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Renewable Energy Thresholds and Oil Price Effects on Decarbonization: Comparative Evidence From China and the United States

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ABSTRACT

The United States and China are the two world's largest renewable energy consumers that spearhead global energy transition efforts. Nonetheless, the motivation of energy transition is affected by oil prices since oil is a key economic catalyst. This paper performs the Fourier Autoregressive Distributed Lag (FARDL) and Fourier multi-threshold nonlinear ARDL (FMTNARDL) models to assess the relationship between carbon dioxide (CO₂) emissions, oil prices, and renewable energy disaggregated by source (hydro, solar, wind, and others) in the United States and China, from 1980 to 2022. This research aims, first, to examine the threshold effects of renewable energy consumption on CO₂ emissions. Second, to investigate the intertwined effects of renewable energy consumption and oil prices on CO₂ emissions. The findings are as follows: Firstly, solar and others energy demonstrate threshold effects on CO₂ emissions in the United States, while in China, threshold effects are evident for hydro and wind. Secondly, the moderating effects of oil prices only exist for the case of China. This study suggests to sustain renewable energy investments and maintain high consumption levels to preserve the decarbonization effect of renewable energy. To avoid diminishing returns, the United States and China should promote innovations in solar, hydro, and wind technologies. Additionally, the United States should increase the incentive for renewable energy substitution by implementing renewable energy-targeted tax incentives and carbon tax, whereas China should increase biofuel consumption in the oil-reliant industries, particularly petrochemical and transport industries.

JEL Classification: Q20, Q41, Q50

1 | Introduction

Energy transition has been broadly acknowledged as a critical strategy for addressing environmental challenges and achieving sustainable development. However, the environmental effects of renewable energy are multifaceted and intrinsically complex, as different renewable energy technologies are characterized by

distinct natural features, technological applications, and industrial practices [1, 2]. Consequently, the relationship between renewable energy and carbon dioxide (CO₂) emissions may vary across renewable energy sources and consumption levels. Additionally, energy price dynamics, particularly oil prices, also play a pivotal role in influencing the decarbonization effectiveness of renewable energy deployment by altering energy

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substitution decisions, investment incentives, and technological innovation [3]. These factors suggest that the relationship between renewable energy and CO₂ emissions is potentially non-linear and sensitive to prevailing energy market conditions.

To further explain, renewable energy projects often face technological immaturity, underdeveloped supply chains, low energy efficiency, and high up-front costs, which significantly dampen their decarbonization potentials and generate short-term environmental costs [4]. For instance, major hydroelectric dam projects entail reservoir impoundment, which can disrupt the balance of ecosystems through the modification of natural lagoon systems [5]. The manufacturing of solar photovoltaics (PV) produces solar e-wastes that are nonbiodegradable and detrimental to the environment [2]. Wind turbines can cause wildlife fatalities via habitat disruption and powerline collisions. Bioenergy involves thermochemical processes that emit poisonous gases to the atmosphere. Empirical studies have also verified the heterogeneous impacts of renewable energy consumption on CO₂ emissions from different sources [6–9].

Nonetheless, the environmental costs can be offset over time as scale and technique effects of renewable energy adoption set in [10]. As renewable energy consumption expands, economies of scale can improve the cost efficiency, while increased investments in renewable energy can stimulate green innovation and technological advancement, thereby enhancing the positive environmental benefits of renewable energy. These dynamics indicate potential behavioral changes in the environmental effects of renewable energy once consumption surpasses a critical threshold level. To illustrate, the adverse impacts of nonbiodegradable solar e-wastes are partially mitigated through the development and diffusion of solar PV panel recycling and recovery techniques as solar energy consumption scales up [11].

However, renewable energy deployment expansion does not always foster a reform in the industrial framework and supportive investment climate in the renewable energy industry. Particularly, this occurs when growing energy demand is fulfilled by both fossil fuel and renewable energy, implying that the domestic energy consumption landscape remains dominated by fossil fuel energy [12]. Besides, resource misallocation and incoherence in the investment strategy may also hamper green innovation and technological breakthroughs [13, 14]. Hence, identifying the turning point at which each type of renewable energy effectively mitigates carbon emissions is crucial, underscoring the need for clear and well-defined energy strategies that optimize renewable investments for maximized decarbonization potentials.

The subtle dynamics between renewable energy consumption and CO₂ emissions are also influenced by oil prices, given that crude oil is the most dominant energy commodity in the global market [15]. In theory, decreased oil prices reduce overall production costs, incentivize fossil fuel consumption, impede renewable energy transition, and increase CO₂ emissions [16]. Conversely, increased oil prices raise overall production costs, discourage fossil fuel adoption, motivate renewable energy substitution, and lower CO₂ emissions. However, this relationship could be different to the oil exporters since they are economically dependent on oil revenue [17]. In this context, rising oil prices connote a scale effect that

increases economic output, encourages fossil fuel consumption, slows down renewable energy transition, and drives up CO₂ emissions. On the other hand, increased national wealth driven by oil price spikes foster green technological advancement and structural transformation from oil-dependent economy to a circular economy, implying technique and composition effects. Essentially, the oil prices-CO₂ emissions relation in the oil-rich nations is determined by the relative strengths of the scale, technique, and composition effects.

Against this backdrop, this paper compares the environmental effects of renewable energy consumption between the United States and China. To be specific, the first objective is to examine the threshold effects of renewable energy consumption on CO₂ emissions in the United States and China. The second objective is to analyze the moderating role of oil prices in the renewable energy-CO₂ emissions nexus. The aggregate and disaggregated levels of renewable energy consumption are considered to account for potential heterogeneity across renewable technologies. The United States and China provide an ideal setting for this analysis because they are responsible for 44% of the global CO₂ emissions, while also representing 43% of the global renewable energy consumption [18].

The United States and China have very distinctive renewable energy compositions. Wind energy constitutes the largest share of renewable energy consumption, recorded at 36.5% in the United States, followed by bioenergy and geothermal energy (22.8%), solar energy (20.5%), and hydro energy (20.1%), [19]. On the flip side, China's renewable energy development prioritizes hydro energy, which accounts for 41.5% of the renewable energy composition, followed by wind energy (30.0%), solar energy (19.8%), as well as bioenergy and geothermal energy (8.7%). This indicates that the United States and China have different priorities in renewable energy development and varying levels of advancement across various renewable energy types. Moreover, the United States and China are the two largest players in the global oil market. The former is the most dominant oil exporter in the world, contributing to 13.4% of global oil exports, whereas the latter is the world's largest oil importer, accounting for 20.1% in 2023 [18].

Given the heavy reliance of the United States and China on fossil fuels, their energy consumption decisions can be heavily influenced by international crude oil price fluctuations, thereby affecting their environmental quality. To illustrate, the oil price upsurge driven by the global oil shortages in the 1970s catalyzed renewable energy development in the United States, particularly wind energy, as part of strategic efforts to enhance economic resilience and energy security [20]. Consequently, CO₂ emissions dropped by 8% from the 1981–2000 period to the 2001–2020 period [18]. On the other hand, the 2009 oil price plummet caused by the global financial crisis led to negative annual growth in the renewable energy industry in China when crude oil became a substantially more cost-competitive economic driver. More precisely, the booming phase of the solar PVs export industry since 2004 was forcibly ceased in 2008 due to the crisis [21]. As a result, CO₂ emissions in China soared by nearly 20% in just 3 years, from 2008 to 2011 [18].

While oil prices play a pivotal role in shaping the impact of renewable energy on CO₂ emissions, the moderating effects of oil prices may be heterogenous across different renewable energy sources, influenced by the substitutability of specific renewables in industrial applications, the degree of oil dependency in their developments, and energy policies. Renewable energy with greater substitutability in specific industrial applications tend to show stronger moderating effect. For instance, bioenergy, particularly biofuel and ethanol, has better substitutability than other renewable energy sources in the transport and chemical industries, indicating that bioenergy is preferred to partially replace oil during oil price hikes [22, 23].

Second, renewable energy technology having high reliance on oil is likely to have less significance in reducing CO₂ emissions when oil price becomes expensive. For example, petrochemicals are essential inputs for the manufacturing of wind blades and maintenance of wind facilities, implying that high oil prices can potentially hamper wind energy development and diminish its decarbonization effect [24]. Third, energy policies such as energy subsidy can undermine the mitigating effect of specific renewables on CO₂ emissions [25]. Energy subsidy lowers oil prices and reduces the incentive for consuming close substitutes such as bioenergy in the transport and chemical sectors.

Table 1 presents the chronological summary of oil prices and renewable energy consumption movement by sources between 1980 and 2022. There are five major oil price shock events that occurred during this period. The first event is the 1980s oil glut that led to a slump in the oil price by 50.51%. Consequently, there were drastic spikes in the consumptions of solar (74,750%), wind (630,737%), and others (59.44%) in the United States. Interestingly, hydro consumption was the only renewable energy source that declined by 2.58%. In China, hydro energy was the only renewable energy source consumed during this period, with an increase of 103.38%.

Subsequently, the global financial crisis during the 2007–2008 period caused an oil price hike by 34.35%. Correspondingly, hydro, solar, wind, and others in the United States rose by 2.65%, 48.16%, 59.71%, and 6.39%, respectively. Similarly, all renewable energy types in China also surged during this period, including hydro (30.45%), solar (32.51%), wind (137.60%), and others (44.07%). The following event is the oversupply in the

global oil market from 2014 to 2016, resulted from the U.S. shale revolution and oil demand drop in China and Europe that caused a slump in the oil price by 55.80%. During this period, hydro, solar, wind, and others in the United States grew by 1.91%, 87.45%, 23.48, and 5.83%, respectively. On the other hand, there was also a disproportionate growth in hydro (7.54%), solar (179.60%), wind (48.98%), and others (22.50%) in China.

In 2020, the COVID-19 outbreak instigated a plummet in the oil price by 34.84% in the United States, followed by a drop in hydro consumption by 1.31%. Conversely, there were upward movements in solar (21.83%), wind (13.79%), and others (4.51%). Contrarily, there was an upswing in the consumption growth of hydro (3.48%), solar (16.13%), wind (14.68%), and others (16.75%) in China. A drastic rise in oil price is observed during the Russia–Ukraine war outbreak in 2022. In the United States, hydro, solar, and wind escalated by 3.47%, 23.69%, and 14.55%, respectively, while others decreased by 1.30%. On the flip side, China underwent a drop in hydro consumption by 0.13%, whereas solar, wind, and others soared by 30.32%, 15.88%, and 6.06%, respectively.

Table 1 shows that the growth rate in each renewable energy type in the two economies reacts to oil price shock events differently. Empirically, it is also evidenced that oil prices exhibit heterogeneous impacts across different renewable energy sources. Atems et al. [26] concluded that oil prices positively affect solar, biomass, and geothermal consumption in the United States at different magnitudes. However, oil prices are found to be insignificant in affecting hydro and wind consumption in the United States. Besides, Magazzino and Giolli [27] argued that oil prices tend to promote hydro and wind, while discouraging geothermal energy in Italy. Given the varying effects of oil prices on each renewable energy type, the environmental effects of different renewable energy technologies may be sensitive to oil price fluctuations. This justifies the need to disaggregate renewable energy consumption in this analysis.

There are several contributions highlighted in this study. First, it provides a comparative analysis between the United States and China. Existing literature either concerns about country-specific or panel countries that include both the United States and China and provides no meaningful analogy between the two countries in terms of the environmental behaviors of renewable energy and

TABLE 1 | Summary of oil price and renewable energy consumption changes with respect to oil price events between 1980 and 2022.

Events	Δ Oil price (%)	Δ Hydro (%)		Δ Solar (%)		Δ Wind (%)		Δ Others (bioenergy and geothermal) (%)	
		United States	China	United States	China	United States	China	United States	China
1980s oil glut	−50.51	−2.58	103.38	74,750	0.00	630,737	0.00	59.44	0.00
Global financial crisis (2007–2008)	34.35	2.65	30.45	48.16	32.51	59.71	137.60	6.39	44.07
Oversupply in global oil market (2014–2016)	−55.80	1.91	7.54	87.45	179.60	23.48	48.98	5.83	22.50
COVID-19 (2020)	−34.84	−1.31	3.48	21.84	16.13	13.79	14.68	4.51	16.75
Russia-Ukraine war (2022)	42.33	3.47	−0.13	23.69	30.32	14.55	15.88	−1.30	6.06

oil prices [28–31]. Comparing the two leading nations in the global energy transition sheds light on the effectiveness of carbon reduction strategies under different institutional and market conditions.

Second, this comparative study accounts for both aggregate and disaggregated aspects of renewable energy consumption. This is different from existing papers like Ansari [32], Li et al. [33], and Shang et al. [34] that ignore the unique differences across renewable energy sources. Aggregate-level analysis provides an overall assessment of the decarbonization role of renewable energy, while disaggregated-level insights identify specific renewable energy sources that deliver the strongest decarbonization benefits in each country, thereby facilitating more targeted policy design and resource allocation.

Third, this study determines the threshold effects of renewable energy consumption on CO₂ emissions in the United States and China. Unlike past studies focusing on behavioral dynamics arising from temporal trends [8, 35], this study captures potential behavioral changes arising from scale and technical effects as renewable energy consumption expands. This method facilitates the understanding of specific renewable energy sources in lowering CO₂ emissions at a specific consumption threshold. Prioritizing the development of the most effective and efficient renewable energy type in mitigating CO₂ emissions at a given threshold point can substantially maximize environmental outcomes and optimize resource usage.

Fourth, this research provides fresh insights into the moderating role of oil prices in the interplay between renewable energy consumption and CO₂ emissions. Relevant studies like Atems et al. [26], Barrales-Ruiz and Neudörfer [16], and Raihan and Mainul Bari [29] scrutinize the direct effects of renewable energy and oil prices on CO₂ emissions, while overlooking the nuanced interaction between these variables via the substitution effect. By analyzing the moderating role of oil prices, this study determines how oil price movements affect the decarbonization potential of renewable energy, thereby helping policymakers capitalize on oil price fluctuations to accelerate the energy transition.

Fifthly, this paper delivers methodological contribution by integrating Fourier functions into the autoregressive distributed lag (ARDL) model. The Fourier transform is known to have strong computational efficiency and high model flexibility because it accounts for unknown structural shifts in the model without requiring specified break dummies [36]. Considering the relatively long sample period from 1980 to 2022, CO₂ emissions are prone to dynamic shifts arising from evolving economic, structural, and technological landscapes in the United States and China, making the Fourier functions integrated ARDL model a suitable estimation technique. To the best knowledge of the authors, this is among the first papers that incorporate the Fourier technique in the multiple threshold nonlinear ARDL (FMTNARDL) framework. This would broaden the methodological framework for capturing threshold effects in the empirical research.

This paper is structured as follows. The next section reviews the relevant literature on the relationship between renewable energy, oil prices, and CO₂ emissions. Section 3 presents the model, data, and methodology. Section 4 reports and discusses the empirical

findings. The final section summarizes the whole paper, followed by a discussion of the policy implications.

2 | Literature Review

Renewable energy is a sustainable energy that is inexhaustible and highly accessible [2]. It releases substantially lower CO₂ emissions compared to fossil fuels and serves an optimal substitute of its energy counterpart. Expanding renewable energy consumption implies less fossil fuel consumption, leading to a decline in CO₂ emissions. The empirical connection between renewable energy and CO₂ emissions has been vastly studied. For instance, Nuta et al. [37] verified the benign impact of renewable energy consumption for both European and Asian emerging economies. The same conclusion is reached by Adebayo and Özkan [28], Raihan and Mainul Bari [29], Zhang [38], and Zeng et al. [39] for the case of the United States, China, BRICS nations, and 53 country group, respectively.

However, there are a few papers that present opposing results, such as Altun [40], who found a positive correlation between renewable energy consumption and CO₂ emissions for the G7 economies. They explained that the construction, manufacturing, transportation, and end-of-life management of renewable energy projects can be pollution-intensive. In the same vein, Rehman et al. [41] and Pata and Samour [42] reported that there is no long-term relationship between renewable energy consumption and CO₂ emissions in the global context and France, respectively. Another strand of studies uncovers asymmetric relationship between the two variables. Horvey and Odei-Mensah [43] deduced that renewable energy consumption has a threshold effect on CO₂ emissions for the case of Africa, which is corroborated by Chen et al. [44]. These papers asserted that the benign effect of renewable energy on the environment becomes evident only when its consumption is scaled up. Furthermore, Shang et al. [34] discovered a U-shaped relationship between renewable energy consumption and CO₂ emissions in China. They argued that energy conservation and efficiency measures are necessary to control carbon emissions.

While many empirical studies focus on the environmental impacts of renewable energy from the aggregate perspective, Estevao and Lopes [45] argue that disaggregated data has stronger explanatory power in this context. Nonetheless, there are mixed conclusions concerning the relationship between disaggregated renewable energy and CO₂ emissions. Hydro, solar, wind, geothermal, and bioenergy consumptions have been confirmed to show significant mitigating effect on CO₂ emissions in the empirical works of Idroes et al. [46], Pata et al. [7], and Waris et al. [47] for the context of the top 10 geothermal-producing nations, Germany, and G20 countries, respectively. On the other hand, Adebayo et al. [48], Wang et al. [49], and Wang et al. [1] revealed contrasting results for the Europe, BRICS economies, and China, respectively.

Inconclusive findings on the relationship between renewable energy and CO₂ emissions from a disaggregated perspective have motivated scholars to explore the complexity of this relationship by scrutinizing its potential asymmetric effect. Lee et al. [9] argued that renewable energy consumption may not affect CO₂ emissions linearly at the disaggregated level due to the ununiform technological establishment and policy initiatives.

Conducting a panel threshold analysis, they unearthed that the mitigating power of solar energy becomes stronger above the threshold, whereas wind energy only delivers environmental benefits beyond the threshold in the top 10 renewable energy consumers. Employing a quantile regression, Pata et al. [7] informed that hydro energy ameliorates CO₂ emissions at lower quantiles, but promotes CO₂ emissions growth at higher quantiles in the Europe. On the other hand, Kuşkaya et al. [35] discovered that the decarbonization effect of solar energy only emerges at lower frequencies between 5 and 8 years in the United States by employing the wavelet analysis. The time-varying effect of disaggregated renewable energy is also supported [6], and Yu et al. [50] and Kuşkaya and Bilgili [51].

Crude oil is a primary energy input in the global production system [52]. Therefore, the volatility of oil prices can significantly impact the global energy consumption patterns and CO₂ emissions. High oil prices discourage fossil fuel consumption and lower CO₂ emissions. The inverse correlation between oil prices and CO₂ emissions has been extensively evidenced in the literature. Zhang and Khan [53] concluded that oil prices demonstrate a negative effect on CO₂ emissions in the APEC nations. In line with Zhang and Khan [53], Naimoglu [54] added that energy-importing emerging nations tend to have inefficient energy technologies, resulting in energy losses and increased fossil fuel demand to compensate for the energy leakage, thereby deteriorating energy productivity.

For China, Jahanger et al. [30] uncovered that oil prices are effective in diminishing CO₂ emissions in the transport sector. This outcome is supported by the firm-level analysis conducted by Wei et al. [55]. The negative oil prices-CO₂ emissions relation is also verified by Rasheed et al. [56], Husaini et al. [25], and Umar et al. [57] for the case of Europe, Asia, and Africa, respectively. Nonetheless, Barrales-Ruiz and Neudörfer [16] pointed that not all oil price hikes reduce CO₂ emissions and explained that the substitution effect of renewable energy takes place only during supply-driven oil price shock.

In contrast, Hassan and Mhlanga [58] informed that oil prices are a major driver of CO₂ emissions in the African oil-producers. They argued that oil price upsurge encourages oil consumption in oil-exporting economies since oil earnings constitute a major revenue stream. Kassouri et al. [59] discovered that oil prices positively affect CO₂ emissions, irrespective to the type of shocks in the United States. This outcome is supported by Dehdar et al. [60] across 50 American states. Zhang et al. [61] unveiled that while increased oil price promotes CO₂ emissions in both the United States and China, the positive effect is substantially stronger in the United States.

The nexus between oil prices and renewable energy is built on the premise of the substitution effect [62]. Oil is the dominant fossil fuel energy and a major input in the global production systems; thus, its prices have profound impact on energy consumption patterns. High oil price signifies expensive energy costs that discourage fossil fuel consumption. This would motivate renewable energy substitution as a cheaper alternative in order to maintain basic economic functions [63]. The significant role of oil prices in influencing renewable energy development has been extensively proven in the literature. Magazzino and Giolli [27]

unfolded that the oil price hike fosters renewable energy development in Italy by shifting investment preference to renewable energy technologies during positive oil price shocks to hedge for market risk. Mukhtarov [64] documented that rising oil price is an effective driving force for renewable energy deployment in China, which aligns with Qing et al. [65] for the OECD countries and Atems et al. [26] for the United States.

However, the positive effect of oil prices on renewable energy consumption tends to weaken or vanish in oil-rich nations. Tambari et al. [66] unearthed that oil prices are positively correlated with renewable energy in the oil-importing African economies, but lose significance in the oil-exporting African nations. Besides, Mukhtarov et al. [67] explicated that high oil rent economies, like Iran, lack motivation to progress in green technologies because they tend to indulge in remunerative oil yield and that the cost of energy transition is high. In line with this argument, Samour and Pata [68] and Karacan et al. [69] both come to a conclusion that oil prices negatively impact renewable energy in energy-rich economies like Turkey and Russia, respectively.

The present literature has extensively scrutinized the relationships among renewable energy consumption, oil prices, and CO₂ emissions separately. While the substitution effect of renewable energy has been emphasized in the literature [62, 70], it merely appears in the form of an interpretation, but not empirically investigated. Hence, this research extends the existing literature by explicitly accounting for the substitution effect in the form of an interaction between renewable energy consumption and oil prices. Moreover, this paper extends the works of Estevao and Lopes [45] and Idroes et al. [46] by incorporating disaggregated renewable energy consumption in the interaction term. This study analyzes the interactions between oil prices and different renewable energy technologies, encompassing hydro, solar, wind, geothermal, and bioenergy.

On top of that, this research bridges the literature gap by analyzing possible behavioral changes in the renewable energy-CO₂ emissions interplay induced by scale and technique effects. This is different from the prevailing empirical studies that only account for the aggregate aspect of renewable energy, such as Altun [40] and Nuta et al. [37]. Besides, this study distinguishes itself from the past studies, such as Horvey and Odei-Mensah [43] and Chen et al. [44], by examining the asymmetric effects of renewable energy consumption on CO₂ emissions across different sources. Additionally, this paper adds value to the literature by initiating a comparative analysis between the United States and China. Relevant literatures such as Adebayo and Özkan [28], Raihan and Mainul Bari [29], Jahanger et al. [30], and Sahu et al. [31] do not offer comparative insights between the two most significant players in the renewable energy and oil markets. Therefore, this research compares the essential environmental factors, including renewable energy and oil prices in the contexts of the United States and China.

3 | Model, Methodology, and Data

The EKC model introduced by Grossman and Krueger [71] serves as the theoretical backbone of this research. The empirical model of the study is presented as follows:

$$\begin{aligned} \text{CO}_{2t} = & \beta_0 + \beta_1 \text{GDP}_t + \beta_2 \text{GDP}_t^2 + \beta_3 \text{REC}_{j,t} \\ & + \beta_4 \text{OIL}_t + \beta_5 \text{FOSSIL}_t + \beta_6 \text{TECH}_t + \mu_t, \end{aligned} \quad (1)$$

where CO_2 is carbon dioxide emissions (measured in tons), GDP is gross domestic product (measured in constant 2015 US dollars), GDP^2 is squared of gross domestic product, REC_j is renewable energy consumption (measured in kWh) with j equals to total, hydro, solar, wind, and others (bioenergy and geothermal), OIL is oil prices indicated by Brent crude (measured in USD per barrel), FOSSIL is fossil fuels consumption (measured in kWh), TECH is technological innovation (measured in total patent applications), t signifies time index, and μ_t is the normally distributed residual term. There are five models in this study. Model 1, 2, 3, 4, and 5 focus on total, hydro, solar, wind, and others, respectively.

Renewable energy is a sustainable alternative of fossil fuels for energy consumption. Increased share of renewable energy consumption implies the reduction in overall fossil fuel consumption, thereby playing a crucial role to reduce CO_2 emissions [48, 72]. Renewable energy consumption is divided into aggregate and disaggregated levels, whereby the disaggregated level comprises hydro, solar, wind, and others (geothermal and bioenergy). Renewable energy has different degrees of decarbonization effects, depending on the unique natural traits, industrial applications, and technological developments across various sources [1, 2].

Oil prices affect the overall fossil fuel consumption of a nation, motivation for renewable energy substitution, and CO_2 emissions level [16]. Rising oil prices incentivize renewable energy deployment and contribute to the reduction in CO_2 emissions. However, this linkage could be more complicated for the oil-exporters because oil revenue forms a vital income stream to the country [58]. A positive relationship between oil prices and CO_2 emissions has been evidenced mostly in the oil-rich economies [59, 60].

GDP, fossil fuel consumption, and technological innovation are employed as control variables. According to the EKC hypothesis, there is an inverted U-shaped trend between GDP and CO_2 emissions under the influences of scale, composition, and technique effects [73]. Fossil fuel combustion is a direct factor of CO_2 emissions; therefore, the greater the fossil fuel consumption, the higher the CO_2 emissions. Evidently, fossil fuel combustion releases 34 billion tons of CO_2 emissions annually [74]. Technological innovation advances renewable technologies, making them more efficient and effective in diminishing CO_2 emissions [75].

The first objective of the study is to examine the threshold effects of renewable energy consumption on CO_2 emissions across different renewable energy sources in the United States and China. The assumption of a linear relationship may oversimplify the complex dynamics of the actual economic environments [52]. According to the empirical evidence, renewable energy tends to demonstrate significant environmental benefits when its consumption exceeds 50% threshold [43, 44]. The asymmetric relationship between renewable energy consumption and CO_2 emissions becomes significantly more apparent when renewable energy sources are disaggregated [7, 49, 76]. This is because different renewable energy sources are associated with heterogeneous

technologies, costs, and operational frameworks, which may evolve over time as economies of scale and green technologies develop [1, 2, 10].

Thus, this study employs the multiple threshold nonlinear autoregressive distributed lag (MTNARDL) approach developed by Pal and Mitra [77] to capture the threshold dynamics between renewable energy consumption and CO_2 emissions. The MTNARDL extends from the nonlinear ARDL (NARDL) by dividing the exogenous variable into several sums for multiple thresholds [78]. This allows MTNARDL to capture multi-regime nonlinearity of the exogenous variable by considering different breakpoints. Besides, MTNARDL offers more flexibility in threshold selection by allowing for threshold predetermination at different quantiles along the data distribution. This study is interested in determining the behavioral changes at the 75th percentile of renewable energy consumption because this is the consumption threshold of which the behavioral changes are likely to occur [2, 43, 44]. Hence, renewable energy consumption is split into two partial sum series as follows:

$$\text{REC}_{j,t} = \text{REC}_{j,t}(\varphi_1) + \text{REC}_{j,t}(\varphi_2). \quad (2)$$

The two partial sum series in Equation (2) are constructed to capture the threshold effects of renewable energy consumption at different aggregation levels at the 75th percentile, as shown below:

$$\text{REC}_{j,t}(\varphi_1) = \sum_{i=1}^t \Delta \text{REC}_{j,i} I\{\Delta \text{REC}_{j,i} \leq T_{75}\}, \quad (3)$$

$$\text{REC}_{j,t}(\varphi_2) = \sum_{i=1}^t \Delta \text{REC}_{j,i} I\{\Delta \text{REC}_{j,i} > T_{75}\}, \quad (4)$$

where $I\{\}$ denotes an indicator function which assumes value 1 if the condition stipulated in the bracket $\{\}$ is fulfilled, otherwise, the value would be 0. This study applies the Fourier functions, introduced by Yilanci et al. [79], in the MTNARDL model to account for unknown structural shifts without having the need for additional adjustments to the estimated model. This would improve the estimation power of the traditional ARDL model by effectively reducing over-parameterization risk and maintaining theoretical consistency in the model [80]. Thus, the FMTNARDL technique provides good size and power properties, while enhancing structural robustness and comprehensiveness of the model [81]. The FMTNARDL model of this study is expressed as follows:

$$\begin{aligned} \Delta \text{CO}_{2t} = & \beta_0 + \gamma_1 \sin \frac{2\pi kt}{T} + \gamma_2 \cos \frac{2\pi kt}{T} + \sum_{h=1}^p \varphi_1 \Delta \text{CO}_{2t-h} \\ & + \sum_{i=0}^q \varphi_2 \Delta \text{GDP}_{t-i} + \sum_{k=0}^r \varphi_3 \Delta \text{GDP}_{t-k}^2 \\ & + \sum_{i=0}^s \sum_{l=0}^z \varphi_4 \Delta \text{REC}_{j,t-i-l}(\varphi_j) + \sum_{m=0}^u \varphi_5 \Delta \text{OIL}_{t-m} \\ & + \sum_{n=0}^v \varphi_6 \Delta \text{FOSSIL}_{t-n} + \sum_{o=0}^w \varphi_7 \Delta \text{TECH}_{t-o} \\ & + \beta_1 \text{CO}_{2t-1} + \beta_2 \text{GDP}_{t-1} + \beta_3 \text{GDP}_{t-1}^2 + \beta_4 \text{REC}_{j,t-1}(\varphi_j) \\ & + \beta_5 \text{OIL}_{t-1} + \beta_6 \text{FOSSIL}_{t-1} + \beta_7 \text{TECH}_{t-1} + \mu_t, \end{aligned} \quad (5)$$

where t denotes the trend, T represents the sample period, γ is the displacement of the frequency component, and k signifies the

frequency of Fourier. p, q, r, s, u , and v indicate the order of lag term. The Akaike Information Criterion (AIC) is used to select the optimal lag terms represented by h, i, k, l, m, n , and o . φ_j signifies the threshold that splits renewable energy consumption variables into two regimes, that is, the regime below the threshold ($\varphi_1 = \text{REC}_{j,i} \leq T$) and the regime above the threshold ($\varphi_2 = \text{REC}_{j,i} > T$). The threshold effect of renewable energy on CO_2 emissions holds if $\varphi_1 \neq \varphi_2$, otherwise, the threshold effect would be absent. The long-run cointegration of Equation (5) is tested with the null hypothesis, $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$. The null hypothesis is rejected if the F-statistic exceeds the upper bound critical value, implying the existence of long-run relationship. Contrarily, there is no long-run cointegration if the F-statistic is below the lower-bound critical value. In the case when the F-statistic falls in between the upper and lower bounds, the test result becomes inconclusive.

The second objective of the study is to assess the moderating role of oil prices in the relationship between renewable energy consumption and CO_2 emissions in the United States and China. The moderating effect of oil prices is determined by the interaction between oil prices and renewable energy consumption at different aggregation levels. The empirical model of objective two is constructed as follows:

$$\begin{aligned} \text{CO}_{2t} = & \beta_0 + \beta_1 \text{GDP}_t + \beta_2 \text{GDP}_t^2 + \beta_{j,3} \text{REC}_{j,t} \\ & + \beta_4 \text{OIL}_t + \beta_{j,5} (\text{REC}_j \times \text{OIL})_t + \beta_6 \text{FOSSIL}_t \\ & + \beta_7 \text{TECH}_t + \mu_t. \end{aligned} \quad (6)$$

This interaction term offers granular information about the substitution effect of oil prices. It provides insights into how the impacts of aggregate and disaggregated renewable energy consumption on CO_2 emissions change in response to oil price movements. The marginal effects of aggregate and disaggregated renewable energy consumption on CO_2 emissions are identified by accounting for the partial derivatives of Equation (6), as presented below:

$$\frac{\partial \text{CO}_{2t}}{\partial \text{REC}_{j,t}} = \delta_{j,3} + \delta_{j,5} \text{OIL}_t. \quad (7)$$

The Fourier ARDL (FARDL) proposed by Yilanci et al. [79] is performed to capture the possible structural shifts for improved practical relevance and comprehensiveness of the research. For this objective, hypothesis testing depends on the signs of $\beta_{j,3}$ and $\beta_{j,5}$. If both $\beta_{j,3}$ and $\beta_{j,5}$ are significantly negative, renewable energy consumption causes a decline in CO_2 emissions and oil prices amplify this effect. This implies that the expansion of renewable energy consumption curbs fossil fuel-induced CO_2 emissions [82]. Simultaneously, rising oil prices create uncertainties in the global oil market [83]. This scenario creates a substitution effect that stimulates the replacement of expensive fossil fuels with relatively cheaper renewable energy in national production and energy consumption [62].

If $\beta_{j,3}$ is significant and negative, whereas $\beta_{j,5}$ is significantly positive, renewable energy consumption would lower CO_2 emissions and this effect would be constrained by oil price escalation. This phenomenon is usually applied in the oil-

exporting countries that rely on oil revenue. These countries enjoy increased oil revenue and are likely to continue expanding oil-related industries in order to further exploit the advantages of rising oil prices [67]. Besides, there are high opportunity costs associated with energy transition in the oil-rich nations due to their fiscal and economic reliance on crude oil [84]. Therefore, oil price spikes enhance national wealth in some countries and decrease their motivations to deploy renewable energy.

On the flip side, renewable energy consumption would elevate CO_2 emissions and this effect would be moderated by oil price surge if $\beta_{j,3}$ is significantly positive and $\beta_{j,5}$ is significantly negative. Renewable energy consumption could induce environmental costs, especially at the initial stages of renewable energy development whereby the country is lacking cost-effectiveness and technological efficiency [4]. For instance, the manufacturing and disposal of nonbiodegradable solar PVs and wind turbines can contribute to environmental pollution before recovery and recycling techniques are innovated and diffused [19, 85]. Nevertheless, oil price hikes serve as a moderating role to alleviate the adverse impact of renewable energy consumption by disincentivizing fossil fuel consumption and encouraging renewable energy expansion. Scale effect arising from renewable energy expansion fosters technological advancement of efficient green technologies that maximizes the environmental benefits of renewable energy in the long run [10].

In the last scenario, both $\beta_{j,3}$ and $\beta_{j,5}$ are significantly positive. This infers that the growth in renewable energy consumption raises CO_2 emissions, while the oil prices enhance this effect. The lack of scale and technique effects in renewable energy consumption, particularly during the early developmental stages can exert detrimental impacts on the environment [10]. The hazardous effects are further strengthened by oil price hikes when an oil-rich economy continues its economic reliance on oil revenue and does not seek to phase out fossil fuel consumption [83]. This would hamper the development of scale and technique effects in renewable energy consumption and intensify environmental damage.

Focusing on the United States and China, this study has 43 observations, spanning from 1980 to 2022. The details about each variable are listed in Table 2. All data is converted into natural logarithmic form to ensure normality [89]. The detailed information about the data employed for this study is presented in Table 2.

Table 3 presents the descriptive statistics of the dataset. The United States has mean and median of $\ln \text{CO}_2$ that are greater than those of China, implying that the United States has a greater cumulated CO_2 emissions than China. Similarly, the mean and median of all renewable energy types of the United States are also greater than those of China except for $\ln \text{HYDRO}$, suggesting stronger overall renewable energy development in the United States. It is noted that $\ln \text{CO}_2$, $\ln \text{WIND}$, and $\ln \text{OTHERS}$ have positive kurtosis (leptokurtic) and negatively skewed distribution in both countries, suggesting that the rates of changes in these three variables are uneven and erratic.

TABLE 2 | Data descriptions and sources.

Variables	Indicators	Description	Measurement	Sources
CO ₂ emissions	CO ₂	Total CO ₂ emissions of a country	Million tons	British Petroleum (BP) Statistics [86]
Renewable energy consumption	Renewable Energy Consumption	Total consumption of renewables, hydro, solar, wind, and others (bioenergy, and geothermal)	Terawatt-hour	BP Statistics [86]
Oil prices	Brent crude	Europe Brent Spot Price FOB Dollars per Barrel	USD per barrel	Energy Information Administration [87]
GDP	GDP	Total national income	Constant 2015 USD	World Development Indicators [88]
Fossil fuel consumption	Fossil fuel consumption	Total fossil fuel consumption	Terawatt-hour	BP Statistics [86]
Technological innovation	Number of patent applications	Number of patents registered by a country per year	Number of patent applications by residents and nonresidents	World Development Indicators [88]

4 | Findings and Discussion

This study begins with the stationarity test to avoid spurious regression by employing the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) method. The KPSS results in Table 4 confirm that all variables are

stationary at first difference for both countries, validating the use of the FMTNARDL and FARDL techniques to address the two objectives of this study.

TABLE 4 | KPSS unit root test.

TABLE 3 | Descriptive statistics.

Variables	Mean	Std. Dev.	Skewness	Kurtosis
United States				
lnCO ₂	8.5452	0.0852	−0.1779	2.1324
lnREC	7.1865	0.3569	0.8388	2.4977
lnHYDRO	6.6759	0.1282	0.3808	2.5279
lnSOLAR	0.6800	3.5321	−0.4374	2.7572
lnWIND	2.2927	4.3576	−0.9841	2.7085
lnOTHERS	5.6362	0.6723	−0.2568	1.9238
lnBRENT	3.5971	0.6631	0.2301	1.7673
lnGDP	14.9662	2.6237	−4.5682	26.0407
lnFOSSIL	9.9521	0.0862	−0.6842	2.4685
lnTECH	12.5603	0.6266	−0.2531	1.6167
China				
lnCO ₂	8.3504	0.6778	−0.0433	1.5192
lnREC	6.8739	1.1204	0.2912	1.7852
lnHYDRO	6.7577	0.9669	0.0747	1.6264
lnSOLAR	−1.4988	4.6657	0.5067	1.9855
lnWIND	0.5272	5.1218	−0.2670	1.7488
lnOTHERS	1.0447	4.5411	−0.6571	1.9423
lnBRENT	3.5971	0.6630	0.2300	1.7673
lnGDP	14.2382	2.7384	−3.4244	18.14153
lnFOSSIL	9.5403	0.6949	−0.0437	1.5535
lnTECH	10.3152	4.1890	−1.5865	4.6683

Variables	Level		First difference	
	Constant	Trend	Constant	Trend
United States				
lnCO ₂	0.7375**	0.2048**	0.3248	0.1037
lnREC	0.7145**	0.1880**	0.2722	0.0805
lnHYDRO	0.5652**	0.1700**	0.1045	0.0825
lnSOLAR	0.7711***	0.2346***	0.1871	0.1090
lnWIND	0.7485***	0.1863**	0.2750	0.0388
lnOTHERS	0.7997***	0.2623***	0.2048	0.0779
lnBRENT	0.5538**	0.1213*	0.2058	0.0966
lnGDP	0.8264***	0.2773***	0.1204	0.0728
lnFOSSIL	0.4841*	0.1972**	0.1476	0.0823
lnTECH	0.8019***	0.1708**	0.3382	0.0663
China				
lnCO ₂	0.8091***	0.4563***	0.1313	0.1035
lnREC	0.8187***	0.1964**	0.2591	0.1185
lnHYDRO	0.8176***	0.1158**	0.1625	0.1181
lnSOLAR	0.7868***	0.1810**	0.3418	0.0704
lnWIND	0.7910***	0.1615**	0.0643	0.0609
lnOTHERS	0.7555***	0.1628**	0.1493	0.0823
lnBRENT	0.5538**	0.1213*	0.2058	0.0966
lnGDP	0.7557***	0.2176**	0.3133	0.1003
lnFOSSIL	0.8124***	0.4479***	0.1285	0.1030
lnTECH	0.7094**	0.1556**	0.1958	0.0983

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

4.1 | Estimation Results for the United States

4.1.1 | FMTNARDL Estimation

Table 5 documents the results of the FMTNARDL technique for the United States. The hypothesis testing of nonlinearity in the models is determined by the Wald test. Based on Table 5, the F-statistics of the Wald test in Model 1, 3, and 5 are significant with at least 5% significance level, confirming the presence of nonlinearity in the three models. In Model 1, REC only shows significant and negative effect on CO₂ after reaching the 75th percentile threshold (1774.40 TWh). Beyond the threshold, every percentage increase in REC reduces CO₂ by 0.2370%.

In Model 3, SOLAR exerts a negative influence on CO₂ before and after reaching the 75th percentile threshold (24.77 TWh). However, the negative effect diminishes after the threshold. Precisely, CO₂ decreases by 0.0513% when SOLAR expands by 1% before the threshold. Beyond the threshold, a percentage expansion in SOLAR will lower CO₂ by 0.0065%. In Model 5, OTHERS demonstrates a significant behavioral change on CO₂ from positive to negative after reaching the 75th percentile threshold (558.70 TWh). Before the threshold, a percentage expansion in OTHERS leads to a growth in CO₂ by 0.1246%. Beyond the threshold, CO₂ slumps by 0.0444% when OTHERS accelerates by 1%.

TABLE 5 | FMTNARDL results for the United States.

Variables	Coefficients				
	Model 1	Model 2	Model 3	Model 4	Model 5
Lag length	2,1,3,3,3,3,3,3	3,3,2,3,3,3,3,3	2,2,1,2,2,2,2,2	3,3,3,3,2,3,2,3	1,1,2,2,2,2,0,2
Long-run coefficients					
REC <1774.40 TWh	−0.0383	—	—	—	—
REC >1774.40 TWh	−0.2370**	—	—	—	—
HYDRO <864.27 TWh	—	−0.2203	—	—	—
HYDRO >864.27 TWh	—	−0.3573	—	—	—
SOLAR <24.77 TWh	—	—	−0.0513**	—	—
SOLAR >24.77 TWh	—	—	−0.0065*	—	—
WIND <390.02 TWh	—	—	—	0.0758	—
WIND >390.02 TWh	—	—	—	0.0189	—
OTHERS <558.70 TWh	—	—	—	—	0.1246***
OTHERS >558.70 TWh	—	—	—	—	−0.0444*
BRENT	0.0066	0.1285*	0.0262***	−0.0249	0.0135*
GDP	1.6092**	0.5108	−0.2006	0.6730	0.4480***
GDP2	−1.4360***	−0.3406	0.2653	−0.4801	−0.3886***
FOSSIL	1.3883***	1.7391**	0.8314***	1.4299***	1.1667***
TECH	0.1375*	−0.3262	−0.2020*	−0.0305	−0.0785**
ECT	−0.8888***	−0.4375***	−0.6817***	−0.6831***	−0.9979***
SIN	−0.1163***	0.0138***	−0.0048**	0.0152***	−0.0320***
COS	−0.0257***	0.0031**	−0.0314***	0.0372***	−0.0022*
Bounds test					
F-Stat	6.3154***	7.1600***	5.3690***	6.3021***	74.3138***
Wald test					
F-Stat	5.9596**	1.2354	3.2129**	3.2616*	4.3302***
Diagnostic test					
Breusch-Godfrey LM test	3.0221	2.1115	3.3464	2.6033	3.3130
Jarque-Bera test	0.9765	0.5288	0.5050	0.7513	0.0702
Ramsey RESET test	0.3373	1.1466	0.5057	0.3183	0.0143
ARCH test	0.7028	0.0068	0.0153	0.1755	0.3124

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

With respect to the control variables, GDP and GDP2 are significant with positive and negative signs, respectively, in Model 1 and 5, indicating that EKC is only present in these two models. The significant positive relationship between FOSSIL and CO₂ is consistent across all five models. TECH affects CO₂ positively in Model 1, and the effect becomes negative in Model 3 and 5. The long-run cointegration in the five models is supported by the negative ECT coefficients, significant at 1% significance level.

According to Table 5, there are periodic fluctuations in CO₂ emissions, as evidenced by the significant Fourier terms (SIN and COS) across the five models. This suggests that the FMTNARDL model offers a superior fit for this study as compared to the traditional MTNARDL model. Table 5 also informs that all the models are free from autocorrelation, normality, misspecification, and heteroskedasticity issues. The results of CUSUM and CUSUM square tests in Figure 1 confirm the stability of the models.

4.1.2 | FARDL Estimation With Interaction Term

Table 6 reports the FARDL results for the moderating effects of oil prices in the interplay between renewable energy consumption and CO₂ emissions for the United States. The findings show that all the interaction terms, including REC*BRENT, HYDRO*BRENT, SOLAR*BRENT, WIND*BRENT, and OTHERS*BRENT are statistically insignificant in influencing CO₂. This indicates that oil prices do not moderate the relationship between renewable energy consumption and CO₂ emissions in the United States.

For the control variables, the significant positive sign of GDP and negative sign of GDP2 in Models 1–3 corroborate the existence of EKC in these three models. The positive effect of FOSSIL on CO₂ is consistent across the five models. On the other hand, the significant negative effect of TECH on CO₂ is found in Models 1 and 2. The negative ECT coefficients in all the models, significant at 1% significance level, confirm the long-run cointegration in the models.

Besides, the Fourier terms (SIN and COS) are statistically significant in all the models, implying the presence of structural shifts and justifying the use of the Fourier ARDL technique in this study. In regards to the diagnostic tests, all the five models are free from all diagnostic problems. Figure 2 also inform that all the models are stable.

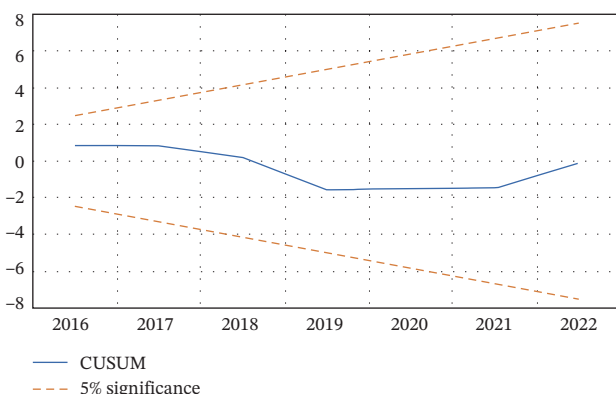


FIGURE 1 | CUSUM and CUSUMQ tests for Model 1 for the FMTNARDL results for the United States. *Note:* For the other models, the CUSUM and CUSUMQ tests likewise indicate stability.

4.2 | Estimation Results for China

4.2.1 | FMTNARDL Estimation

Table 7 reports the FMTNARDL outcomes for China. The F-statistics of the Wald test in Model 1, 2, and 4 are significant at least at 10% significance level, verifying the presence of nonlinearity in the three models. In Model 1, the effect of REC on CO₂ changes from insignificant to negative after the 75th percentile threshold (2780.10 TWh). This denotes that CO₂ will decline by 0.0294% when REC increases by 1% beyond its threshold.

In Model 2, the negative effect of HYDRO on CO₂ remains consistent before and after the 75th percentile threshold (2365.62 TWh). Nevertheless, the negative effect shrinks after the threshold. Before the threshold, a percentage growth in HYDRO will reduce CO₂ by 0.1793%. Beyond the threshold, CO₂ will decrease by 0.0678% for every percentage increase in HYDRO. In Model 4, the significance of WIND in affecting CO₂ is only exhibited after 75th percentile threshold (282.55 TWh). Beyond the threshold, CO₂ will surge by 0.0023% when WIND expands by 1%.

Pertaining to the control variables, EKC only stands in Model 4, where there is a statistically significant positive GDP and negative GDP2. The positive effect of FOSSIL and negative effect of TECH on CO₂ are consistent across the five models. The long-run cointegration in all the models is verified by the negative ECT coefficients, which are statistically significant at 1% significance level.

Based on Table 7, the significant Fourier terms (SIN and COS) indicate that the Fourier ARDL approach provides a more robust statistical finding than traditional ARDL approach. The diagnostic test outcomes confirm that there are no econometric issues in all the models. Figure 3 also inform that all the models are stable.

4.2.2 | FARDL Estimation With Interaction Term

Table 8 shows the FARDL results for the moderating effects of oil prices in the interplay between renewable energy consumption and CO₂ emissions for China. The findings unveil that HYDRO*BRENT has a coefficient of −0.0048, significant at 10% significance level, whereas HYDRO is statistically significant with a coefficient of 0.0163 at 10% significance level. Applying the equation below, the marginal effects of HYDRO are computed

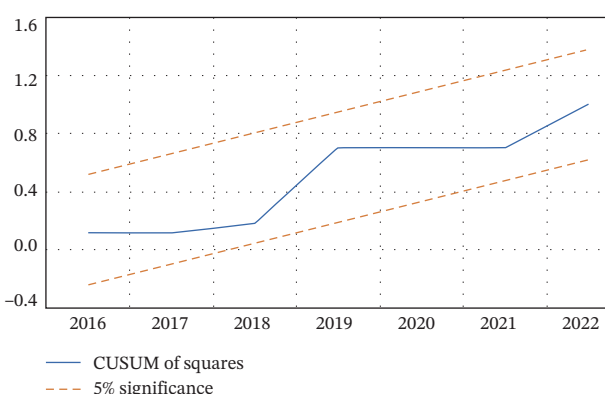


TABLE 6 | Results of indirect relationship between renewable energy consumption, oil prices, and CO₂ emissions in the United States.

Variables	Coefficients				
	Model 1	Model 2	Model 3	Model 4	Model 5
Lag length	3,1,3,0,3,2,0,0	3,1,1,0,3,2,0,0	2,0,1,3,3,3,3,0	3,3,3,0,2,2,0,0	1,1,0,1,2,0,1,0
Long-run coefficients					
REC	−0.0581***	—	—	—	—
HYDRO	—	−0.0455***	—	—	—
SOLAR	—	—	−0.0012	—	—
WIND	—	—	—	−0.0134*	—
OTHERS	—	—	—	—	−0.0055
BRENT	0.0076	0.0017	0.0064	0.0032	−0.0041
REC*BRENT	0.0011	—	—	—	—
HYDRO*BRENT	—	0.0004	—	—	—
SOLAR*BRENT	—	—	−0.0002	—	—
WIND*BRENT	—	—	—	0.0177	—
OTHERS*BRENT	—	—	—	—	0.0030
GDP	0.2275**	0.3692***	0.2318***	−0.1067	0.1424
GDP2	−0.1790**	−0.3184***	−0.2532***	−0.0393	−0.1546*
FOSSIL	1.3246***	1.4361***	1.4363***	1.6616***	1.1340***
TECH	−0.0707**	−0.0700**	0.0041	0.0083	−0.0329
ECT	−0.8010***	−0.7385***	−1.2696***	−0.6710***	−0.6742***
SIN	0.0145***	0.0127***	0.0186***	−0.0076***	−0.0221***
COS	0.0121***	0.0165***	0.0173***	−0.0053***	0.0100***
Bounds test					
F-Stat	144.4237***	155.9208***	5.6200***	80.9157***	6.5815***
Diagnostic test					
Breusch-Godfrey LM test	0.4529	0.3855	2.3099	1.0655	1.4520
Jarque-Bera test	0.3896	0.1562	1.6520	0.7647	2.7817
Ramsey RESET test	0.3963	0.0256	0.5552	0.0236	0.2416
ARCH test	0.1752	0.3587	0.4077	0.2028	0.1370

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

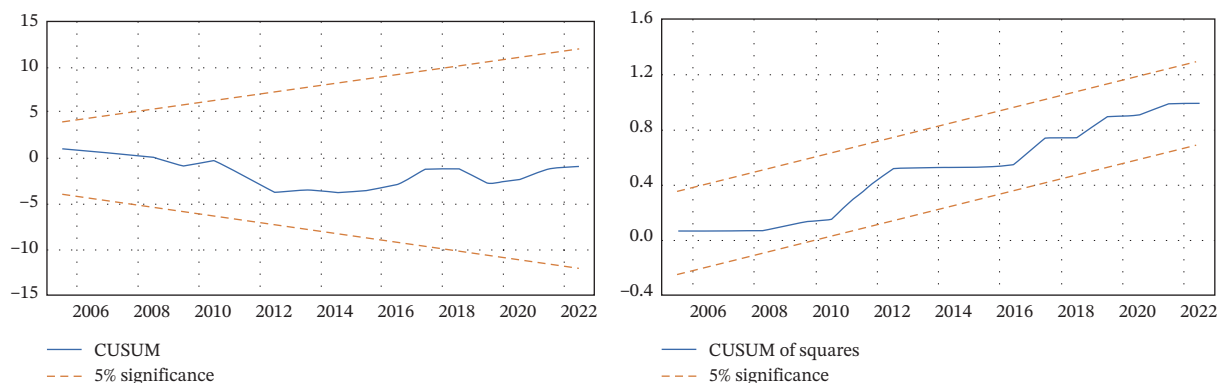


FIGURE 2 | CUSUM and CUSUMQ tests for Model 1 for the moderating effects of oil prices in the relationship between renewable energy consumption and CO₂ Emissions in the United States. Note: For the other models, the CUSUM and CUSUMQ tests likewise indicate stability.

TABLE 7 | FMTNARDL results for China.

Variables	Coefficients				
	Model 1	Model 2	Model 3	Model 4	Model 5
Lag length	1,2,2,1,1,1,0,2	2,2,3,2,3,3,3,3	1,1,0,0,0,0,1,0	1,1,1,0,0,0,1,0	1,0,0,0,0,0,1,0
Long-run coefficients					
REC <2780.10 TWh	−0.0147	—	—	—	—
REC >2780.10 TWh	−0.0294*	—	—	—	—
HYDRO <2365.72 TWh	—	−0.1793***	—	—	—
HYDRO >2365.72 TWh	—	−0.0678*	—	—	—
SOLAR <9.85 TWh	—	—	0.0021	—	—
SOLAR >9.85 TWh	—	—	−0.0017	—	—
WIND <282.55 TWh	—	—	—	0.0024	—
WIND >282.55 TWh	—	—	—	0.0023**	—
OTHERS <121.96 TWh	—	—	—	—	−0.0005
OTHERS >121.96 TWh	—	—	—	—	0.0016
BRENT	−0.0050	−0.0285**	−0.0036	−0.0014	0.0001
GDP	0.1030**	−0.1444	0.0429	0.1206***	0.0404
GDP2	−0.0540	0.0674	−0.0535	−0.1217***	−0.0401
FOSSIL	1.1137***	1.2592***	1.1213***	1.1497***	1.0977***
TECH	−0.0024*	−0.0028**	−0.0047***	−0.0043***	−0.0043***
ECT	−0.9746***	−1.3497***	−0.5573***	−0.5581***	−0.6256***
SIN	−0.3654***	−0.0092***	0.0100***	−0.0033***	−0.1099***
COS	0.0348***	−0.0020***	0.0121***	−0.0009	0.0991***
Bounds test					
F-Stat	627.0747***	5.0127***	9.6094***	12.4167***	7.3559***
Wald Test					
F-Stat	3.3411***	2.9035*	1.8944	3.4101**	0.5396
Diagnostic test					
Breusch-Godfrey LM test	2.6568	1.6874	1.6739	0.8616	0.7380
Jarque-Bera test	0.1089	3.5658	0.3096	0.4746	2.3871
Ramsey RESET test	0.4950	0.7619	0.8199	0.1419	1.1574
ARCH test	0.1726	0.1313	1.0371	1.3302	0.2475

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

at the minimum (USD 12.72), mean (USD 36.49), and maximum (USD 111.67) levels of BRENT.

$$\frac{\partial \text{CO}_2}{\partial \text{HYDRO}} = 0.0163 - 0.0048 \text{BRENT}.$$

Figure 4 illustrates the marginal effects of HYDRO on CO₂ across varying levels of BRENT. It is found that CO₂ will grow by 0.0040% when HYDRO accelerates by 1% at the minimum level of BRENT. Simultaneously, CO₂ will decline by 0.0009% at the mean level and 0.0063% at the maximum level of BRENT when HYDRO accelerates by 1%. This indicates that

the positive relationship between HYDRO and CO₂ is reversed by BRENT, of which the moderating power strengthens as BRENT rises.

In reference to Table 8, OTHERS*BRENT is significant with a coefficient of 0.0097 at 1% significance level, whereas OTHERS has a coefficient of −0.0071, significant at 1% significance level. The formula below is utilized to quantify the marginal effects of OTHERS*BRENT.

$$\frac{\partial \text{CO}_2}{\partial \text{OTHERS}} = -0.0071 + 0.0097 \text{BRENT}.$$

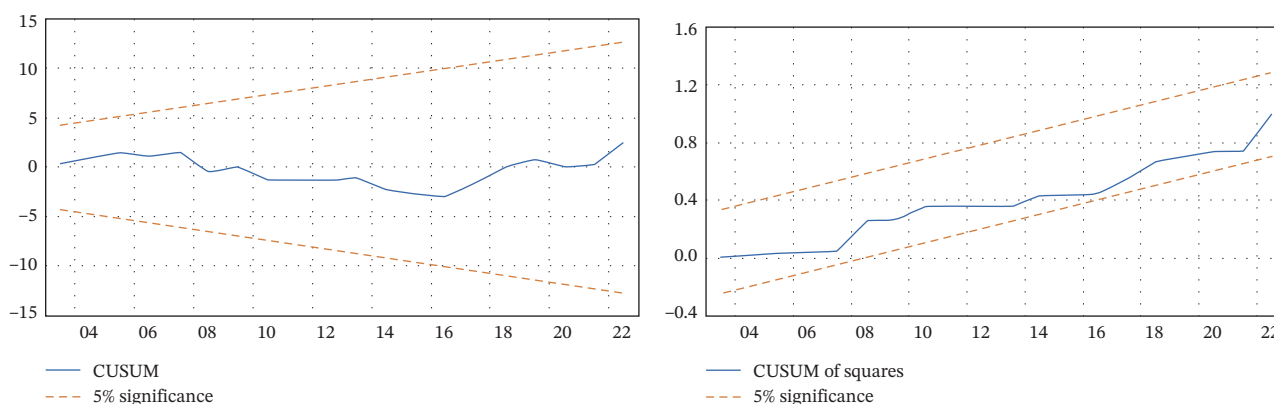


FIGURE 3 | CUSUM and CUSUMQ tests for Model 1 for the FMTNARDL results for China. *Note:* For the other models, the CUSUM and CUSUMQ tests likewise indicate stability.

TABLE 8 | Results of indirect relationship between renewable energy consumption, oil prices, and CO₂ emissions in China.

Variables	Coefficients				
	Model 1	Model 2	Model 3	Model 4	Model 5
Lag length	1,1,0,0,0,1,0	1,0,0,2,2,2,2,2	1,0,0,0,0,0,1,0	1,1,1,1,0,0,1,0	1,2,1,1,2,2,2,2
Long-run coefficients					
REC	−0.0212	—	—	—	—
HYDRO	—	0.0163*	—	—	—
SOLAR	—	—	−0.0028	—	—
WIND	—	—	—	0.0001	—
OTHERS	—	—	—	—	−0.0071***
BRENT	−0.0012	0.0033	−0.0005	0.0009	−0.0072**
REC*BRENT	−0.0017	—	—	—	—
HYDRO*BRENT	—	−0.0048*	—	—	—
SOLAR*BRENT	—	—	−0.0001	—	—
WIND*BRENT	—	—	—	0.0027	—
OTHERS*BRENT	—	—	—	—	0.0097***
GDP	0.0079**	0.2658***	0.0026	0.1241*	0.2966***
GDP2	−0.0753**	−0.1961***	−0.0102	−0.1250*	−0.2001***
FOSSIL	1.1385***	1.1465***	1.0949***	1.1108***	1.1143***
TECH	−0.0059***	−0.0080***	−0.0052***	−0.0044***	−0.0017*
ECT	−0.5151***	−1.1770***	−0.5665***	−0.6503***	−1.2748***
SIN	−0.0018***	−0.0014**	0.0122***	0.1722***	−0.0822***
COS	0.0008	−0.0006	0.0241***	0.2010***	0.1003***
Bounds test					
F-Stat	10.1494***	6.9818***	9.2478***	10.6389***	5.8596***
Diagnostic test					
Breusch-Godfrey LM test	2.3325	1.1367	1.5563	2.3932	2.2864
Jarque-Bera test	3.1007	3.1997	1.6146	0.5837	0.2367
Ramsey RESET test	0.6621	0.8099	0.5071	0.3868	0.1792
ARCH test	0.7198	1.9944	0.4553	1.7204	0.1310

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

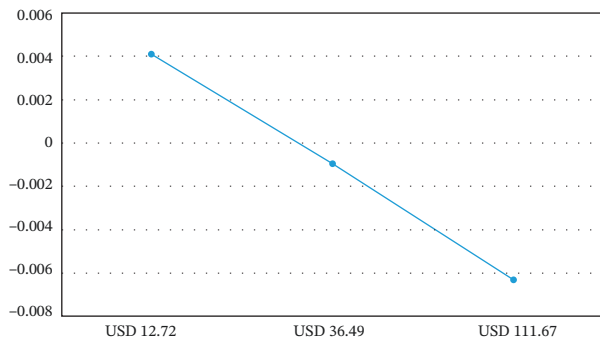


FIGURE 4 | Marginal effects of HYDRO on CO₂ at different levels of BRENT.

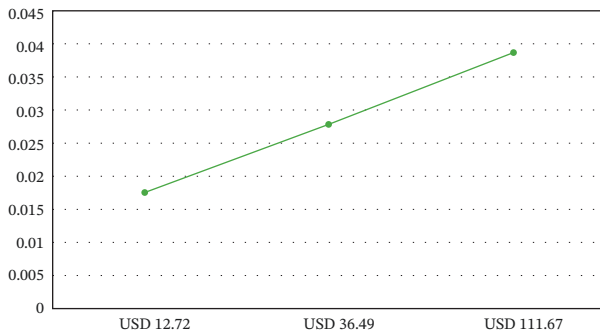


FIGURE 5 | Marginal effects of OTHERS on CO₂ at different levels of BRENT.

Figure 5 shows the marginal effects of OTHERS on CO₂ depending on the level of BRENT. To interpret, a percentage increase in OTHERS will stimulate an upsurge of 0.0175%, 0.0277%, and 0.0386% in CO₂ at the minimum, mean, and maximum levels of BRENT, respectively. This implies the significant moderating role of BRENT in reversing the negative effect of OTHERS on CO₂ to positive and that, the effect is enhanced with higher levels of BRENT.

In relation to the control variables, GDP and GDP2 manifest positive and negative impacts on CO₂, respectively, in Model 1, 2, 4, and 5, affirming the presence of EKC in China. Besides, the positive FOSSIL-CO₂ relation and negative TECH-CO₂ relation are found consistently across the five models. The ECT

coefficients are statistically significant at 1% significance level, confirming the existence of long-run cointegration in all the models.

Furthermore, the Fourier terms (SIN and COS) in all the models are statistically significant, affirming the superiority of the Fourier ARDL technique over the conventional ARDL technique in handling structural changes in the models. Additionally, all the models have passed the standard diagnostic tests, denoting that the statistical findings are robust and reliable. The CUSUM and CUSUM squares test results in Figure 6 validate the stability of the models.

4.3 | Robustness Analysis

To ensure that the empirical conclusion obtained in this study is not driven by the choice of the threshold cutoff, this study included a robustness analysis using the 50th percentile threshold cutoff. Considering that the present literature has emphasized that behavioral changes of renewable energy happen beyond the 50% consumption threshold [2, 43, 44], 50th percentile threshold is employed as an alternative benchmark for validating the stability of the results. Comparing the findings between the two threshold specifications helps determine whether the identified asymmetric relationships between renewable energy and CO₂ emissions hinge on a particular cutoff value.

To assess the sensitivity of the empirical results with the 75th percentile threshold cutoff, FMTNARDL is performed using the 50th percentile threshold. Based on Tables 9 and 10, the FMTNARDL results using the 50th percentile threshold support the robustness of the primary findings. For the United States, the presence of threshold effects is identified for REC, SOLAR, and OTHERS. Particularly, the effect of REC on CO₂ becomes significant and negative only beyond the 50th percentile threshold (1159.15 TWh), which is consistent with the primary finding. Similarly, the impact of SOLAR on CO₂ only becomes significantly negative after surpassing the 50th percentile threshold (1.69 TWh). This result is consistent with the baseline result that the decarbonization effect of SOLAR only emerges after the 50th percentile threshold and diminishes beyond the 75th percentile threshold (24.77 TWh). Conversely, OTHERS become statistically significant only after the 50th percentile threshold (247.25 TWh), where its coefficient becomes positive. In line with the primary finding, the

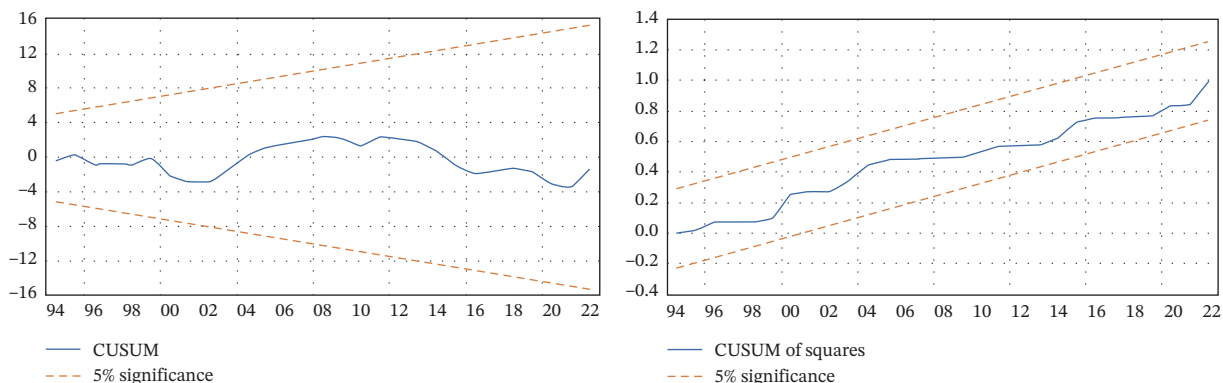


FIGURE 6 | CUSUM and CUSUMQ tests for Model 1 for the moderating effects of oil prices in the relationship between renewable energy consumption and CO₂ Emissions in China. *Note:* For the other models, the CUSUM and CUSUMQ tests likewise indicate stability.

TABLE 9 | FMTNARDL results for the United States at the 50th percentile threshold.

Variables	Coefficients				
	Model 1	Model 2	Model 3	Model 4	Model 5
Lag length	3,1,3,3,2,2,3,3	2,2,2,0,1,1,2,1	1,1,2,3,3,3,3,3	1,0,0,2,1,0,1,0	1,1,0,1,0,0,0,0
Long-run coefficients					
REC <1159.15 TWh	0.0856	—	—	—	—
REC >1159.15 TWh	−0.6345**	—	—	—	—
HYDRO <766.87 TWh	—	−0.3401	—	—	—
HYDRO >766.87 TWh	—	−0.3639	—	—	—
SOLAR <1.69 TWh	—	—	−0.0302	—	—
SOLAR >1.69 TWh	—	—	−0.0083*	—	—
WIND <19.99 TWh	—	—	—	−0.0153	—
WIND >19.99 TWh	—	—	—	−0.0015	—
OTHERS <247.25 TWh	—	—	—	—	−0.0336
OTHERS >247.25 TWh	—	—	—	—	0.0260**
BRENT	0.0285**	0.0470	0.0259**	0.0203	−0.0150***
GDP	−0.2982	−0.7974	0.1644	0.1253	0.2633***
GDP2	0.4818	0.5878	−0.2277	−0.1090	−0.2611***
FOSSIL	0.2784	2.4026*	1.5182***	1.1494***	1.2769***
TECH	0.1913*	−0.2500	0.0601	−0.1172	0.0075
ECT	−0.6274***	−0.1454***	−0.9007***	−0.4338***	−0.9384***
SIN	0.0060***	0.0046***	−0.0262***	−0.0183***	0.0195***
COS	0.0152***	−0.0004	0.0038***	−0.0057***	0.0157***
Bounds test					
F-Stat	7.8839***	4.1014***	4.0701***	4.0096***	201.7637***
Wald test					
F-Stat	2.8901*	2.1661*	3.3267**	0.9152	3.6253***
Diagnostic test					
Breusch-Godfrey LM test	3.2423	2.2807	1.8577	1.5458	1.6674
Jarque-Bera test	1.3274	0.4763	0.6978	1.2611	0.2587
Ramsey RESET test	0.0883	0.7655	0.4611	1.7265	0.4461
ARCH test	1.0203	0.2832	2.6948	0.1730	0.3484

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

sensitivity analysis indicates that OTHERS increases CO₂ after exceeding the 50th percentile threshold. However, this carbon-promoting effect reverses beyond the 75th percentile threshold (558.70 TWh), where OTHERS begin to reduce CO₂.

For China, while the threshold effect of REC on CO₂ is statistically insignificant at the 50th percentile threshold (825.35 TWh), this result is in line with the general conclusion of the primary results. This outcome suggests that the carbon-mitigating effect of REC is only realized after exceeding the 75th percentile threshold (2780.10 TWh), as evidenced in the baseline findings. According to Table 10, HYDRO only significantly reduces CO₂ beyond the 50th percentile threshold (815.03 TWh). Aligning with the primary finding, the decarbonization power of

HYDRO manifests after reaching the 50th percentile threshold and declines beyond the 75th percentile threshold (2365.72 TWh). On the other hand, WIND contributes to CO₂ expansion upon reaching the 50th percentile threshold (2.11 TWh), which supports the baseline result.

Overall, the sensitivity analysis results complement the primary results by confirming that the threshold effects of renewable energy consumption on CO₂ emissions remain qualitatively consistent when using the 50th percentile threshold cutoff. Despite minor variations in the statistical significance, no empirical and conceptual contradictions are observed between the sensitivity analysis and primary findings, thus, strengthening the reliability of the original estimates.

TABLE 10 | FMTNARDL results for China at the 50th percentile threshold.

Variables	Coefficients				
	Model 1	Model 2	Model 3	Model 4	Model 5
Lag length	1,0,2,1,2,2,0,2	1,0,1,0,0,0,1,0	1,0,0,0,0,0,1,0	1,1,1,0,0,0,1,0	1,1,0,0,0,0,1,0
Long-run coefficients					
REC <825.35 TWh	−0.0116	—	—	—	—
REC >825.35 TWh	−0.0134	—	—	—	—
HYDRO <815.03 TWh	—	−0.0257	—	—	—
HYDRO >815.03 TWh	—	−0.0203**	—	—	—
SOLAR <0.09 TWh	—	—	0.0040	—	—
SOLAR >0.09 TWh	—	—	−0.0017	—	—
WIND <2.11 TWh	—	—	—	0.0029	—
WIND >2.11 TWh	—	—	—	0.0027**	—
OTHERS <9.58 TWh	—	—	—	—	0.0010
OTHERS >9.58 TWh	—	—	—	—	0.0002
BRENT	−0.0089**	−0.0066**	−0.0012	−0.0012	−0.0012
GDP	−0.2258*	0.0787***	0.0130	0.1268***	−0.0490
GDP2	0.1445*	−0.0736***	−0.0207	−0.1285***	0.0283
FOSSIL	1.1110***	1.1262***	1.1032***	1.1566***	1.1063***
TECH	−0.0020	−0.0051***	−0.0053***	−0.0042***	−0.0055***
ECT	−0.9981***	−0.5734***	−0.5539***	−0.5771***	−0.4904***
SIN	0.0775***	0.0023***	0.0132***	−0.0032***	0.0218***
COS	0.1197***	0.0010	0.0267***	−0.0013**	0.0472***
Bounds test					
F-Stat	689.6967***	9.8950***	9.6094***	11.9547***	8.6317***
Wald test					
F-Stat	3.0869***	38.1378***	1.1298	3.1285**	0.9840
Diagnostic test					
Breusch-Godfrey LM test	3.8173	1.5490	1.6596	0.9142	1.9235
Jarque-Bera test	1.2037	0.2887	1.1730	0.6915	0.4731
Ramsey RESET test	0.8169	1.4872	0.4546	0.6986	0.3281
ARCH test	1.7678	1.5785	0.1966	0.6205	0.1432

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

TABLE 11 | Result summary.

Variable	Threshold effects of renewable energy		Moderating impacts of oil prices	
	United States	China	United States	China
REC	Insignificant to negative	Insignificant to negative	No effect	No effect
HYDRO	No asymmetry	Weaker negative	No effect	Negative
SOLAR	Weaker negative	No asymmetry	No effect	No effect
WIND	No asymmetry	Insignificant to positive	No effect	No effect
OTHERS	Positive to negative	No asymmetry	No effect	Positive

4.4 | Discussion

The empirical findings are summarized in Table 11, with six key results highlighted for discussion. First, at the aggregate level, it is found that renewable energy consumption begins to yield advantageous environmental effects only after the thresholds in the United States (17740.40 TWh) and China (2780.10 TWh). This result supports the inferences of Horvey and Odei-Mensah [43] and Chen et al. [44] that renewable energy consumption poses a lagged negative effect on CO₂ emissions. Although renewable energy offers substantial environmental benefits due to lower lifecycle emissions of between 400 and 1000 g CO₂ eq/kWh compared to fossil fuels [90], its early environmentally benign effects are constrained by expensive up-front costs, poor energy efficiency, and underdeveloped value chains in the early development of renewable energy industry [4]. Energy transition achieves decarbonization through scale and technique effects, which take time to materialize [10]. Expansion in economies of scale promotes the establishment of renewable energy value chain and drastically improve the cost-effectiveness of renewable energy. Besides, developing renewable energy industry fosters attractive investment climate that encourages innovation in energy efficiency and decarbonization effect of renewable energy.

Overall, the environmental benefits of renewable energy exhibit at a relatively lower consumption threshold in the United States compared to China. This is mainly driven by the relatively early regulatory supports and stronger technological foundation in renewable energy in the United States. The United States implemented a minimum renewable electricity procurement requirement under the Public Utility Regulatory Policies Act in 1978, which served an early cornerstone commitment in renewable energy development [91]. Besides, both the Department of Defense and Department of Energy in the United States have played crucial roles in pushing for clean technology research and development since the early 2000s through strong coordination at the federal level [92]. On the other hand, renewable energy became part of China's legislative framework since 2005 [93]. The significant time difference in regulatory support for renewable energy development at the central governmental level implies that the United States possesses a relatively stronger technological foundation and mature value chains in the renewable energy industry.

The contrasting decarbonization efficiencies of renewable energy consumption in the United States and China are also reflected in their varied EKC pathways. The EKC pattern appears to be more pronounced in the United States than in China, suggesting structural differences in their development pathways. As previously highlighted, the United States renewable energy sector has benefited substantially from earlier renewable energy policy support, stronger investments in renewable technologies, and transition from coal-based energy toward natural gas and renewable energy, which have enabled its economic growth to be decoupled from CO₂ emissions at higher income levels [94]. In contrast, China's rapid industrialization has been historically dependent on coal-based manufacturing and energy production, which is arguably the most pollution-intensive energy source, leading to more persistent environmental costs associated with economic growth [95]. Although China has accelerated its energy transition through recent policy initiatives and technological advancements,

the later institutional commitment to renewable energy development indicates a more gradual mitigation of the environmental costs associated with higher income levels. Essentially, the differing EKC trajectories of the United States and China are consistent with their distinct energy structures, technological maturity, and policy frameworks.

Second, based on Table 11, hydro consumption is insignificant in affecting CO₂ emissions in the United States before and after the threshold, whereas the decarbonization effect of hydro consumption deteriorates after the threshold (2365.72 TWh) in China. This outcome contradicts the findings of Adebayo et al. [96] and Bilgili et al. [97], revealing that the relationship between hydro consumption and CO₂ emissions changes from positive to negative. The result discrepancy is attributed to the difference in the techniques and natures of data employed. Unlike Adebayo et al. [96] and Bilgili et al. [97] that initiated a time-frequency domain analysis that detect time-varying dynamics between variables, this study employs the FMTNARDL model that captures asymmetric relationship at predetermined thresholds (in this research, 75th percentile), while accounting for unspecified structural shifts. In terms of data, Adebayo et al. [96] and Bilgili et al. [97] used quarterly and monthly data, whereas this study utilizes annual data.

The United States and China adopt contrasting energy development priorities, whereby hydro plays a more imperative role in China's energy mix compared to that of the United States. Hydro energy has remained China's primary renewable energy source for meeting growing energy demand, reflected in the development of mega hydropower projects such as the Three Gorges Dam, the Baihetan Dam, and the Jinping-I Dam. This is because hydropower emits 100 times less CO₂ than conventional thermal power, and could potentially reduce 9% of global annual CO₂ emissions through coal power displacement [98, 99]. However, China's large-scale hydropower facilities usually involve large-scale construction, lagoon alteration, and land flooding, which are detrimental to the ecosystem and natural habitat [2]. Additionally, large hydropower facilities can promote widespread anaerobic decomposition of organic matter that can intensify GHG emissions [100]. These factors collectively contribute to the drop in the marginal environmental benefits of hydro consumption over time. Contrarily, hydro energy is gradually marginalized in the U.S.'s national energy mix, with merely 3% of over 90,000 dams currently used for electricity generation [101]. According to Sharma et al. [102], hydropower dams in the United States have an average operational age of around 60.5 years, resulting in higher risk for operational failure and deteriorated energy efficiency. Dam infrastructure aging and heightened operational costs collectively reduced the decarbonization efficacy of hydro energy.

Third, Table 11 shows that the effectiveness of solar consumption in carbon reduction diminishes after the threshold (24.77 TWh) in the United States. This outcome contradicts the evidences of Lee et al. [9] and Pata et al. [7] that the CO₂ mitigating effect improves over time. Solar energy is considered a flexible and strong energy substitute due to its high scalability and strong integrability with other renewable energy technologies [2]. Replacing natural gas with an acre of solar panels can avoid between 175 and 198 metric tons of CO₂ emissions per year, which is 208–236 times more than

an acre of forest [103]. However, the production and disposal stages of solar PV cells generate nonbiodegradable byproducts that can jeopardize environmental quality. Additionally, the installation of conventional concentrating solar thermal plants (CSP) requires ~32 acres of land, potentially resulting in habitat loss and a reduction in the natural carbon sink [104]. These issues collectively dampen the decarbonization potential of solar consumption in the long run.

Comparatively, the solar energy industry in the United States is more established than that of China. Solar energy development has received federal support since the 1970s, initially aimed at diversifying the energy mix in response to the oil price crises, while also benefiting from applications in offshore oil operations and NASA's space exploration programs [105]. These events fostered early technological innovation and efficiency improvements in the U.S. solar energy sector. The scale effect subsequently emerged in 1983 when the first state Net Energy Metering (NEM) program was introduced [106]. In 2011, the SunShot initiative was introduced to stimulate cost-competitive solar energy development, which further incentivized solar energy adoption in the United States [92]. In contrast, solar energy was deemed as a vital export rather than for domestic consumption in China in the early 2000s [21], with large-scale consumption commenced only after 2010 [107]. Following the 2012 solar industry shakeout due to the Eurozone crisis, China's solar sector evolved from fragmented industrial structure into a more consolidated and globally competitive powerhouse, which facilitated technological advancements and cost-efficient production [108]. By contrast, the U.S. solar sector had already developed a relatively mature technological and industrial ecosystem by the 1970s through the application of solar technologies in specialized industries. These divergent development trajectories reflect differences in the institutional prioritization and market positioning of solar energy technology in the United States and China.

Fourth, according to Table 11, wind consumption has no significant impact on CO₂ emissions in China before reaching the threshold (282.55 TWh). Nevertheless, the adverse environmental impact of wind consumption begins to materialize after its threshold. This is inconsistent with the findings of Lee et al. [9] that wind energy benefits the top 10 renewable energy consumers after reaching its consumption threshold. The result inconsistency is due to the fact that Lee et al. [9] involves a panel of other countries, while this time series study focuses only on China, other than the methodological difference.

While the operation of wind farms does not have substantial hazardous effect on the environment, vast amount of CO₂ is emitted from the construction of wind farms, manufacturing, and transportation of wind turbines, as evidenced in Dalian, China [109]. Besides, the manufacturing and disposal of wind turbines can also produce poisonous gases that harm the environment [1]. China's wind energy development began about a century later than the United States in the 1980s, suggesting profound technological gaps between the two countries in wind energy technologies [20]. The beneficial environmental potentials of wind energy in China are mainly restricted by two factors. First, the national average climatic conditions for wind energy in China are less favorable, with Tibet having most of the country's wind resources [110]. Second, China has high wind curtailment

rate due to heavy reliance on coal for power generation and backup, which leads to inflexible power output adjustments and poor integration of wind energy. This is significantly different from the United States energy development pathway, as the United States depends more heavily on natural gas, which is more flexible than coal in power integration with renewable energy [111]. Overall, compared with the United States, China's relatively late institutional commitment and coal-heavy energy composition substantially undermine the decarbonization effectiveness of wind energy technologies.

Fourth, according to Table 11, the presence of nonlinearity between other energy (bioenergy and geothermal) consumption and CO₂ emissions has been substantiated for the United States, but not in China. Specifically, the nonlinear effect switches from positive to negative in the United States after the consumption threshold (558.70 TWh). This finding aligns with the conclusions of Kartal et al. [6] and Bilgili et al. [112] that the impacts of other energy consumption on CO₂ transitions from positive to negative. Bioenergy technology involves thermochemical and combustion processes that are hazardous to the environment [113]. On the other hand, the installation and drilling processes of geothermal power plants do not only pollute the environment but also lead to subsidence risk [2]. Nevertheless, these adverse effects can be contained with increased consumption in the two renewable energy types through the implementations of stringent operational standards, strengthened regulatory frameworks, and enhanced innovation.

In the long run, the replacement of coal with biomass has the potential of reducing CO₂ emissions by 29 million tons on an annual basis [114]. On the other hand, geothermal energy releases 72 g CO₂ eq/kWh of GHG emissions, as compared to 678 g CO₂ eq/kWh GHG emitted by oil, indicating strong emissions mitigating effect [115]. While the United States and China are almost on par in biomass consumption, the former is far more dominant in biofuel consumption. The United States is the world's largest biofuel consumer, with consumption levels about 16 times greater than China's [86]. The U.S. bioenergy sector is supported by large-scale energy crop production, particularly corn-based crops, and the federal Renewable Fuel Standard, which mandates biofuel blending [116]. Conversely, China's relatively limited per-capita arable land discourages energy crop cultivation, thereby impeding bioenergy development [117].

Moreover, geothermal installed capacity in the United States is about 100 times more than that in China [87]. The U.S. geothermal industry has benefited considerably from venture capital and private investment, as reflected in the development of next-generation geothermal technologies that allow sophisticated geothermal reservoir engineering [118]. This has substantially improved the cost efficiency of geothermal energy in the United States, leading to a vast array of commercial utilizations, including electricity generation, heating, and heat pumps. While China is leading in the direct application of geothermal energy for district heating, geothermal energy remains relatively marginal in electricity generation, mainly attributed to land restrictions, cost, development risks, and public resistance [8, 119]. In short, the combination of targeted policy support, market-based incentives, and favorable geographical endowments of the United States has

fostered bioenergy and geothermal energy developments more effectively than China.

The sixth result informs that oil prices do not significantly moderate the relationship between renewable energy consumption and CO₂ emissions in the United States. This empirical finding affirms the outcomes of Esmaeili et al. [70] and Tambari et al. [66]. Esmaeili et al. [70] explain that the United States high oil endowment absorbs external oil price shocks and protects domestic industries from increased production costs arising from oil price hikes, thereby weakening the incentive for renewable energy substitution in the oil-dependent industries.

On the contrary, oil prices significantly moderate the relationship between renewable energy consumption and CO₂ emissions in China at the disaggregated level. Specifically, the effectiveness of hydro consumption in curbing carbon emissions in China is enhanced during rising oil prices. This finding provides a firm support to the concept of substitution effect linking renewable energy consumption, oil price dynamics, and CO₂ emissions. Rising oil prices pose a dual effect on China's energy landscape. As a net oil importer, oil price spikes not only increase the cost burden on China's oil-intensive industries but also exert a positive spillover effect on coal prices due to escalated demand for coal as a cheaper alternative, thereby jeopardizing its energy security [66, 120]. These factors serve as critical driving forces for China to seek cheaper energy alternatives to enhance energy resilience. Fundamentally, the divergent crude oil trade positions of the United States and China contribute to different degrees of imported oil dependency and urgency for the energy transition.

To cushion the adverse impacts of oil price hikes and enhance energy resilience, China pivots toward renewable energy development, particularly hydro energy [121]. In specific, China pursues a widespread transport electrification, covering consumer vehicles, freight, and public transport [122, 123]. Concurrently, heightened demand for electricity is increasingly met by renewable energy, with hydro energy accounting the largest share of clean electricity in China and outpacing coal in electricity generation growth [124]. Essentially, China's strategic shifts in energy and electricity development reinforce the decarbonization effect of hydro energy consumption amid positive oil price shocks, even within a coal-dominated system.

It is interesting to note that the environmentally benign effects of other energy consumption are constrained by the surging oil prices in China. In China, the growth in other energy consumption is overshadowed by solar and wind energy sources, especially when oil prices are soaring. To illustrate, the growth rate of others consumption contributed by the positive oil price shock during the Russia-Ukraine conflict outbreak in 2022 was only 6.06%, as compared to the growth rate of solar and wind consumptions at 30.32% and 15.88%, respectively [86]. This may be attributable to the fact that the Chinese government tend to increase oil subsidy to buffer the negative impact of positive oil price shocks on key economic sectors, especially the petrochemical and transport industries [125]. For reference, China provided oil subsidy worth USD 510 billion in 2022 [126]. As the direct substitute of oil, the cost effectiveness of bioenergy declines when oil is subsidized. This phenomenon substantially lowers the motivation of bioenergy

adoption, undermines economies of scale, and weakens investment incentives, resulting in limited carbon-mitigating effect.

5 | Conclusion and Policy Implications

In summary, this research performs an empirical analysis on the impacts of renewable energy consumption and oil prices on CO₂ emissions in the United States and China, across a sample period from 1980 to 2022. There are two objectives that this study aims to achieve. First, this study scrutinizes the threshold effects of renewable energy on CO₂ emissions across different levels of consumption aggregation. Second, this paper examines the moderating effects of oil prices in the relationship between renewable energy and CO₂ emissions across different levels of consumption aggregation.

The empirical outcomes of this study are as follows: (1) Renewable energy is only effective in mitigating CO₂ emissions in the United States and China beyond consumption levels of 17740.40 TWh and 2780.10 TWh, respectively. In terms of the disaggregated aspect, the decarbonization effect of solar energy weakens after the consumption level reaches 24.77 TWh, while the relationship between others energy and CO₂ emissions changes from positive to negative beyond a consumption level of 558.70 TWh. For China, the mitigating effect of hydro consumption diminishes after its threshold at 2365.72 TWh, while wind consumption only shows positive effect on CO₂ emissions after its threshold at 282.55 TWh. (2) China excels at capitalizing oil price spikes to improve the carbon-mitigating effect of hydro consumption, whereas the moderating effect of oil prices is absent in the United States. Nonetheless, the decarbonization effect of others consumption is dampened with rising oil prices in China.

Overall, the empirical findings portray that the varying decarbonization effectiveness of each renewable energy type is primarily shaped by country-specific energy policy priorities, institutional frameworks, and market positions. As a major oil producer, the United States faces relatively weaker pressure from oil price fluctuations, with its energy transition being driven predominantly by federal policy initiatives and market-based investment incentives. On the other hand, China's energy landscape is mainly guided by the centralized policy planning and state-led industrial consolidation, while its high dependence on imported oil reinforces the strategic importance of energy transition and decarbonization efforts for enhanced energy resilience.

Based on the results obtained, this study presents some policy recommendations to contain climate risks for the United States and China. Considering that the carbon mitigation of renewable energy manifests only at high consumption levels, both nations should sustain renewable energy investments and maintain such levels to preserve its decarbonization effect. To achieve a smooth and nonburdensome energy transition, rigid energy policies, like renewable portfolio standards and feed-in tariffs should be complemented with supportive policies, such as low-interest loans and tax credits. This will effectively foster a conducive investment environment that further realizes the potentials of renewable energy technologies in mitigating climate challenge.

Given that some renewable energy technologies will likely to exhibit diminishing environmental returns, particularly solar energy for the United States, and hydro and wind energy for China, the governments of both nations should prioritize technological innovation in these technologies rather than focusing solely on expanding consumption. The policymakers should coordinate public and private investments in the research and development of solar energy technologies in the United States, and hydro energy and wind energy in China, to enhance their positive environmental impacts and minimize adverse externalities. To achieve that, more cohesive and consolidated research laboratories, supported by national and state-level resources, need to be established. This can effectively cultivate synergy in research collaborations among energy experts and facilitate technological breakthroughs in renewable energy technologies.

In view of the finding that oil prices have limited influence on the oil prices-CO₂ emissions relation, the U.S. government should formulate independent and direct support mechanisms for renewable energy development, such as renewable energy-targeted tax incentives, rather than depending on oil price spikes to incentivize energy transition. Besides, carbon tax should be introduced to reduce the incentive of fossil fuel consumption and motivate renewable energy substitution. For China, the emissions mitigating effect of hydro consumption is amplified at higher oil prices, suggesting that China should leverage high oil prices to accelerate energy transition. China's policymakers may decrease the cost-effectiveness of oil prices by reducing oil subsidies and imposing carbon pricing, while crafting hydro-specific incentives such as hydro-specific tax exemption to encourage hydro energy adoption. On the flip side, considering that the positive environmental effects of bioenergy and geothermal consumption are reversed at higher oil prices in China, China's policymakers need to focus on reforming its high oil-reliant industries, particularly the petrochemical and transport industries by mandating biofuel blending. This will not only diversify China's energy mix but also reduce the need for oil subsidies in the event of oil price shocks.

This study comes with some limitations that are worth considering. One of which is the absence of nonlinear analysis for oil prices. Since oil prices are highly volatile in nature, the impact of oil prices on CO₂ emissions may vary across different shocks. In that respect, the moderating effect of oil prices in the renewable energy-CO₂ emissions relation may also differ under positive and negative shocks. Additionally, this paper does not account for the prices of other fossil fuels, mainly coal and natural gas. Not including these factors could potentially disregard the effects of other fossil fuel prices on CO₂ emissions. Another limitation is that this study combines bioenergy and geothermal into one variable due to data limitations. Thus, the findings are unable to capture the specific effects of bioenergy and geothermal on CO₂ emissions.

Several suggestions for future research are drawn from the limitations of this study. First, future studies could account for the nonlinear effects of oil price shocks. This can offer a more pragmatic measure when confronting different oil price shocks. Second, peer researchers can consider incorporating coal and natural gas prices, both as regressors and moderators. This can

improve the comprehensiveness of the study regarding price changes of different fossil fuels. Third, future research could incorporate better-defined renewable energy technologies, particularly bioenergy and geothermal and possibly, extend to latest renewable technologies, like hydrogen and marine energy. This can provide more specified approaches according to different renewable energy sources. Encompassing the latest renewable technologies can increase the relevance of the study in the technologically advancing world.

Author Contributions

Wen Hui Lee: data curation, formal analysis, investigation, writing – original draft, writing – reviewing and editing. **Dzul Hadzwan Husaini:** conceptualization, methodology, data curation, visualization, investigation, writing – original draft, writing – reviewing and editing. **Hooi Hooi Lean:** conceptualization, methodology, supervision, validation, writing – original draft, writing – reviewing and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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