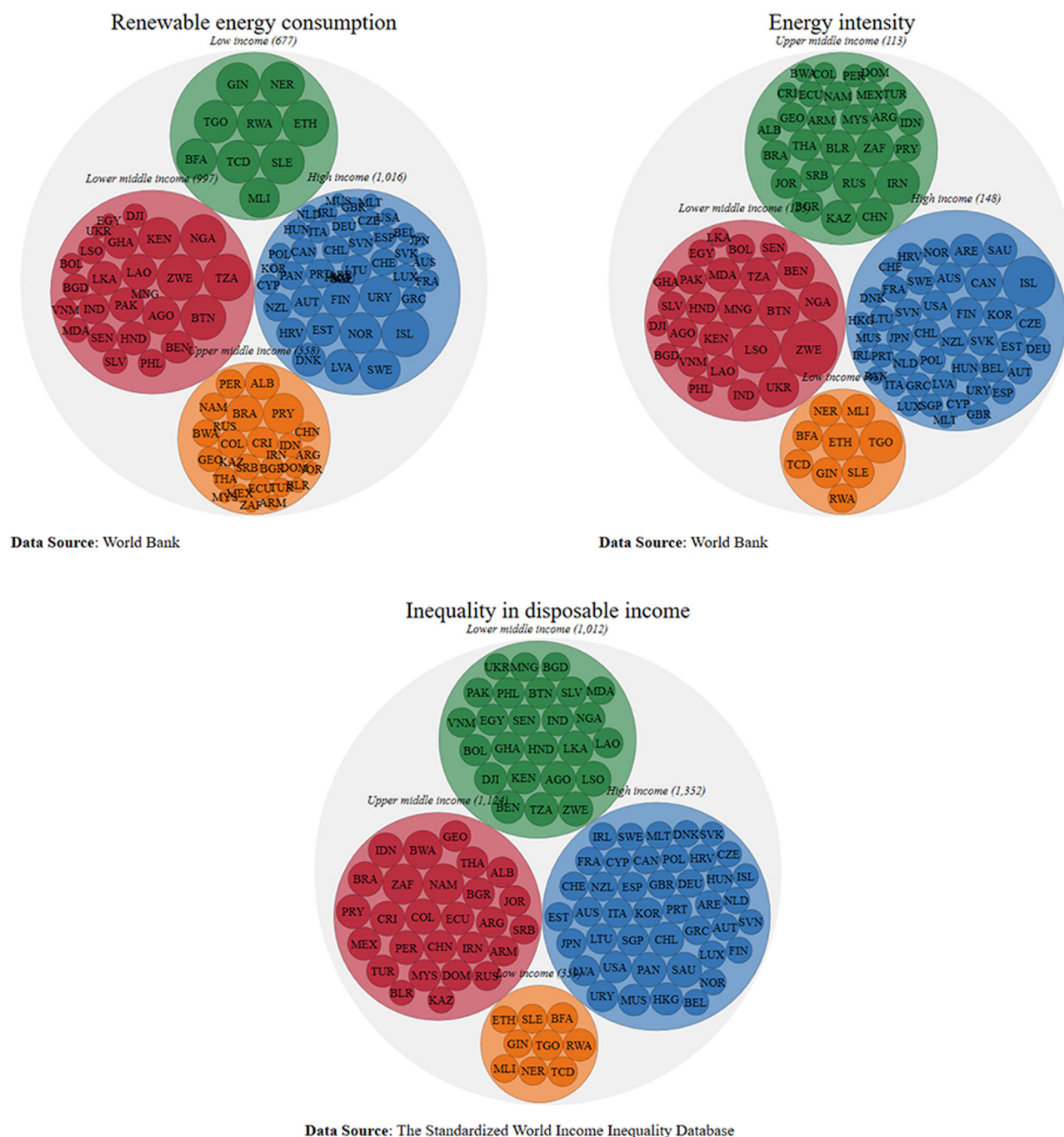
Fig. 7 Comparison of the differences in renewable energy consumption, energy intensity, and income inequality levels in the sample countries for the year 2020 (reflected in the relative size of the bubbles), grouped by income level. The country differences in energy intensity, renewable energy consumption, and income inequality are most pronounced in the high-income group, followed by the upper-middle-income and lower-middle-income groups. The differences among countries in the low-income group are not significant for all three variables.

the proportion of renewable energy consumption leads to a decrease in energy intensity by 0.111%. In the second threshold interval ($lnginidisp > 3.584$), a 1% increase in the proportion of renewable energy consumption results in a decrease in energy intensity by 0.078%. For samples within a high-income inequality level, the role of renewable energy consumption in reducing energy intensity is diminished by 29.730%. For the middle-income group, we continue to confirm the single threshold effect of income inequality (Table A.4). The threshold estimate for $lnginidisp$ is 3.597, and the marginal effects of renewable energy consumption on energy intensity in two income inequality

intervals are −0.173 and −0.112, significant at 1% and 5% statistical critical values, respectively. High-income inequality attenuates the effect of renewable energy consumption in reducing energy intensity by 35.260%. Columns (2) and (4) of Table 10 display the estimation results for Eq. 5, i.e., the outcomes of the panel threshold model after controlling for both country and year-fixed effects. There are no significant differences between the estimation results of Eqs. 4 and 5, indicating the robustness of our conclusions. Compared to the high-income group, the role of renewable energy consumption in reducing energy intensity in middle-income countries is more significantly

Table 10 The regression results of the panel threshold model (income grouping).

	(1) th1_HIC	(2) th2_HIC	(3) th1_MC	(4) th2_MC
lnRNEW(Regime 1)	−0.111**	−0.099**	−0.173***	−0.160***
	(−2.54)	(−2.40)	(−2.92)	(−2.87)
lnRNEW(Regime 2)	−0.078*	−0.071	−0.112**	−0.097*
	(−1.78)	(−1.65)	(−2.14)	(−1.86)
lngini_disp	−0.579**	−0.513**	−0.469	−0.608
	(−2.12)	(−2.17)	(−1.36)	(−1.62)
lnpgdp	−0.552***	−0.554***	−0.560***	−0.478***
	(−5.35)	(−3.84)	(−4.94)	(−4.14)
lnfdi	0.000	−0.001	0.011	0.012
	(0.02)	(−0.24)	(1.38)	(1.36)
urb	−0.012	−0.010	−0.002	0.002
	(−1.17)	(−0.92)	(−0.22)	(0.21)
lnIS	−0.076	−0.077	−0.030	−0.070
	(−0.82)	(−0.75)	(−0.30)	(−0.66)
pri	0.052**	0.096**	0.005	−0.005
	(2.14)	(2.07)	(0.23)	(−0.13)
lnden	−0.383**	−0.489**	−0.118	0.052
	(−2.49)	(−2.17)	(−0.62)	(0.22)
_cons	12.182***	12.227***	9.360***	8.388***
	(9.10)	(5.29)	(4.12)	(3.63)
N	473	473	572	572
Adj. R-sq	0.719	0.735	0.395	0.398
Threshold	3.584	3.584	3.597	3.597
Threshold C.I.	[3.578, 3.597]	[3.578, 3.597]	[3.595,3.600]	[3.595,3.600]
Country_FE	Yes	Yes	Yes	Yes
Year_FE	No	Yes	No	Yes

Notes: *t*-statistics in parentheses; *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
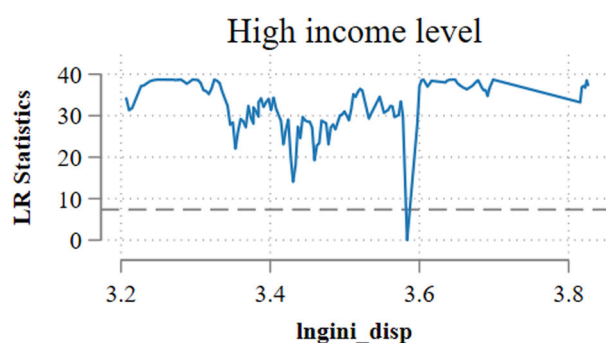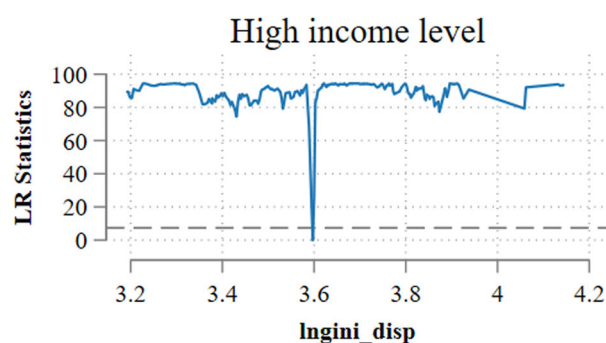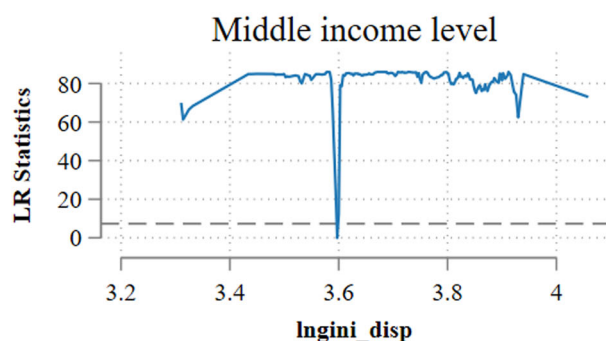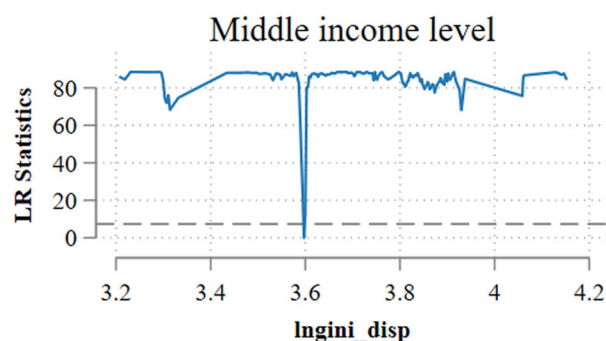
Fig. 8 The likelihood ratio statistic for threshold value testing when the threshold value γ takes different values, and the critical value of the threshold value γ at a 5% significance level (marked with a horizontal short line). Grouped by income level. The results of Fig. 8 indicate that in both the high-income group and the middle-income group, the impact of renewable energy consumption on energy intensity exhibits a significant single threshold effect of income inequality.

Table 11 Regression results of panel threshold model (regional grouping).

	(1) th_Asia	(2) th_Europe	(3) th_America	(4) th_Africa
lnRNEW(Regime 1)	−0.107*	−0.146***	−0.078	−0.309**
	(−1.95)	(−3.02)	(−1.21)	(−2.27)
lnRNEW(Regime 2)	−0.035	−0.090	−0.101	−0.251*
	(−0.64)	(−1.65)	(−1.52)	(−1.90)
lngini_disp	−0.722	−0.667**	−0.285	−0.775
	(−1.34)	(−2.05)	(−1.23)	(−1.51)
lnpgdp	−0.249	−0.656***	−0.200**	−0.948***
	(−1.39)	(−4.19)	(−2.24)	(−10.47)
lnfdi	0.011	−0.003	0.001	0.009*
	(0.95)	(−0.62)	(0.21)	(2.05)
urb	−0.005	0.008	−0.029***	−0.004
	(−0.57)	(0.99)	(−7.20)	(−0.33)
lnIS	0.361***	−0.023	−0.183***	−0.017
	(4.51)	(−0.24)	(−5.11)	(−0.47)
pri	−0.008	0.051*	−0.032*	0.041
	(−0.22)	(1.91)	(−1.95)	(1.70)
lnden	−0.396	−0.327	−0.398**	−0.011
	(−1.03)	(−1.45)	(−2.15)	(−0.04)
_cons	7.678***	11.613***	8.701***	13.699***
	(3.23)	(4.12)	(5.40)	(6.00)
N	209	506	187	242
Adj. R-sq	0.462	0.677	0.561	0.729
Threshold	3.597	3.605	3.873	3.930
Threshold C.I.	[3.595,3.600]	[3.593,3.608]	[3.867,3.877]	[3.922,3.932]
Country_FE	Yes	Yes	Yes	Yes
Year_FE	No	No	No	No

Notes: t-statistics in parentheses; *$p < 0.1$; ** $p < 0.05$; ***$p < 0.01$.

suppressed by income inequality. A plausible explanation is that income inequality could be more severe in middle-income countries. This might lead to fewer individuals capable of affording renewable energy utilization, thereby diminishing these countries' capacities to reduce energy intensity. In high-income countries, despite the presence of income inequality, a higher overall income level allows more people to afford renewable energy (Fraser et al., 2023).

The heterogeneity checks of region. We have also analyzed regional heterogeneity. Based on the geographical location characteristics of the countries within the sample, we classified the sample into four regions: Asia, Europe and the Middle East, America, and Africa. We estimated the panel threshold model (Eq. 4) separately for each region. In all four areas, we detected a significant single-threshold effect of income inequality. The estimated results are shown in Table 11, and the likelihood ratio test statistics are provided in Fig. 9.

Within the interval of income disparity, the consumption of renewable energy most significantly curbs energy intensity in African nations, followed closely by Europe and the Middle East, and subsequently by Asia. However, in the Americas, the restraining effect of renewable energy consumption on energy intensity is not prominent. Within the high-income disparity interval, there is a significant shift in the impact of renewable energy consumption on energy intensity compared to low-income disparity intervals. In the Americas and Asia, there is no discernible influence of renewable energy consumption on energy intensity. In contrast, in Africa, under the statistical threshold of 10%, the marginal effect of renewable energy consumption on energy intensity becomes −0.251, a reduction of 18.770%. For Europe and Latin America, the coefficient of lnRNEW decreases to −0.09, with a p-value of 0.106, nearing the statistical threshold of 10%, the restraining effect of renewable energy consumption

on energy intensity has decreased by approximately 38.356%. The distribution of energy resources, technological development, economic level, and policy support may lead to regional variations in the restraining effects of renewable energy consumption on energy intensity(Sun et al., 2021a). The socio-economic structure varies across regions, potentially influencing the impact of income inequality on renewable energy consumption and energy intensity (Oteng-Abayie et al., 2023). The policy environment in different regions may also influence the moderating effect of income inequality on the restraining effect of renewable energy on energy intensity. In some regions, governments may provide subsidies or other incentives to encourage the use of renewable energy, which may help reduce energy intensity. However, in other regions, such policies may be absent or insufficient to offset the impact of income inequality (Zhang and Wang, 2022).

Asymmetric check. The threshold model of the panel merely estimates the average effect of renewable energy consumption on energy intensity, overlooking the impact on other distribution locations of energy intensity. To further investigate the asymmetric effects of renewable energy consumption on energy intensity, we employ the Panel Unconditional Quantile Regression (UQR) method based on the Re-centered Influence Function (RIF) for estimation.

Quantile regression does not necessitate any distributional assumptions for the model, and the estimation of model parameters is not influenced by sample moment conditions or outlier data. Therefore, it is highly robust to employ quantile regression to estimate the relationships between macroeconomic variables. Koenker and Bassett (1978) proposed the Conditional Quantile Regression (CQR) method, however, the results of CQR are influenced by individual characteristics and fail to capture the general marginal effects of explanatory variables on the dependent
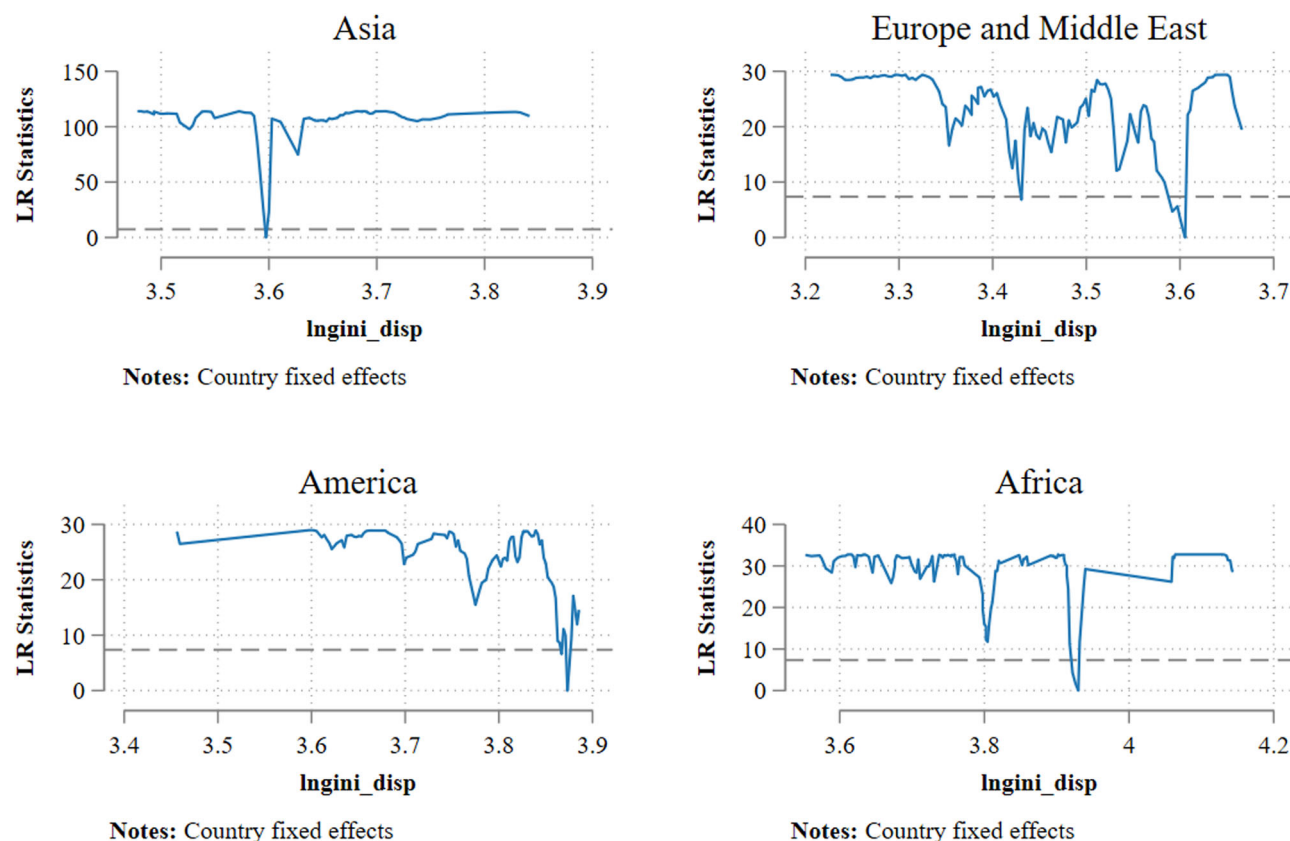
Fig. 9 The likelihood ratio statistic for threshold value testing when the threshold value γ takes different values, and the critical value of the threshold value γ at a 5% significance level (marked with a horizontal short line). Grouped by region. The results of Fig. 9 indicate that in different regional groups, the impact of renewable energy consumption on energy intensity exhibits a significant single threshold effect of income inequality.

Table 12 Unconditional panel quantile regression results.									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	Q10	**Q20**	**Q30**	**Q40**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
lnRNEW	−0.025	−0.062***	−0.080***	−0.106***	−0.131***	−0.156***	−0.178***	−0.162***	−0.108***
	(−1.56)	(−4.98)	(−7.28)	(−10.63)	(−13.55)	(−14.69)	(−14.30)	(−8.41)	(−3.93)
lngini_disp	−0.816***	−0.926***	−0.903***	−1.048***	−1.026***	−0.952***	−0.851***	−0.767***	−0.666***
	(−7.55)	(−10.75)	(−11.70)	(−13.24)	(−13.00)	(−10.95)	(−8.70)	(−6.23)	(−4.03)
lnpgdp	−0.274***	−0.188***	−0.245***	−0.269***	−0.273***	−0.232***	−0.271***	−0.266***	−0.285***
	(−6.23)	(−6.05)	(−9.92)	(−11.53)	(−11.37)	(−8.99)	(−9.80)	(−8.35)	(−6.39)
lnfdi	−0.056***	−0.044***	−0.050***	−0.030***	−0.036***	−0.043***	−0.035***	−0.032***	−0.007
	(−4.04)	(−3.04)	(−3.91)	(−2.62)	(−3.22)	(−4.20)	(−3.21)	(−2.72)	(−0.47)
urb	0.005***	−0.002	0.001	−0.002	−0.004***	−0.006***	−0.004***	−0.001	−0.002
	(2.65)	(−1.15)	(0.56)	(−1.28)	(−3.12)	(−4.91)	(−3.11)	(−0.71)	(−1.16)
lnIS	0.274***	0.050	0.067	0.046	−0.022	−0.090*	−0.096*	−0.048	0.018
	(4.54)	(0.95)	(1.40)	(1.02)	(−0.49)	(−1.87)	(−1.76)	(−0.76)	(0.23)
pri	0.016	−0.095*	−0.164***	−0.082*	−0.063	−0.121**	−0.112*	−0.209***	−0.017
	(0.29)	(−1.87)	(−3.52)	(−1.78)	(−1.32)	(−2.29)	(−1.91)	(−2.93)	(−0.18)
lnden	−0.103***	−0.139***	−0.125***	−0.113***	−0.117***	−0.133***	−0.137***	−0.137***	−0.122***
	(−7.19)	(−12.27)	(−12.53)	(−11.20)	(−11.31)	(−11.40)	(−10.54)	(−8.65)	(−5.43)
_cons	5.885***	7.103***	7.567***	8.547***	9.030***	9.072***	9.188***	8.695***	8.162***
	(9.12)	(14.29)	(18.13)	(21.67)	(23.78)	(21.51)	(17.91)	(12.66)	(7.82)
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1144	1144	1144	1144	1144	1144	1144	1144	1144

Notes: *t*-statistics in parentheses; *p < 0.1; **p < 0.05; ***p < 0.01.

variables. Firpo et al. (2009) introduced the Recentered Influence Function (RIF) into quantile regression, facilitating the analysis of the marginal effects of explanatory variables on the unconditional distribution of dependent variables at the π quantile.

Table 12 displays the outcomes of the unconditional quantile regression of the panel, while the variations in the coefficients corresponding to the explained variables are depicted in Fig. 10. The marginal effect of renewable energy consumption on energy
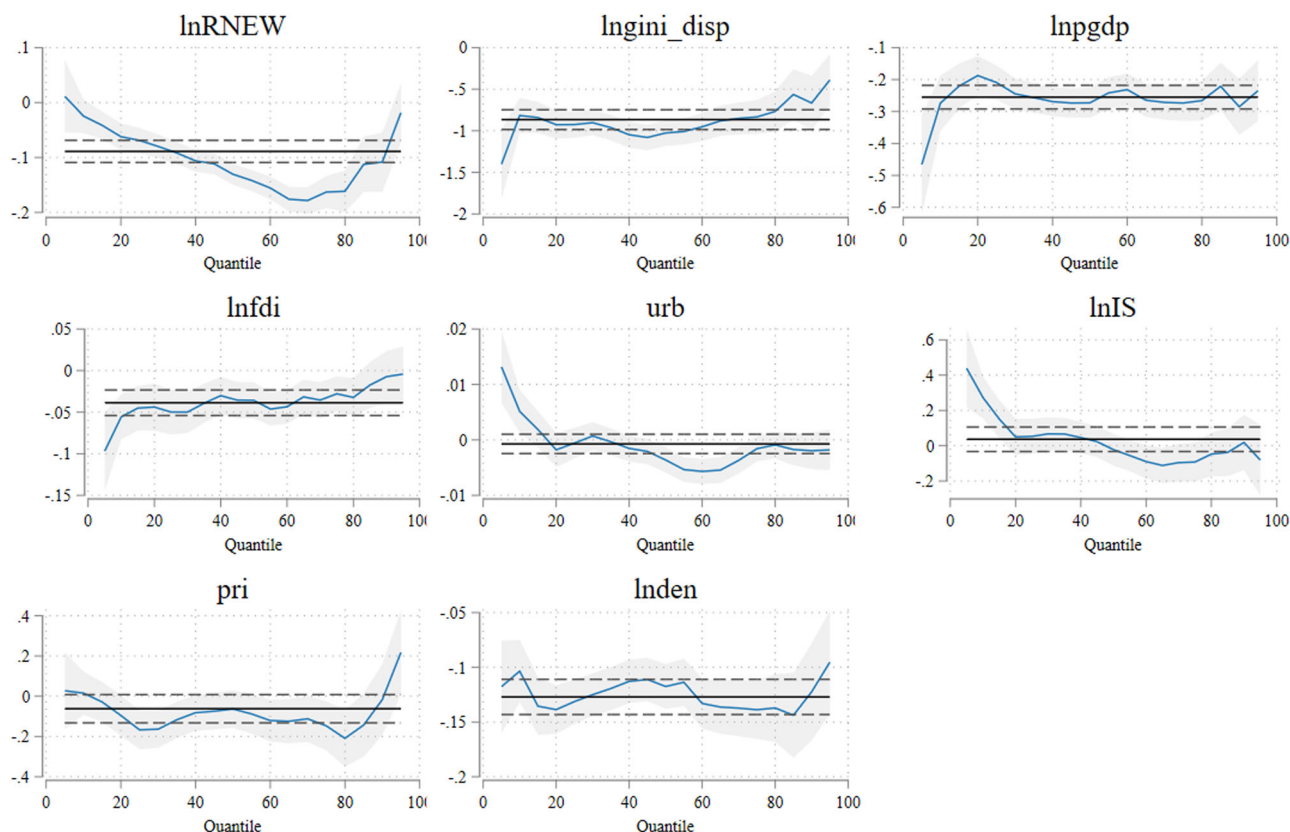
Fig. 10 The marginal effects of renewable energy consumption and other explanatory variables on energy intensity at different quantiles. Figure 10 indicates that the direct impact of income inequality on energy intensity exhibits similar characteristics across different quantiles of energy intensity. This suggests that the changes in energy intensity caused by variations in income inequality are mainly achieved through indirect channels.

intensity is less than zero at all quantiles. Starting from the tenth percentile, the marginal effect of renewable energy on reducing energy intensity gradually increases, peaking at the 70th percentile and then gradually decreasing. In other words, in countries with lower or higher energy intensity, the effect of renewable energy on reducing energy intensity is less significant. This could be attributed to several reasons. Firstly, the baseline effect of energy efficiency. In countries with high energy intensity, the initial energy efficiency is relatively low, making it difficult to improve even with the adoption of renewable energy, hence a less apparent effect in reducing energy intensity. Conversely, in countries with low energy intensity, where initial energy efficiency is already high, the space for improvement in energy efficiency after adopting renewable energy is limited, hence a likewise less apparent effect in reducing energy intensity. Secondly, the impact of technology maturity. In countries with low energy intensity and more mature renewable energy technology, the energy utilization efficiency is already high, which limits further reduction in energy intensity. However, in countries with high energy intensity where renewable energy technology is still in its infancy, there is room for technological advancement, but this improvement requires time, hence, the effect in reducing energy intensity in the short term is less noticeable. Thirdly, the influence of economic development level. Countries with higher levels of economic development, such as Ireland, Malta, and Panama, have a larger energy demand, but their high energy utilization efficiency limits the reduction in energy intensity that can be achieved with the use of renewable energy. Conversely, countries with lower levels of economic development, such as Iceland, Zimbabwe, and Ethiopia, have a smaller energy demand, but their low energy utilization efficiency limits the reduction in energy

intensity that can be achieved with the use of renewable energy. Therefore, countries with medium energy intensity, due to their relatively moderate energy utilization efficiency and technology maturity, can achieve a relatively larger reduction in energy intensity when adopting renewable energy.

As depicted in Fig. 10, the direct influence of income disparity on energy intensity exhibits similar characteristics across different quantiles of energy intensity. Consequently, we can postulate that the direct impact of income inequality on energy intensity tends to be constant and uninfluenced by variations in the level of income disparity. With the results from both the panel interaction term model and the panel threshold model, we can infer that although income inequality directly impacts energy intensity, the alterations in energy intensity provoked by changes in income inequality are primarily accomplished through indirect channels affecting renewable energy consumption. Shifts in income disparity may affect modes of renewable energy consumption. For instance, should income inequality intensify, individuals with lower income may be incapable of affording the costs associated with the use of renewable energy (Asongu and Odhiambo, 2021), subsequently influencing the overall energy intensity. The influence of renewable energy consumption on energy intensity presents heterogeneity at various levels of income inequality. This finding indicates that to alter energy intensity, attention must be paid to the issue of income disparity. By adjusting income distribution and improving the energy consumption capabilities of the low-income population, the overall energy intensity can be influenced.

Conclusions and implications
This work, through the analysis of income inequality's impact on energy intensity in renewable energy consumption, has employed

various statistical methods and models to explore the complex relationship. Instead of asserting causality, our findings highlight the correlation between these variables.

Our findings resonate with existing theories and studies, affirming the link between renewable energy consumption and reduced energy intensity. The inverse relationship between these variables aligns with economic theories emphasizing technological innovation and efficiency improvements stemming from increased renewable energy usage. However, our analysis delves deeper, uncovering the nuanced influence of income inequality on this relationship. It becomes evident that income disparity not only directly impacts energy intensity but also intricately affects renewable energy consumption's effectiveness in curbing energy intensity. As income inequality rises, the efficacy of renewable energy in reducing energy intensity gradually diminishes. In high inequality scenarios, where a minority commands a disproportionate share of resources, the potential for renewable energy to impact energy intensity weakens. This is a crucial revelation, indicating that income distribution plays a pivotal role in determining the success of renewable energy initiatives.

In addition, our exploration transcends mere statistical significance; it unveils substantial policy implications. Unlike previous studies, our research suggests that equitable tax policies, enhanced renewable energy subsidies, public awareness campaigns, and fundamental income distribution reforms are imperative to foster both increased renewable energy consumption and diminished energy intensity. These policy recommendations highlight the need for a more inclusive approach, addressing economic disparities to enhance the effectiveness of renewable energy policies.

The regional and income group analyses accentuate the disparities across different geographies and income strata, emphasizing the need for tailored approaches to address these complexities. These findings beckon policymakers to tailor interventions suiting regional economic disparities and income distribution peculiarities. The unconditional quantile regression unravels an intriguing layer, showcasing how the impact of renewable energy consumption on energy intensity varies at different quantiles. It highlights the significance of initial energy efficiency, technology maturity, and economic development levels in shaping the effectiveness of renewable energy initiatives.

While our study makes significant strides in understanding the relationship between income inequality and energy intensity, it is not without limitations. The primary constraint lies in the availability and quality of data across different regions and time periods. Future research should aim to address these limitations by utilizing more granular data and exploring other potential factors influencing this relationship. Additionally, longitudinal studies could provide deeper insights into the dynamic nature of this interplay over time.

In essence, this exhaustive analysis underscores the imperative of addressing income inequality to harness renewable energy's potential in reducing energy intensity. Equitable income distribution, strategic policy interventions, and heightened awareness remain paramount in fostering sustainable energy transitions and advancing broader sustainable development goals.

Data availability

The datasets publicly available should be through https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/LGNZBT

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