Journal of Cleaner Production 484 (2024) 144343

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

The impact of renewable energy on extreme volatility in wholesale electricity prices: Evidence from organisation for economic co-operation and development countries

Guanghao Wang [a,b,*], Erwann Sbai [a,b], Le Wen [b,**], Mingyue Selena Sheng [a]

[a] Energy Centre, Department of Economics, Business School, University of Auckland, New Zealand
[b] Department of Economics, Business School, University of Auckland, New Zealand

ARTICLE INFO

Handling Editor: Panos Seferlis

Keywords:
Dynamic panel threshold regression
Renewable energy
Electricity prices
Price extreme volatility

ABSTRACT

As global climate change intensifies, the Paris Agreement aims to limit global temperature increases to within 2 °C above pre-industrial levels, with efforts to limit the increase to 1.5 °C. A key strategy to achieve this goal is accelerating the transition of the power grid to renewable energy sources. This study uses annual data and constructs annual extreme positive and negative wholesale electricity price fluctuations from daily weighted wholesale electricity spot prices. It examines the impact of various renewable energy sources on extreme positive and negative wholesale electricity price fluctuations in 32 Organisation for Economic Co-operation and Development countries from 2015 to 2023. Using dynamic panel threshold regression, we find that the proportion of renewable energy generation significantly reduces extreme price fluctuations once certain thresholds are exceeded. This finding underscores the importance of developing renewable energy sources such as hydropower, wind power, solar power, and biomass energy. It also highlights the challenges posed by the intermittency and unpredictability of renewable energy at lower penetration levels. Policy recommendations include developing energy storage technologies, building modern grid infrastructure, and formulating policy incentives to support the diversification of renewable energy. Future research should focus on the long-term impacts of renewable energy integration and the role of policy frameworks in supporting this transition, ensuring a comprehensive and sustainable energy transformation.

1. Introduction

The Paris Agreement, reached in 2015, represents a global consensus on addressing climate change, aiming to keep the global average temperature increase well below 2 °C above pre-industrial levels, and to pursue efforts to limit the temperature increase to 1.5 °C. To achieve this ambitious goal, countries have accelerated their transition to renewable energy. Since electricity accounts for 20% of global final energy consumption (Ember, 2023), increasing the share of renewable energy in electricity production has become a crucial part of the global energy transition. The Organization for Economic Co-operation and Development (OECD) countries consume nearly 40% of the world's energy (IEA, 2023), playing a significant role in this transition. Therefore, focusing on renewable energy consumption is vital for the global economy, especially in OECD countries, as it is an important tool in addressing climate change (Tao et al., 2023). For example, supported by subsidies and priority grid access, the share of renewable energy in Germany's national electricity production increased from 30% in 2015 to about 54% in 2023 (Ember, 2024a). Similarly, through the implementation of carbon-friendly policies, the share of renewable energy in Nordic countries' grids has been steadily rising since 2015. Notably, Norway achieved a renewable energy dependence rate of 98.83% (Ember, 2024a). Likewise, the shares of renewable energy in New Zealand and Australia have significantly increased, rising from 81% to 14% in 2015 to 88% and 38% in 2023, respectively (Ember, 2024a). Multiple conflicts and wars between Russia and Ukraine have caused severe fluctuations in fossil fuel prices, significantly exacerbating the urgency of the global transition to renewable energy (Alam et al., 2023). Even before the war in Ukraine, Europe's wholesale electricity prices soared from an average of €35 per megawatt-hour (MWh) in 2020 to nearly €250 per

* Corresponding author. Energy Centre, Department of Economics, Business School, University of Auckland, New Zealand.
** Corresponding author.
E-mail addresses: guanghao.wang@auckland.ac.nz (G. Wang), l.wen@auckland.ac.nz (L. Wen).

https://doi.org/10.1016/j.jclepro.2024.144343
Received 6 March 2024; Received in revised form 12 November 2024; Accepted 25 November 2024
Available online 28 November 2024

MWh in December 2021, an increase of over 400%. By March 2022, the average wholesale electricity price exceeded €500 per MWh (Ember, 2024a). Due to the stability issues of traditional energy sources such as natural gas and oil, governments and energy companies have become more proactive in exploring and expanding the use of renewable energy to ensure the security, reliability, and economic viability of energy supply. Consequently, the adoption of heat pumps, electric vehicles, and electrolysers has significantly increased, putting pressure on various industries to reduce emissions and accelerate the development of clean energy infrastructure. This crisis has highlighted the risks of relying on a single or limited number of energy supply sources, while also accelerating the diversification of the global energy structure. Renewable energy sources such as solar, wind, and hydropower have become ideal alternatives to fossil fuels due to their clean and sustainable characteristics. Furthermore, Cevik & Ninomiya (2023) assessed 24 European countries and found that wholesale electricity prices decreased in countries with higher renewable energy penetration and non-reliance on single-source power generation. Currently, many countries have introduced policies supporting renewable energy projects, including financial subsidies, tax incentives, and investments in technological research and development to stimulate the production and consumption of renewable energy (Newbery, 2023). According to Forrest and MacGill (2013), an increase in renewable energy not only reduces the reliance on fossil fuels and mitigates the impact of fossil fuel price fluctuations on wholesale electricity prices, but also decreases operational costs through the merit order effect. The merit order effect refers to the priority dispatch of renewable sources like wind and solar power in the electricity market, due to their near-zero marginal costs, over more expensive conventional sources such as coal and natural gas (Wen et al., 2020). This change in dispatch order can directly lead to a decrease in wholesale electricity prices. Therefore, increasing the supply of renewable energy not only reduces the grid's reliance on volatile fossil fuels but also effectively stabilizes and reduces fluctuations in wholesale electricity prices, bringing economic benefits and price stability to the entire power market.

In addition, the literature indicates that the intermittent of renewable energy introduces production uncertainties, which can lead to imbalances between supply and demand, reduced grid stability, and increased price volatility. Renewable energy, especially wind and solar power, lowers wholesale energy prices through the "merit order effect." Since the marginal cost of renewable energy is nearly zero, it is prioritized in dispatch, consequently decreasing the demand for more expensive fossil fuel generation. However, the volatility of renewable energy sources contributes to greater fluctuations in the upper quartiles of wholesale markets prices (Mwampashi and Nikitopoulos, 2023). This effect is particularly pronounced in markets with high penetration rates of variable renewable energy (VRE) (Hirth, 2013). Previous studies have reached different conclusions regarding the impact of wind power generation on wholesale price volatility. For example, Mauritzen (2010) found that wind power reduced price volatility in Denmark, while Ketterer (2014) found that wind power increased price volatility in Germany. The market value of wind and solar power declines as their penetration rates increase, mainly due to their variability and the temporal correlation with electricity prices. Without adequate market support mechanisms or advancements in energy storage and grid management technologies, this decline challenges the economic competitiveness of renewable energy at high penetration rates, thereby reducing their ability to stabilize prices through capacity fluctuations (Mills et al., 2019). Additionally, Rintamäki et al. (2017) found that centralized renewable energy plants and outdated policies hindered their effectiveness. Keeley et al. (2020) studied the merit order effect in Germany by combining regression analysis and machine learning with hourly data. They found that wind and solar power reduced spot market prices by an average of 9.64 euros/MWh from 2010 to 2017. The impact of wind power was relatively stable throughout the day, while the impact of solar power was more significant during peak hours. The study also noted that the merit order effect of renewable energy weakened under high generation conditions, reducing their ability to mitigate price fluctuations. Mohan et al. (2020) introduced the concept of the "volatility cliff," suggesting that as the penetration rate of intermittent renewable energy increases, price volatility may reach unacceptable levels, emphasizing the reliance on mature market mechanisms in markets with high renewable energy penetration. Ciarreta et al. (2020) analyzed the structural changes in Spanish electricity spot price volatility and found that stable regulatory policies and market-based measures are necessary to reduce price volatility with increased renewable energy penetration. Wen et al. (2022) used a spatial econometric model to evaluate the seasonal impact of wind power generation on node prices in New Zealand's hydro-dominated electricity market and found that a combination of renewable energy generation effectively mitigated price volatility (Dong et al., 2019). Moreover, Silva & Horta (2018) studied the impact of wind energy supply on price volatility in the Iberian electricity market from 2010 to 2015, finding that variable renewable energy supply (especially wind power) increased price volatility and noted that mature market regulatory capacity and renewable energy generation technologies could mitigate this volatility. Studies on the Australian National Electricity Market found that as renewable energy penetration and technology maturity increased, the frequency of extremely low prices increased over time, while the frequency of extremely high prices decreased (Rai and Nunn, 2020). Additionally, Mwampashi et al. (2021) and their further research (Mwampashi et al., 2022) found that systems dominated by multiple variable renewable energy sources could reduce the overall risk faced by the grid. Nyangon and Byrne (2023) also pointed out that incorporating a diverse mix of renewable energy sources helps mitigate grid risk. Mays and Jenkins (2023) emphasized the importance of integrating various renewable energy sources for grid stability.

In summary, we can see that all articles emphasize that a combination of renewable energy generation and mature market regulatory capacity helps mitigate electricity price volatility and reduce overall grid risk (Abban and Hasan, 2021). However, previous research, while focusing on average grid volatility and overall risk levels (Singh and Pal, 2019), has also predicted price fluctuations in electricity prices (Nyangon and Akintunde, 2024). But there is little distinction between positive and negative price fluctuations. Even when distinguishing between positive and negative price fluctuations, the scope of countries and types of energy studied in the research remains relatively limited. In addition, threshold effects are rarely considered in these studies (Rai and Nunn, 2020). Moreover, previous research has neglected extreme positive and negative price fluctuations. In fact, these extremely unpredictable fluctuations are the main reasons for significant shocks to the electricity market (Maciejowska, 2020). Retailers need to purchase electricity on the spot market to meet unexpected demand. When prices soar, they must buy electricity at extremely high prices, leading to a substantial increase in costs. At the same time, because a significant portion of retail contracts are usually at a fixed rate, retailers cannot immediately pass the whole wholesale price increases to consumers. In extreme cases, such as the Texas power outage in 2021, soaring prices led some power retailers to go bankrupt because they could not bear the huge electricity costs (Prete and Blumsack, 2023). Additionally, extremely low prices reduce wholesalers' revenues, which may not cover fixed costs and operating expenses, creating significant financial pressure and facing risks and pressures similar to retailers during periods of extremely high prices. Generally, electricity retailers and wholesalers can respond to volatility situations through corresponding hedge positions and electricity reserves. This is because general price fluctuations are predictable and common, and retailers and wholesalers usually prepare and plan in advance. Through hedging strategies, retailers can reduce the uncertainty brought by random demand and ensure stable profits during market price fluctuations (Wang et al., 2024). Wholesalers can maintain stable operations and revenue during price fluctuations by reserving electricity and managing risk positions. Therefore, for general market volatility, electricity market participants have sufficient coping ability and will not cause serious impacts on their finances and operations. Moreover, previous research usually focuses on a single type or a few types of renewable energy, often limited to a few countries, and lacks a broader perspective on countries undergoing electricity system transitions.

In conclusion, due to the long-term fixed nature of retail electricity prices and data availability, we chose to use the extreme volatility of wholesale electricity prices to measure the volatility faced by the electricity market. Since extreme volatility risk lasting several days or even a week can pose a threat to electricity retailers and wholesalers (while intraday extreme risks are unlikely to cause significant losses), this study uses annual data to construct annual extremely positive and negative fluctuations in wholesale electricity prices using weighted daily spot prices. We examine the impact of various renewable energies on extreme positive and negative fluctuations in wholesale electricity prices from 2015 to 2023 in 32 OECD countries. Fig. 1 shows the weighted average share of renewable energy generation and the weighted average risk value (VaR) and gain value (VaG) of wholesale electricity prices for the 32 OECD countries. We observed that from 2015 to 2019, as the share of renewable energy generation increased, the risk value did not significantly decrease but rather showed an upward trend. However, from 2020 to 2023, as the share of renewable energy generation further increased, the trend of the risk value changed and began to decline. This suggests a possible nonlinear relationship. Similarly, when we observe the trend of gain value and the share of renewable energy generation, we can see that from 2015 to 2020, as the share of renewable energy generation increased, the gain value did not significantly decrease but rather showed an upward trend. However, from 2021 to 2023, as the share of renewable energy generation further increased, the trend of the gain value changed and began to decline. (Here, the risk value and gain value refer to the maximum drop and rise in wholesale electricity prices within the 95% confidence interval, divided by the annual average wholesale electricity price. For specific definitions, see the methods section.)

This suggests potential non-linear situations. It also indicates that previous articles may have simplified the relationship between renewable energy and extreme price volatility, overlooking potential nonlinear factors. Therefore, in this context, it is particularly important to study the impact of renewable energy (including its subcategories such

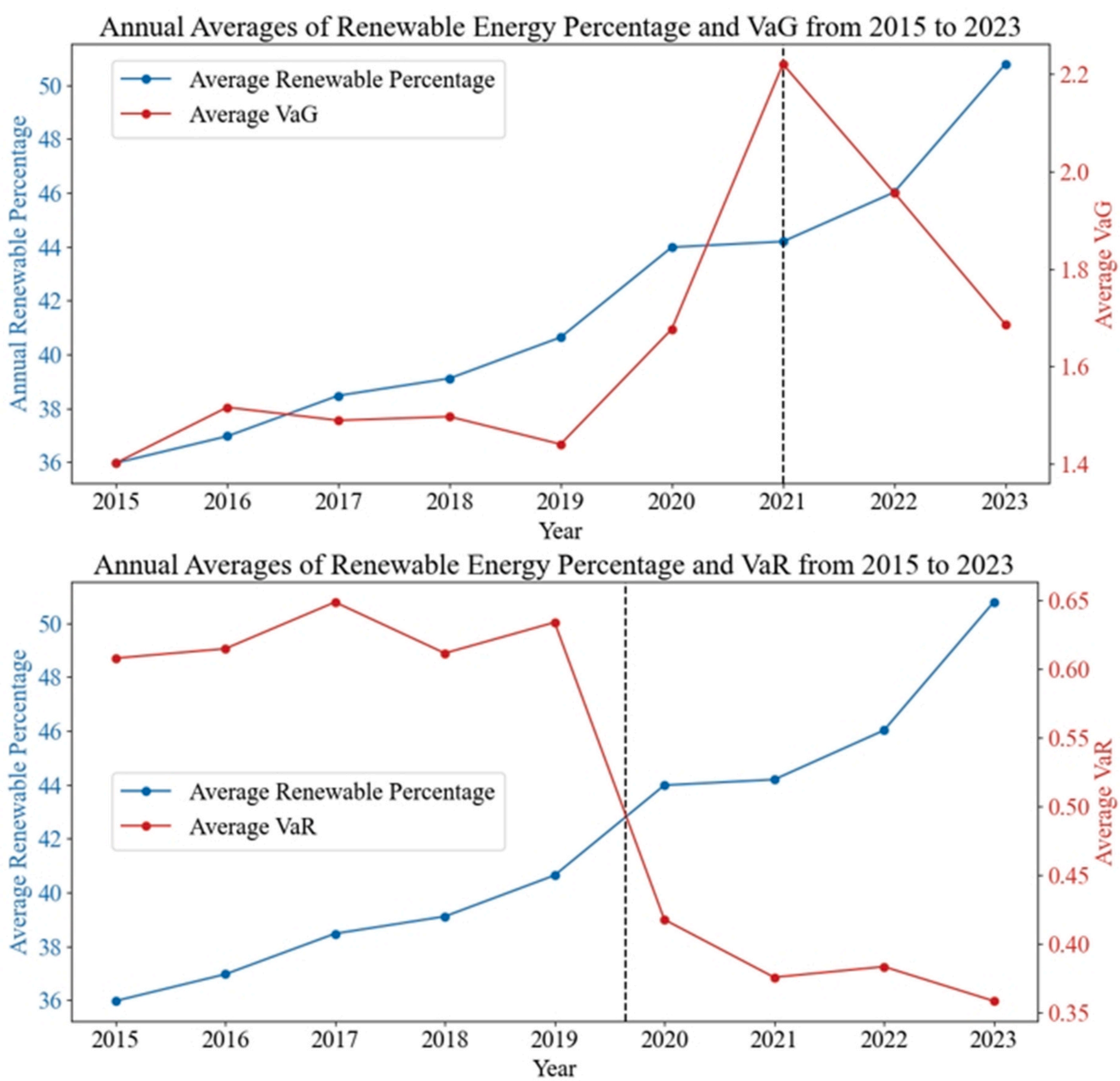

Fig. 1. Trends in the share of renewable energy in electricity generation and electricity price volatility
Noted: The VaG and VaR in Fig. 1 are constructed using the method in Section 2.3 of the methodology. The average value is also calculated based on the VaR and VaG of all countries in each year. In addition, except for Section 2.3, all VaG and VaR in the full text are adjusted after Section 2.3.

as wind power, solar power, hydropower, biomass, and other renewable energies) on the extreme volatility of wholesale electricity prices in OECD countries. OECD countries play a leading role in global energy and climate policies. Similarly, for the above reasons, to conduct a more in-depth study, this paper employs dynamic panel threshold regression models to investigate the impact of renewable energy and its sub-categories on the volatility of wholesale electricity prices in OECD countries from 2015 to 2023. This detailed study aims to explore the specific impact of different renewable energies on extreme price volatility and to research into potential non-linear relationships. Based on the dynamic panel threshold, we find that for extreme negative whole-sale price volatility, the impact of renewable energy generation is not significant when it is below a specific threshold. However, once this threshold is exceeded, the ability of renewable energy to suppress extreme negative price volatility significantly increases. Similarly, for extreme positive wholesale price volatility, the impact of renewable energy is not significant when it is below a certain threshold. Once this threshold is exceeded, the ability of new energy to reduce extreme positive price volatility significantly increases. Analyzing the relationship between renewable energy growth and price volatility in these countries can provide valuable data and strategies for other countries' efforts to address climate change. Additionally, the energy transition in OECD countries is a model for global clean energy development. Studying the impact of renewable energy on electricity prices in these countries can reveal key factors that promote or hinder the transition, providing insights for the broader adoption of clean energy. This analysis not only helps understand the impact of renewable energy on electricity markets but also provides valuable references for future energy policy formulation.

The rest of this paper is structured as follows: Section 2 describes the data and methodology used. Section 3 presents the empirical results and discusses them based on the findings. Section 4 concludes and offers some policy recommendations.

2. Methodology

2.1. Data description

The data used for regression analysis and modelling in this study, along with their sources and statistical description, are presented in Table 1 and Table 2 below. "Electricity demand" refers to the annual total electricity demand of the selected countries. "Renewable percentage" denotes the proportion of renewable energy in the total power generation. "Value at Risk" is derived from the daily wholesale electricity prices of the selected countries using the historical simulation method, and it is used to measure the extreme negative volatility of wholesale electricity prices. "Value at Gain" is derived using historical simulation methods based on the daily wholesale electricity prices of selected countries, and it is used to measure the extreme positive volatility of wholesale electricity prices. "GDP based on 2015″ refers to the Gross Domestic Product valued in 2015 U.S. dollar prices. "Solar percentage," "Wind percentage," "Other renewable percentage," "Hydro percentage," and "Bioenergy percentage" indicate the proportions of solar, wind, other renewable sources, hydro, and bioenergy in the total power generation, respectively. "FDI" represents the ratio of Foreign Direct Investment to the total GDP. "EE" stands for the energy efficiency of the selected countries, calculated based on the three-stage Super Slacks-Based Measure (SBM) (the specific calculation formula and method are provided in Appendix A). "RTB" indicates the use of real-time bidding policies, with values 0, 1, and 2 (specific details are provided in Appendix B). "FD" is the Financial Development Index, and "Population" refers to the total population. Also, the countries included in our sample are also listed and presented in Appendix B. Net Import is the annual total of imported electricity for each country. A positive value indicates that the country imports more electricity than it exports, while a negative value indicates that it exports more than it imports.

Below is a more detailed introduction to the selected variables.

2.1.1. Core dependent variable

Based on previous discussions, this paper aims to explore how the integration of renewable energy into the grid affects extreme positive and negative fluctuations in wholesale electricity prices. Therefore, this study chooses to use Value at Risk (VaR), calculated from daily day-

Table 1
Data description.

Variables	Unit	Source
Electricity demand	GWh	Ember
Renewable percentage	%	Ember
Adjusted Value at risk	Index	Ember & Official website of each country
Adjusted Value at gain	Index	Ember & Official website of each country
Net Import	TWh	Ember & Official website of each country
GDP calculated using 2015 as the base year	$	World Bank & Official website of each country
Solar percentage	%	Ember
Wind percentage	%	Ember
Other renewable percentage	%	Ember
Hydro percentage	%	Ember
Bioenergy percentage	%	Ember
FDI	%	World Bank & OECD Stata & Official website of each country
EE	Index	Build by SBM model
RTB	Dummy variable	(Mays and Jenkins, 2023) & Official website of each country
FD	Index	IMF
Population	People number	World Bank & Official website of each country

*Note: World Bank: https://data.worldbank.org/; Ember: https://ember-climate.org/; OECD Stata: https://www.oecd.org/; IMF: https://data.imf.org/(more data details are in Appendix B).

Table 2
Statistical description.

Variables	Unit	Mean	sd	min	max	Obs
Electricity demand	GWh	4.509	1.500	1.548	8.377	288
Renewable percentage	%	43.609	26.360	6.209	100	288
Adjusted Value at risk	Index	0.515	0.185	0.126	0.997	288
Adjusted Value at gain	Index	1.654	0.384	1.004	2.849	288
Net Import	TWh	0.073	20.178	−64.06	66.67	288
GDP Based on 2015	Logarithmic $	10.694	0.312	10.125	11.633	288
Solar percentage	%	3.842	4.665	0.000	22.849	288
Wind percentage	%	12.829	12.876	0.000	58.467	288
Other renewable percentage	%	1.809	5.898	0.000	32.027	288
Hydro percentage	%	20.863	25.778	0.000	96.368	288
Bioenergy percentage	%	4.506	5.026	0.000	26.542	288
FDI	%	2.498	6.300	−15.381	74.503	288
EE	Index	0.757	0.095	0.625	1.055	288
RTB	Dummy variable	1.097	0.462	0.000	2.000	288
FD	Index	0.642	0.214	0.194	0.980	288
Population	Logarithmic People number	16.354	1.403	13.253	19.632	288

ahead wholesale price data over a year, as a measure of such price volatility (Section 3.3 presents the detailed construction method). Additionally, using daily wholesale price data combined with historical simulation to calculate annual VaR has significant analytical advantages, particularly in capturing the dynamic characteristics of the market (Karandikar et al., 2009). This method can detect subtle daily fluctuations, which is crucial for understanding broader volatility trends throughout the year (Qiao et al., 2021). Finally, we divide the obtained values by the average wholesale electricity price for the year. By focusing on the relationship between renewable energy penetration and extreme price fluctuations, this study aims to gain a deeper understanding of how the increase in the share of renewable energy impacts the stability and risk profile of the electricity market. Note that the VaR and VaG are constructed using the weighted daily wholesale electricity prices for each year. Most of the data from the European market is provided by Ember. The missing data from Ember is supplemented by the author through downloads from the electricity or energy regulatory authorities of various countries, and the weighted wholesale prices are calculated according to Ember's methodology.

2.1.2. *Core independent variables*

Building on the discussion above, one of the core explanatory variables in this paper is the Renewable percentage (*Renewable*), which represents the proportion of a country's electricity generated from renewable energy sources within its power grid. Moreover, renewable energy comes from a variety of sources, such as hydroelectric power, wind power, and others. To further investigate the impact of different types of renewable energy on the stability of grid prices, we have also categorized renewable energy generation into several main source categories for subsequent research: *Hydro percentage*, *Wind percentage*, *Bioenergy percentage*, *Solar percentage*, and *Other renewable percentage* (Geothermal energy and other renewable energy sources that are difficult to categorize). This classification will assist in further exploring the effects of renewable energy on the volatility of wholesale electricity prices.

2.1.3. *Control variables*

In analysing the impact of renewable energy penetration on the volatility of wholesale electricity prices, selecting control variables is critical to isolate the specific effects of renewable energy sources from other influencing factors. The chosen control variables, including Foreign Direct Investment to the total GDP (FDI), GDP based on 2015 (GDP), the total population (Population), electricity demand (ED), energy efficiency (EE), real-time bidding policy (RTB), and Financial Development Index (FD), are integral for several reasons.

FDI as a percentage of GDP is a key indicator of international economic engagement and has a significant impact on energy market dynamics. First, foreign direct investment often brings advanced technology and management expertise, which can improve the efficiency of a country's energy industry, particularly in the renewable energy sector. Foreign companies may introduce new capital to develop infrastructure for wind and solar power, accelerating the deployment of green energy (Keeley and Matsumoto, 2018). Second, FDI can enhance competition in the energy market, encouraging local companies to improve operational efficiency and reduce energy production costs. This competitive pressure may lead to a decrease in energy prices, especially in the electricity market, where price volatility could decrease as supply expands (Loi and Jindal, 2019). Lastly, FDI is often accompanied by policy liberalization and improved legal frameworks, providing a more transparent and stable environment for energy markets. This attracts more long-term investments, further contributing to electricity price stability. Therefore, FDI not only serves as a measure of economic engagement, but also indirectly influences electricity price dynamics by enhancing technology, fostering competition, and promoting policy stability. GDP, valued in 2015 dollars, provides a stable economic baseline by adjusting for inflation and removing the effects of price changes over time. This allows for a more accurate comparison of economic growth across different periods, giving a clearer picture of real economic performance. By using constant dollars, we can more reliably analyze how economic expansion interacts with energy consumption patterns. A growing economy typically demands more energy, as industrial production, transportation, and residential energy use all increase (Abbasi et al., 2021). This rise in energy consumption can impact the supply-demand balance, influencing both the level and volatility of electricity prices as markets react to shifts in consumption patterns. The total population plays a crucial role in determining electricity demand, as a larger population requires more energy for residential, commercial, and industrial use. As population growth intensifies, especially in urban areas, it puts additional pressure on electricity grids, which may struggle to meet the rising demand without sufficient infrastructure development (Schneider, 2021). This demand surge can cause price volatility, especially during peak times when the grid is under strain. Additionally, population growth can influence long-term energy planning, as governments and energy providers may need to invest more in generation capacity, transmission, and distribution to ensure a stable supply and prevent price spikes due to imbalances in supply and demand. Electricity demand (ED) is a key measure of pressure on the energy supply chain. When demand rises, energy providers often need to rely on a mix of power sources, including variable renewable energy (VRE) like wind and solar. Since VREs are dependent on weather conditions, they can introduce instability into the supply. This variability can lead to price fluctuations, especially during periods of high demand, as backup energy sources—often more expensive—are required to maintain supply (Huisman et al., 2020). Therefore, higher electricity demand can directly impact price stability, particularly in markets that depend heavily on renewable energy. Energy efficiency (EE) measures how effectively energy is utilized and can reduce demand-side pressures on electricity prices. By using energy more efficiently, demand spikes are mitigated, which helps ease the strain on the grid (Dzyuba and Solovyeva, 2020). This can contribute to stabilizing electricity prices, as there is less needed to rely on costly backup energy sources during periods of high demand. Including Real-Time Bidding (RTB) policies as a control variable acknowledges the regulatory and operational frameworks within which electricity markets operate. RTB can introduce both volatility and stability into the market, depending on how it's implemented, by allowing for real-time price adjustments based on supply and demand dynamics. The Financial Development Index (FD) gauges the sophistication of a country's financial markets and institutions (Elzaki, 2023). A more developed financial sector can attract greater investment in energy infrastructure, including renewables. This investment can enhance energy supply stability and influence electricity pricing, potentially reducing price volatility. Together, these control variables provide a comprehensive framework to accurately assess the nuanced impacts of renewable energy's share of grid electricity on wholesale price volatility, accounting for economic, demographic, demand-related, regulatory, and financial factors that also play significant roles in shaping the energy market landscape.

Additionally, we introduced Net Import, the value of imported electricity in TWh for each country in the current year. This allows us to account for the interconnectivity between countries and control its impact on the wholesale electricity prices' VaR and VaG. Net Import reflects the actual situation of electricity imports and exports in each country and the flow of electricity between countries, revealing the mutual influence and spillover effects between markets. By capturing the regulatory role of electricity imports on supply-demand balance and market prices and considering changes in energy policies and market interconnectivity of different countries, we can more accurately analyze and control these factors' impact on electricity market price volatility and risk, thereby improving the model's accuracy and explanatory power. We recognize significant differences among countries; therefore, we use the lagged values of VaR and VaG to control country-specific effects. Utilizing the lagged values of VaR and VaG effectively controls for the differences in electricity markets across countries, as lagged variables can capture the historical states and dynamic characteristics of the markets (Chan and Gray, 2006; Yang et al., 2023). For example, Australia operates within the National Electricity Market (NEM), which functioned solely as an energy-only market until the introduction of a capacity market mechanism on July 1, 2019. This transition reflects an adaptive response to evolving market needs, aiming to enhance reliability and prevent supply shortages during peak demand periods. This structural change allows the NEM to better manage the integration of renewable energy and maintain stability in electricity prices amidst varying supply and demand conditions. Also, these structural differences could profoundly influence how electricity prices respond to the integration of renewable energy across different time periods. The lagged values of VaR and VaG contain effective historical information about each country's electricity market, which necessarily includes market characteristics and some policy lag effects. By incorporating lagged variables into a dynamic regression model, we can reflect the continuity and lag effects of policies and market behaviors. This approach helps us control these complex, hard-to-quantify effects. Additionally, it's important to note that the lagged values provide a more nuanced understanding of market adjustments over time. For example, the impact of a policy change or market shock may not be immediate and can manifest gradually. By accounting for these lagged effects, we can better isolate the true relationship between renewable energy integration and electricity prices. This methodology allows for a more accurate analysis, acknowledging that markets do not operate in a vacuum but are influenced by various temporal factors. Furthermore, incorporating lagged variables enhances the robustness of our model by mitigating potential endogeneity issues. Endogeneity can arise when explanatory variables are correlated with the error term, often due to omitted variable bias or simultaneous causality. By including lagged values, we partially address these concerns, ensuring that our estimates are more reliable and reflect actual market dynamics. This rigorous approach ultimately strengthens the validity of our findings and provides deeper insights into the interplay between electricity prices and renewable energy adoption across different national contexts.

Moreover, based on our research sample of OECD countries from 2015 to 2023, this period coincides with rapid growth in renewable energy and a gradual decrease in nuclear power. In fact, the share of nuclear energy in OECD countries is steadily declining. According to Ember, (2024b) forecast, by 2050, the share of nuclear power generation might only be about 30% of what it was in 2020. Specifically, several OECD countries, including Germany and Belgium, have formulated plans to phase out nuclear energy. Although a few countries like France and Finland are still actively utilizing nuclear energy and plan to increase its usage, the overall trend indicates a relative decline in the significance of nuclear energy. Additionally, due to its stability, nuclear energy has a relatively small overall impact on the volatility of wholesale electricity prices. Therefore, in our study, we consider the impact of nuclear energy on the final results to be potentially insignificant. Additionally, from an econometric perspective, when the sum of all control variables equals 100%, meaning each variable is part of a total, these variables exhibit a perfect linear relationship, leading to multicollinearity issues. Due to the limited impact of nuclear energy, we have removed it from the control variables.

2.2. Model specification

2.2.1. Benchmark model specification

In evaluating the impact of variables related to economics, society, or policymaking, we commonly encounter the challenge posed by hidden diversity (Breuer and Dehaan, 2023). Models that employ fixed effects and those that utilize a dual fixed effects approach are instrumental in mitigating this concern. Through the integration of fixed effects for both entities and temporal periods, dual fixed effects approach effectively eliminate the influence of both entity-specific and time-constant hidden factors on the outcomes of the analysis. To detail, the structure of the dual fixed effects model can be articulated as follows:

$$\begin{aligned}\mathrm{VaR_{it}} = {} & \alpha_0 + \beta_1 \mathrm{Renewable_{it}} + \beta_2 \mathrm{lnGDP_{it}} + \beta_3 \mathrm{lnpopulation_{it}} + \beta_4 \mathrm{lnED_{it}} \\ & + \beta_5 \mathrm{FDI_{it}} + \beta_6 \mathrm{FD_{it}} + \beta_7 \mathrm{RTB_{it}} + \beta_8 \mathrm{EE_{it}} + \beta_9 \mathrm{NetImport_{it}} + \lambda_t + \mu_i + \varepsilon_{it,}\end{aligned} \tag{1}$$

$$\begin{aligned}\mathrm{VaG_{it}} = {} & \alpha_0 + \beta_1 \mathrm{Renewable_{it}} + \beta_2 \mathrm{lnGDP_{it}} + \beta_3 \mathrm{lnpopulation_{it}} + \beta_4 \mathrm{lnED_{it}} \\ & + \beta_5 \mathrm{FDI_{it}} + \beta_6 \mathrm{FD_{it}} + \beta_7 \mathrm{RTB_{it}} + \beta_8 \mathrm{EE_{it}} + \beta_9 \mathrm{NetImport_{it}} + \lambda_t + \mu_i + \varepsilon_{it},\end{aligned} \tag{2}$$

Drawing from Equations (1) and (2), we developed Equations (3) and (4) to dig deeper into the nuances of various renewable energy sources.

$$\begin{aligned}\mathrm{VaR_{it}} = {} & \alpha_0 + \beta_1 \mathrm{BioEnergy_{it}} + \beta_2 \mathrm{Hydro_{it}} + \beta_3 \mathrm{Solar_{it}} + \beta_4 \mathrm{Wind_{it}} \\ & + \beta_5 \mathrm{Other_{it}} + \beta_6 \mathrm{lnGDP_{it}} + \beta_7 \mathrm{lnpopulation_{it}} + \beta_8 \mathrm{lnED_{it}} \\ & + \beta_9 \mathrm{FDI_{it}} + \beta_{10} \mathrm{FD_{it}} + \beta_{11} \mathrm{RTB_{it}} + \beta_{12} \mathrm{EE_{it}} + \beta_{13} \mathrm{NetImport_{it}} + \lambda_t + \mu_i + \varepsilon_{it,}\end{aligned} \tag{3}$$

$$\begin{aligned}\mathrm{VaG_{it}} = {} & \alpha_0 + \beta_1 \mathrm{BioEnergy_{it}} + \beta_2 \mathrm{Hydro_{it}} + \beta_3 \mathrm{Solar_{it}} + \beta_4 \mathrm{Wind_{it}} \\ & + \beta_5 \mathrm{Other_{it}} + \beta_6 \mathrm{lnGDP_{it}} + \beta_7 \mathrm{lnpopulation_{it}} + \beta_8 \mathrm{lnED_{it}} \\ & + \beta_9 \mathrm{FDI_{it}} + \beta_{10} \mathrm{FD_{it}} + \beta_{11} \mathrm{RTB_{it}} + \beta_{12} \mathrm{EE_{it}} + \beta_{13} \mathrm{NetImport_{it}} + \lambda_t + \mu_i + \varepsilon_{it},\end{aligned} \tag{4}$$

2.2.2. Nonlinearity effect model

2.2.2.1. Dynamic panel threshold model. In empirical research, the interactions among various economic, social, and environmental factors often exhibit non-linear characteristics, which linear models struggle to accurately depict. Such models fall short of capturing the intricate dynamics at play among these variables. Introducing threshold regression models offers a solution to this problem by providing a nuanced analysis that acknowledges the non-linear impacts of explanatory variables on a dependent variable. Specifically, threshold regression models excel in illustrating how the influence of explanatory variables on the dependent variable shifts upon reaching a certain threshold, thereby offering a more precise understanding of these complex relationships.

Considering the potential endogeneity issues that may arise in traditional static panel studies, we follow the research of Kremer et al. (2013) and Wang et al. (2023), and established a general dynamic panel threshold regression model, as shown in Equation (5) and Equation (6).

$$\begin{aligned}\mathrm{VaR_{it}} = {} & \alpha_0 + \beta_1 \mathrm{Renewable_{it}} {*} \mathrm{I}(\mathrm{q_{it}} \le \lambda) + \beta_2 \mathrm{Renewable_{it}} {*} \mathrm{I}(\mathrm{q_{it}} > \lambda) \\ & + \beta_3 \mathrm{Var_{it-1}} + \beta_4 \mathrm{lnGDP_{it}} + \beta_5 \mathrm{lnpopulation_{it}} + \beta_6 \mathrm{lnED_{it}} + \beta_7 \mathrm{FDI_{it}} \\ & + \beta_8 \mathrm{FD_{it}} + \beta_9 \mathrm{RTB_{it}} + \beta_{10} \mathrm{EE_{it}} + \lambda_t + \mu_i + \varepsilon_{it},\end{aligned} \tag{5}$$

$$\begin{aligned}\mathrm{VaG_{it}} = {} & \alpha_0 + \beta_1 \mathrm{Renewable_{it}} {*} \mathrm{I}(\mathrm{q_{it}} \le \lambda) + \beta_2 \mathrm{Renewable_{it}} {*} \mathrm{I}(\mathrm{q_{it}} > \lambda) \\ & + \beta_3 \mathrm{Var_{it-1}} + \beta_4 \mathrm{lnGDP_{it}} + \beta_5 \mathrm{lnpopulation_{it}} + \beta_6 \mathrm{lnED_{it}} + \beta_7 \mathrm{FDI_{it}} \\ & + \beta_8 \mathrm{FD_{it}} + \beta_9 \mathrm{RTB_{it}} + \beta_{10} \mathrm{EE_{it}} + \lambda_t + \mu_i + \varepsilon_{it},\end{aligned} \tag{6}$$

The terms $\beta_1 \mathrm{Renewable_{it}} {*} \mathrm{I}(\mathrm{q_{it}} \le \lambda)$, and $\beta_2 \mathrm{Renewable_{it}} {*} \mathrm{I}(\mathrm{q_{it}} > \lambda)$ within the model represent the impact of renewable energy on the dependent variable under different conditions of the threshold variable $\mathrm{q_{it}}$. Specifically, $\beta_1 \mathrm{Renewable_{it}} {*} \mathrm{I}(\mathrm{q_{it}} \le \lambda)$ captures the effect when $\mathrm{q_{it}}$ is less than or equal to the threshold λ, indicating the influence of renewable energy in a lower threshold zone. The term $\beta_2 \mathrm{Renewable_{it}} {*} \mathrm{I}(\mathrm{q_{it}} > \gamma)$ reflects the impact when $\mathrm{q_{it}}$ is greater than λ, representing the effect in the remaining threshold area. These segments allow the model to delineate the nonlinear effects of renewable energy production on the dependent variable across varying levels of the threshold variable. We have selected six threshold variables, namely Renewable, BioEnergy, Hydro, Solar, Wind, and Other renewable energy sources. This approach enables us to gain a more detailed understanding of the impact of different types of renewable energy on renewable power generation and their effects on the fluctuations of wholesale electricity prices. This refined categorization facilitates a nuanced analysis of the diverse roles that various renewable energy sources play in the energy market, allowing for a comprehensive assessment of their contribution to electricity price volatility.

2.2.2.2. Panel smooth transition regression (PSTR). The PSTR model stands out as a versatile statistical instrument capable of delineating non-linear associations, accommodating the heterogeneity inherent in panel data, and adjusting to diverse investigative contexts (Gonzalez et al., 2017; Fok et al., 2005). Its significance is particularly pronounced in the fields of economics and finance, where it is extensively applied to scrutinize various dimensions of macroeconomic indicators, the mechanics of financial markets, and the ramifications of policy interventions. The PSTR model offers a profound methodology for dissecting and comprehending the intricate economic phenomena, enabling researchers to capture the complex interplay of variables in these domains (Wu et al., 2024; Ma and Tang, 2023).

The PSTR model is showed in below:

$$\mathrm{Var}_{\mathrm{it}} = \beta_0 + \beta_1 \text{ Renewable }_{it} + \sum_{j=1}^{r} \beta_{2j} \text{ Renewable }_{it} \times K_j(q_{it}, \varphi, c) + \beta_z Z_{it} + \varepsilon_{it}, \tag{7}$$

$$\mathrm{VaG}_{\mathrm{it}} = \beta_0 + \beta_1 \text{ Renewable }_{it} + \sum_{j=1}^{r} \beta_{2j} \text{ Renewable }_{it} \times K_j(q_{it}, \varphi, c) + \beta_z Z_{it} + \varepsilon_{it}, \tag{8}$$

In this formulation, $\mathrm{Var}_{\mathrm{it}}$ is designated as the dependent variable, representing the variable of interest in region i at time t. The baseline of the model is established by the intercept, β_0. The term Renewable_{it} indicates the level of renewable energy development in region i at time t, serving as the primary explanatory variable of the model. The coefficient β_1 measures the direct impact of renewable energy development on the dependent variable, highlighting its significance in the analysis. The β_{2j} coefficients are associated with the model's non-linear components, capturing the nuanced effects of renewable energy under varying conditions defined by the function $K_j(q_{it}, \varphi, c)$, where q_{it} is a threshold variable, φ denotes the transition speed, and c represents the threshold. Additionally, $\beta_z Z_{it}$ incorporates other explanatory variables Z_{it}, with β quantifying their influence on $\mathrm{Var}_{\mathrm{it}}$, and ε_{it} accounts for the error term in the equation.

$$K_j(q_{i,t}, \varphi, c) = \left\{ 1 + \exp\left[-\varphi \prod_{z=1}^{m} (q_{i,t} - c_z) \right] \right\}^{-1}, \varphi > 0, c_1 \le \ldots \le c_m, \tag{9}$$

Within the PSTR framework, K_j operates as a smooth transition function, smoothly varying between 0 and 1 as dictated by the formula $K_j(q_{i,t}, \varphi, c) = \{1 + \exp[-\varphi \prod_{z=1}^{m} (q_{i,t} - c_z)]\}^{-1}$, with φ being a positive parameter and the thresholds $c_1 \le \ldots \le c_m$ arranged in non-decreasing order. This mechanism allows for a continuous modulation of the regression coefficient within the range set by β_1 and $\beta_1 + \sum_{j=1}^{r} \beta_{2j}$. The determination of m, the count of threshold parameters, and r, the number of employed smooth transition functions, is vital for the model's configuration. The assessment phase involves a rigorous examination, employing statistical tests such as LM, LMF, and LRT. This stage is critical for validating the presence of non-linear effects and determining the necessity to proceed with the PSTR model, contingent on the rejection of H0 : r = 0.Identifying the appropriate r value, which specifies the number of transformation functions, is essential. Should H0 : r = 1 hold, a singular transformation function is deemed adequate. If not, the model requires adjustment to incorporate multiple transformation functions. Finally, the model's refinement involves selecting the precise number of threshold parameters, m, for the transformation functions, based on comparative analysis using the AIC and BIC criteria, to finalize the PSTR model's specification. This step ensures the model accurately captures the dynamic non-linear relationships by fine-tuning the number of thresholds and transformation functions.

As same as panel threshold model, we also have selected five threshold variables, namely Renewable, BioEnergy, Hydro, Solar, Wind, and Other renewable energy sources.

2.3. Construction formula of VaR and VaG

In the previous sections, we mentioned the specific data and methods used to construct indicators for measuring the volatility of wholesale electricity prices. Now, we present the concrete formula:

$$\mathrm{VaR} = P_{\text{sorted-decrease}}\,[N \times (1-\alpha)]\,, \tag{10}$$

$$\mathrm{VaG} = P_{\text{sorted-increase}}\,[N \times (1-\alpha)], \tag{11}$$

Formulas 10 and 11 calculate the Value at Risk (VaR) and Value at Gain (VaG), which is a statistical measure used to assess the level of financial risk within a firm or investment portfolio over a specific time frame. In this context, VaR and VaG are determined by identifying the point at which the sorted daily wholesale electricity price data ($P_{\text{sorted-decrease}}$ and $P_{\text{sorted-increase}}$) reaches the threshold determined by the confidence level $(1-\alpha)$ in one year. Here, N represents the total number of daily price observations within the year, and α is the confidence level, typically set to represent the extreme lower tail of the distribution (e.g., 5% for a 95% confidence level). The resulting VaR value represents the maximum expected loss in electricity prices under normal market conditions, calculated over a specified time period (annually), at the given confidence level.

Subsequently, to better measure the volatility of wholesale electricity prices each year, we further processed VaR and VaG (In the regression models and subsequent reports of the paper, the VaG and VaR mentioned are all adjusted values according to the specified formula):

$$\text{Adjusting VaR} = \frac{\mathrm{VaR}}{P_{\text{armual\_arg}}}, \tag{12}$$

$$\text{Adjusting VaG} = \frac{\mathrm{VaG}}{P_{\text{armual\_arg}}}, \tag{13}$$

Where, VaR is the Value at Risk and VaG is the Value at Gain, calculated as previously mentioned and $P_{\text{armual\_arg}}$ is the annual average wholesale electricity price. By adjusting VaR and VaG with the annual average price, we can compare the volatility across different years or markets by adjusting for the overall price level, making it a relative measure of risk rather than an absolute one.

In studying wholesale electricity prices, the adjusted methods of "Value at Risk" (VaR) and "Value at Gain" (VaG) present clear advantages over traditional methods. The electricity market mainly comprises electricity wholesalers, retailers, transmission operators, and consumers. In the competitive wholesale and retail electricity markets, retailers purchase electricity from producers through long-term contracts, day-ahead markets, or spot markets, or generate their own to meet demand, before reselling it in the retail market. In the residential sector, retailers must provide fluctuating loads at usually fixed predetermined prices (Boroumand et al., 2015, 2015b; Boroumand and Zachmann, 2012; Bushnell et al., 2008). Regardless of the hedging strategies employed by retailers, they inevitably face short or long positions due to demand uncertainties. Any corresponding adjustments in the spot market will occur at fluctuating hourly prices, while retail prices typically remain fixed for longer periods due to consumer risk aversion (usually at least one year, with implicit transmission).

This asymmetry in price patterns, coupled with changes in demand, can lead to significant losses for retailers who cannot hedge effectively (Boroumand, 2009). Generally, expected price fluctuations are acceptable to retailers, who must hedge against the random nature of demand. Therefore, fluctuations within the normal range can be absorbed through hedging strategies, but extreme events, such as black swan events, with unexpected fluctuations can lead to unbearable losses for retailers. For instance, during the Texas power outage in 2021, several electricity retailers went bankrupt because they could not bear the enormous electricity bills (Prete and Blumsack, 2023). Moreover, retailers cannot pass on wholesale price increases to customers in the long run as this would result in a loss of market share, and most customers would have their electricity prices locked in. Similarly, for electricity wholesalers, expected price fluctuations are acceptable, but if wholesale prices drop significantly beyond expectations, wholesalers may face substantial financial pressure and operational risks. While wholesalers can profit from price increases, they also need to contend with the uncertainties brought by severe price fluctuations. Therefore, wholesalers also require effective risk management strategies to cope with these unforeseen market volatilities. As shown in Fig. 2, we generated a set of hypothetical market price scenarios using a random seed. It is evident that under the same volatility, the VaR and VaG in the two charts are significantly different. Clearly, the market represented by the upper chart experiences a lower risk of extreme prices compared to the market in the lower chart. Despite having the same volatility, the risks faced by market participants are entirely different.

In conclusion, while traditional volatility measurement methods can position the overall picture of price fluctuations, it is usually the extreme situations that truly threaten the health and order of the electricity market. The adjusted methods of "VaR" and "VaG" are better at capturing and quantifying these extreme risks in the market, providing more accurate risk assessment and hedging strategies. These methods not only help retailers and wholesalers better understand market dynamics but also enable them to formulate more reasonable pricing strategies, ultimately gaining an advantage in a highly competitive market. Therefore, adopting the adjusted "VaR" and "VaG" methods is particularly

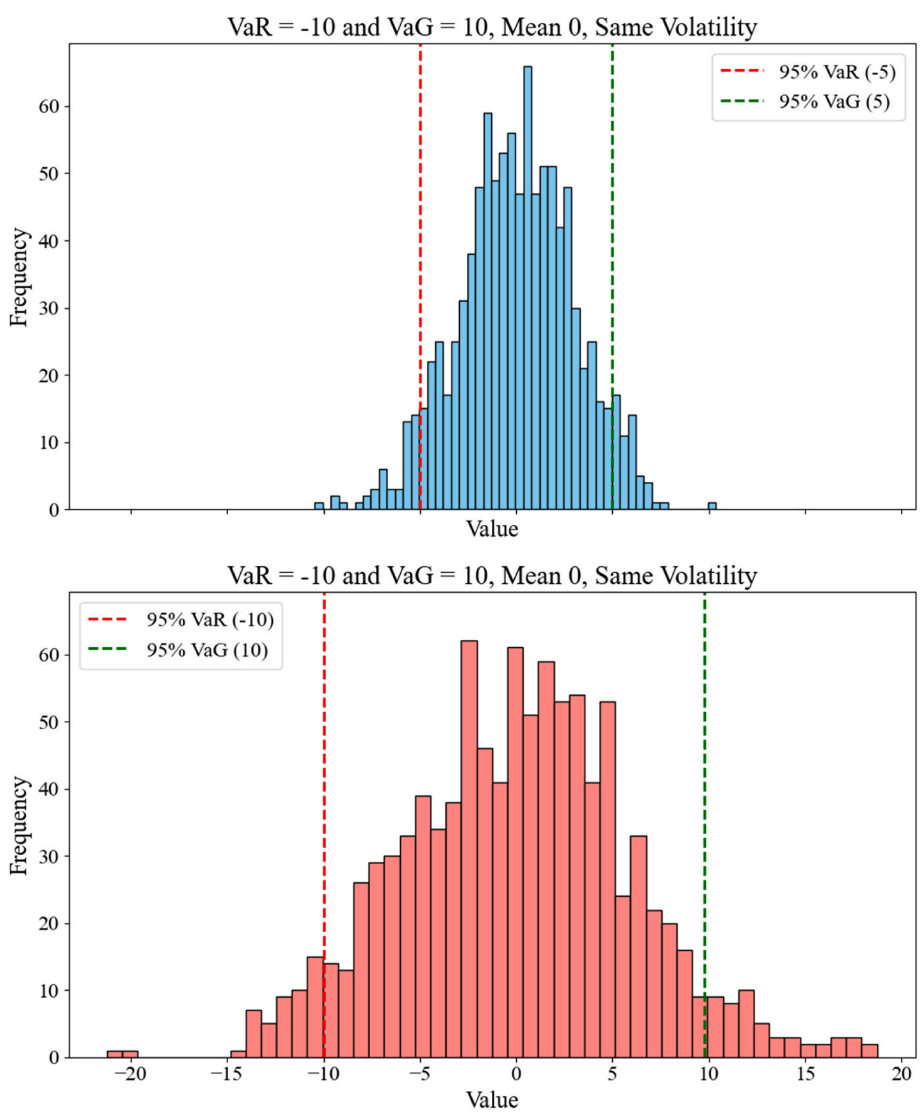

Fig. 2. Price distributions.

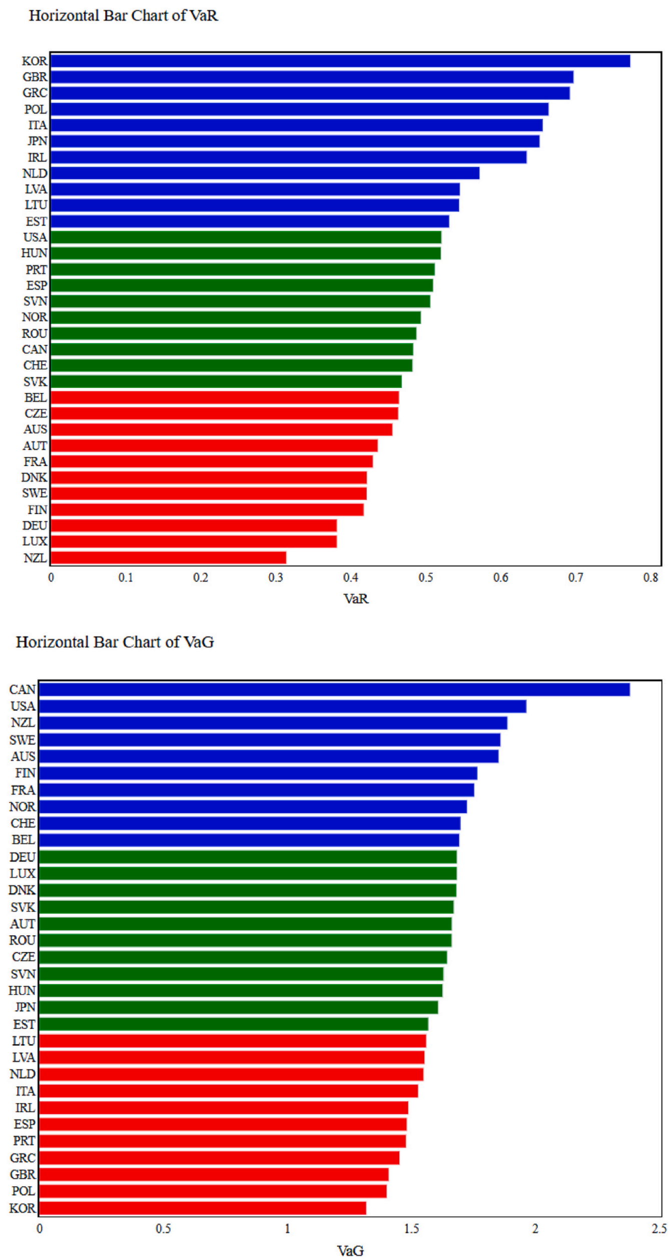

Fig. 3. Average value at risk and value at gain Index (2015–2023).

important and advantageous in electricity market risk management.

3. Empirical result

3.1. Value at risk and value at gain of wholesale electricity prices

Fig. 3 illustrates the specifics of VaR (Value at Risk) and VaG(Value at Gain). Some countries exhibit lower VaR but higher VaG, while others show the opposite, and the underlying reasons can be attributed to the structure of their electricity markets, policy interventions, and the proportion of renewable energy in the grid. Countries with lower VaR but higher VaG (such as New Zealand, Canada, and the United States) typically rely on a high proportion of renewable energy and well-established market regulation mechanisms, resulting in relatively stable electricity prices and lower risks under normal conditions. However, when external shocks occur (such as a rise in international energy prices or a surge in demand), if renewable energy supply is insufficient to meet demand, the power system may have to rely on fossil fuel generation, which is more susceptible to price fluctuations, causing electricity prices to rise sharply, leading to higher VaG. This situation may reflect a "threshold effect" in the proportion of renewable energy: when the share of renewable energy exceeds a certain critical point, it can effectively reduce market risk and volatility, but if the share is insufficient, the electricity market may experience significant fluctuations under stress. Conversely, countries with higher VaR but lower VaG (such as Poland, South Korea, and Greece) tend to rely more on fossil fuels, making their electricity prices more vulnerable to fluctuations in the international energy markets, resulting in higher overall risk (VaR). However, strong government regulation, such as price caps or subsidies, may limit the extent of price increases, keeping price volatility (VaG) relatively low even under market pressure. This difference highlights that the proportion of renewable energy in the grid not only affects the risk and volatility of electricity markets but may also reflect a critical threshold that determines market behavior under different conditions. The volatility of electricity markets in different countries depends not only on energy structures and market mechanisms but may also be influenced by a threshold effect, where exceeding or falling below a critical point could cause significant changes in price volatility and risk.

3.2. Preliminary tests

We conducted panel unit root tests to confirm the stationarity of each variable. We employed three different unit root testing methods: LLC, PP, and Harris-Tzavalis. We found that all regression variables in Equations (1) and (2) are stationary across these three tests, but some regression variables in Equations (3) and (4) are not stationary (see Appendix C for full results). To test for the presence of long-term cointegration among variables in Equations (3) and (4), we conducted a Pedroni test, which indicated that long-term cointegration among the variables in Equations (3) and (4) indeed exists (see Appendix D for full results). Additionally, we carried out tests for multicollinearity, which revealed that no adverse situations are affecting the regression results in either Equations (1)–(4)(see Appendix E for full results). Finally, we performed the Breusch and Pagan (1980) LM test and Pesaran's (2004) CD test (see Appendix F for all results). The results of these two tests did not reject the null hypothesis of no cross-sectional dependence in the data.

3.3. Regression results

3.3.1. Benchmark results

As shown in Tables 3 and 4, the complex dynamics affecting extreme fluctuations in wholesale electricity market prices have been preliminarily revealed. The analysis emphasizes the diverse impact of renewable energy, economic indicators, and policy variables on extreme negative fluctuations in wholesale electricity prices. In Table 3 column (1) and column (3), the share of renewable energy in the grid is significantly negatively correlated with extreme fluctuations in wholesale electricity prices, particularly evident in the System Generalized Method of Moments (SYS-GMM) model. This finding supports the stabilizing role of renewable energy in reducing the risk of extreme downward movements in wholesale electricity prices. Although this result differs from conventional understanding, it aligns with expectations from studies on the tail risks of wholesale electricity prices. Most existing literature supports the potential of renewable energy to lower electricity prices (cite something here), but these studies mainly focus on the middle part of the conventional electricity price distribution rather than extreme fluctuations. The potential of renewable energy to lower prices is primarily reflected in its cost advantage, which can meet peak demand, thereby reducing prices. Historically, negative price events have occurred multiple times, with Germany being one of the first countries to experience negative prices. Particularly during holidays, when wind and solar power generation is high and industrial and commercial demand is low, negative price phenomena frequently occur. In these cases,

Table 3
Benchmark results (VaR).

	(1) Two-way fixed	(2) Two-way fixed	(3) SYS-GMM	(4) SYS-GMM
L.VaR			0. 39295[a]	0. 35714[a]
			(0. 01965)	(0. 03501)
Renewable	−0.00390[a]		−0. 00769[a]	
	(0.00118)		(0. 00090)	
NetImport	0. 00212[a]	0.00182[a]	0.00165[a]	0. 00122[a]
	(0.00062)	(0. 00062)	(0. 00026)	(0. 00034)
lnED	0. 10832	−0. 02562	0. 09945	0. 23946[b]
	(0. 13661)	(0. 14452)	(0. 08684)	(0. 11576)
lnGDP	−0. 10307	0. 02598	0. 02105	0. 45732[a]
	(0. 20395)	(0. 20339)	(0. 10058)	(0. 11355)
lnPopulation	−0. 56007	−0. 68017[b]	−0. 35973[a]	−0. 95167[a]
	(0. 39807)	(0. 43344)	(0. 07787)	(0. 27559)
FDI	−0. 00152	−0. 00150	0. 00051	0. 00065
	(0. 00135)	(0. 00123)	(0. 00048)	(0. 00117)
FD	0. 16986	−0. 24643	0. 60325 [b]	0. 84934[b]
	(0. 22833)	(0. 23517)	(0. 23836)	(0. 39701)
EE	−1.05459[a]	−0. 80099[b]	−1.82170 [a]	−3. 81843[a]
	(0. 37284)	(0. 39652)	(0. 36089)	(0. 80088)
RTB	−0. 04721	−0. 03885	0. 03136	0. 03931
	(0. 06145)	(0. 06971)	(0. 09049)	(0. 11145)
Bioenergy		0. 00314		−0. 00525[b]
		(0. 00293)		(0. 00218)
Hydro		−0. 00432[c]		−0. 01189 [a]
		(0. 00224)		(0. 00381)
Solar		−0. 00189		−0. 00381 [a]
		(0. 00264)		(0. 00237)
Wind		−0. 00746 [a]		−0. 00607 [a]
		(0. 00153)		(0. 00226)
Other		0. 02773		−0. 08469
		(0. 0185)		(0. 00789)
Cons	11.42294	12.84263	6.85477[a]	12.64979
	(7.74536)	(8.12700)	(1.37741)	(4. 38466)
Obs.	288	288	256	256
R-squared	0.7596	0.7671		
AR (1)			−3.2918[a]	−3.1626[a]
AR (2)			1.4009	1.4512
Sargan test			30.0878	27.5783
P-value			0.5128	0. 6428
Country	YES	YES	YES	YES
Year	YES	YES	YES	YES

Note: Robust standard errors in parentheses.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

Table 4
Benchmark results (VaG).

	(1) Two-way fixed	(2) Two-way fixed	(3) SYS-GMM	(4) SYS-GMM
L1. VaG			0.19898[a]	0. 18574[a]
			(0.027744)	(0.03238)
L2. VaG			−0.53930[a]	−0.55463[a]
			(0.01436)	(0.02707)
Renewable	0.00291		0.01602[a]	
	(0.00204)		(0.00331)	
NetImport	−0.00136	−0.00089	−0.00075	0. 00037
	(0.00196)	(0.00202)	(0.00201)	(0. 00281)
lnED	−0.10907	0.00604	0.07835	0. 05713
	(0.37062)	(0.37953)	(0.16802)	(0. 26470)
lnGDP	−0.16850	−0.29449	1.31393[a]	1. 40341[a]
	(0.29870)	(0.31550)	(0.24819)	(0. 42591)
lnPopulation	−0.6.211	1.08430	0.69081[b]	0. 60296
	(0.80173)	(0.87696)	(0.30211)	(0. 43867)
FDI	−0.00429[b]	0.00422[b]	0. 00182	0. 00253
	(0.00215)	(0.00198)	(0. 00237)	(0. 00265)
FD	0. 80971	0.94318[c]	−3.17032[a]	−2.63775[a]
	(0.49340)	(0.53276)	(0. 60731)	(0. 64911)
EE	1.84800[b]	1.38900	5.05715[a]	5.42491[a]
	(0.80419)	(0.89828)	(1.22770)	(1.78727)
RTB	−0.27071	−0.28116	−0. 01672	0. 03303
	(0.18661)	(0.20847)	(0. 27941)	(0. 39136)
Bioenergy		−0.00656		0.01045[b]
		(0.00629)		(0. 00519)
Hydro		0.00292		0. 14481[b]
		(0.00414)		(0. 00580)
Solar		−0.00054		0. 01390[b]
		(0.00513)		(0. 00626)
Wind		0.00886[a]		0. 015009[b]
		(0.00338)		(0.00641)
Other		0.04477		0. 02740
		(0.02975)		(0.02571)
Cons	−13.10903	−14.60625 [b]	−25. 97752[a]	−25.94892[a]
	(13.65004)	(14.58921)	(6. 61852)	(8.38248)
Obs.	288	288	224	224
R-squared	0.6654	0.6665		
AR (1)			−3.6516[a]	−3.6916 [a]
AR (2)			0.76267	0.90692
Sargan test			30.80295	30.07731
P-value			0.1002	0.1166
Country	YES	YES	YES	YES
Year	YES	YES	YES	YES

Note: Robust standard errors in parentheses.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

fossil fuel power plants still need to operate because their shutdown and restart costs are very high. Similarly, the Texas electricity market experienced negative price events in 2015 and 2019, especially when wind power generation surged. Texas has abundant wind resources, and wind farms can generate much more electricity than needed during specific periods. Combined with the significant role of natural gas power plants in supply, these factors jointly led to negative prices. Clean, efficient, and abundant renewable energy electricity triggered negative prices due to the inflexibility and high shutdown and restart costs of fossil fuel power plants (Nicolosi, 2010). However, in countries with high proportions of renewable energy generation, such as Nordic countries or New Zealand, it is rare to see wholesale electricity prices fluctuate to negative values. Additionally, negative prices mostly occurred in the early stages of renewable energy development in these countries. Therefore, we have reason to speculate that when renewable energy reaches a certain proportion compared to other energy sources, the risk of extreme negative values will appear. Furthermore, the extreme decline in wholesale electricity prices not only significantly impacts market prices but also poses substantial risks to electricity retailers. Electricity retailers usually lock in retail prices with customers in advance, making it difficult for them to transfer the risk of extreme price fluctuations. Although most electricity retailers hedge to some extent, these hedging measures mainly target anticipated risks, and they are often caught off guard by “black swan” events, causing most retailers to suddenly face unavoidable risks. Further, we explore the regression results in Table 3 column (2) and column (4). We split the share of renewable energy into Bioenergy, Hydro, Solar, Wind, and Other renewable energy. After capturing the endogeneity and dynamic effects through the SYS-GMM model, it is found that hydropower, wind power, solar power, and bioenergy also reflect the ability to reduce extreme negative fluctuations in wholesale electricity prices, while other renewable energy sources are not significant due to their small proportion. This further stimulates our curiosity about the hypothesis that when renewable energy reaches a certain proportion compared to other energy sources, the risk of extreme negative values will appear.

In Table 4 column (1) and column (3), the share of renewable energy in the grid does not seem to have a significant statistical relationship with extreme positive fluctuations in wholesale electricity prices. However, based on the exploration in Table 3 and Fig. 3, we reasonably speculate that the share of renewable energy needs to reach a certain proportion compared to other energy sources to significantly mitigate or promote extreme positive fluctuations in wholesale electricity prices. Further, we explore the regression results in Table 4 column (2) and

Table 5
Instrument variable test results.

	(1) VaR	(2) VaG
Renewable.hat	−0. 00617*** (0. 00190)	0.00531 (0.00408)
Control Variables	YES	YES
Obs.	288	288
R-squared	0.7024	0.6255
Hansen	0.000	0.000
F-value	180.758	180.760
KPLM	38.698***	38.700***
P-value	0.000	0.000
Country	YES	YES
Year	YES	YES

Note: Robust standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.

column (4). We split the share of renewable energy into Bioenergy, Hydro, Solar, Wind, and Other renewable energy. After capturing the endogeneity and dynamic effects through the SYS-GMM model, it is found that hydropower, wind power, solar power, and bioenergy reflect the ability to increase extreme positive fluctuations in wholesale electricity prices, while other renewable energy sources are not significant due to their small proportion. I want to explain that this may be because the selected time is 2015, which was the early stage of renewable energy generation. Due to immature technology and newly established market rules, it could not well reflect the ability to reduce extreme positive fluctuations in wholesale electricity prices. Based on Fig. 3, we also found that for VaG, its turning point time is later than VaR. Therefore, we introduce a dynamic threshold regression model for further analysis in the subsequent text.

3.3.2. Endogeneity test

Based on the results in Table 5, this section aims to further verify the impact of renewable energy on electricity market price volatility by adopting the Instrumental Variable (IV) method to address the endogeneity issue. In this analysis, the instrumental variable is constructed using the average carbon emissions per unit of electricity production from neighbouring countries. This aims to capture the external impact of renewable energy use on carbon emissions from electricity production, providing an effective tool to address the potential endogeneity of the renewable energy variable. The relationship between the instrumental variable and renewable energy assumes that the carbon emission levels of neighbouring countries reflect regional trends in renewable energy technology and policy, which in turn affect the renewable energy use of the country under study. The carbon emission levels in neighbouring areas may vary due to different rates of renewable energy adoption, which may indirectly influence the renewable energy utilization of the country under study. Thus, the average carbon emissions of neighbouring countries serve as an instrumental variable, helping to isolate the effect of other unobserved factors on renewable energy use and ensuring the consistency of the estimation results (the specific definition and statistical description are provided in Appendix G). In the instrumental variable regression, the coefficient of renewable energy in model (1) is −0.00617, with a significance level of 1%. This indicates that an increase in the share of renewable energy in the grid is significantly associated with a decrease in extreme negative fluctuations in wholesale electricity prices. In model (2), the increase in the share of renewable energy in the grid remains statistically insignificant in reducing extreme negative fluctuations in wholesale electricity prices. This finding is consistent with the previous analysis. Furthermore, the p-value of the Hansen J test is 0.000, indicating that the null hypothesis of the instrument's exogeneity cannot be rejected, meaning the instrumental variable is uncorrelated with the model's error term and is thus appropriate for use. Additionally, the F-value is 180.758, significantly exceeding the Stock-Yogo weak ID test critical value, indicating that the chosen instrumental variable is strong rather than weak.

To validate the robustness of the instrumental variable, we conducted a regression excluding EE. The regression results are provided in Appendix G. The results indicate that there are no significant changes in the findings after removing the regression variable. In conclusion, this study successfully addresses the potential endogeneity issue of the renewable energy variable by using the average carbon emissions per unit of electricity production from neighbouring countries as an instrumental variable. It effectively confirms the significant mitigating effect of renewable energy on extreme negative fluctuations in electricity market prices. These results provide empirical support for the formulation of renewable energy policies and valuable strategic insights for the stable operation of the electricity market. Encouraging and supporting the development of renewable energy not only helps reduce carbon emissions and promote environmental protection but also enhances price stability in the electricity market, marking an elevation in the status and role of renewable energy in the electricity market.

3.3.3. Dynamic panel threshold regression results

Table 6 column (6) illustrate the use of the proportion of renewable energy generation as the threshold variable itself. The findings indicate that when the proportion of renewable energy generation (Renewable) is below the threshold (48.52%), its impact on extremely negative wholesale electricity price volatility is insignificant. Once the proportion of renewable energy generation exceeds the threshold, its ability to impact extremely negative wholesale electricity price volatility strengthens and becomes significant. Firstly, an increase in renewable energy usually leads to a decrease in wholesale electricity prices because renewable energy sources like wind and solar have lower marginal costs, replacing more expensive fossil fuel generation in the power market.

Table 6
Dynamic Panel threshold regression results (VaR).

	(1) Hydro	(2) Wind	(3) Solar	(4) Bioenergy	(5) Other	(6) Whole
Renewable ($q_{it} \leq \lambda$)	−0. 00336 (0.00243)	0. 00031 (0.00195)	−0.00592** (0. 00302)	−0.00526 * (0.00305)	−0. 00853 ** (0. 00380)	−0. 00199 (0. 00467)
	$q_{it} \leq 19.56\%$	$q_{it} \leq 5.73\%$	$q_{it} \leq 0.42\%$	$q_{it} \leq 8.16\%$	$q_{it} \leq 0.43\%$	$q_{it} \leq 48.52\%$
Renewable ($q_{it} > \lambda$)	−0. 00896*** (0. 00329)	−0. 00493*** (0.00204)	−0. 01218 *** (0. 00282)	−0.00051 (0.00342)	−0. 00094 (0.00614)	−0.00866*** (0.00318)
	$q_{it} > \rangle$ 19.5625%	$q_{it} > \rangle$ 5.73%	$q_{it} > \rangle$ 0.42%	$q_{it} > \rangle$ 8.16%	$q_{it} > \rangle$ 0.43%	$q_{it} > \rangle$ 48.52%
Control Variables	YES	YES	YES	YES	YES	YES
Obs.	256	256	256	256	256	256
AR (1)	−2.2871**	−2.0431**	−2.0230**	−1.9927**	−2.4866**	−1.9938**
AR (2)	1.8213*	0.9854	1.1198	0.9420	1.2406	1.1671
Sargan test	24.2417	24.6993	25.9675	25.2716	22.9736	22.71179
Year	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES

Note: Robust standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.

This effect is known as the "merit order effect" (Ballester and Furió, 2015; Mills et al., 2019). However, in the initial stages of renewable energy development, due to technical instability and unpredictability, as well as immature electricity market policies, the instability in power supply increases, making wholesale electricity prices more prone to extreme negative volatility (Johnson and Oliver, 2019; Alam, 2021). This situation is particularly evident in the early stages, as the grid and market have not fully adapted to the integration of renewable energy. However, when the proportion of renewable energy generation exceeds the threshold, its ability to reduce extreme negative price volatility strengthens and becomes significant. Research by Seel et al. (2018) shows that as the proportion of renewable energy increases, its contribution to stabilizing the power market and reducing price volatility becomes more significant. This can be explained through several mechanisms: firstly, large-scale investment in renewable energy reduces reliance on fossil fuels, thereby lowering the fundamental drivers of price volatility. Simultaneously, fossil fuel power plants gradually reduce their roles, only stabilizing peak and trough electricity prices as renewable energy rises. Secondly, a higher proportion of renewable energy increases system supply diversity, enhancing the ability to adapt to different weather and demand conditions, thus strengthening the overall resilience of the power system. Finally, with technological advancements and market maturation, renewable and fossil energy configuration gradually optimizes, further enhancing its ability to reduce extreme negative price volatility in the power market (Ballester and Furió, 2015; Johnson and Oliver, 2019; Seel et al., 2018). In summary, the increase in the proportion of renewable energy generation has a multi-layered and dynamic impact on wholesale electricity price volatility. As the proportion of renewable energy increases, its positive contribution to market price stability gradually becomes evident, especially when it exceeds a specific threshold. When the generation proportions of hydro, wind, and solar exceed their respective thresholds (19.56%, 5.73%, 0.42%), their significant negative impact on extreme negative electricity price volatility indicates that the increase in these renewable energy sources helps reduce extreme negative price volatility in the power market (Table 6 column (1) (2) (3)). As previously mentioned, this effect may arise from improved supply stability due to technological maturity and scale expansion, along with the changing roles and reduction of traditional fossil fuel power plants (Rintamäki et al., 2017). This prevents prices from being negatively affected by the initial stages of technological and market immaturity.

When other renewable energy sources (primarily geothermal) and bioenergy generate at lower proportions (below their respective thresholds of 0.43% and 8.16%) (Table 6 column (4) (5)), their significant negative impact on extreme negative electricity price volatility may be due to their relatively fixed costs and power output, making them less prone to market shocks from technological immaturity (Moya et al., 2018). When other renewable energy and bioenergy exceed their thresholds, their ability to stabilize wholesale electricity prices slightly declines and becomes insignificant. This may be because mainstream renewable energy sources (Hydro, Wind, and Solar) with increasing proportions and technological maturity mainly undertake the role of reducing extreme negative price volatility. Moreover, in most countries, the contribution of other renewable energy and bioenergy to overall renewable energy generation is relatively small (Rai and Nunn, 2020). Similarly, Table 7 column (6) shows the use of the proportion of renewable energy generation as the threshold variable itself. The findings indicate that when the proportion of renewable energy generation (Renewable) is below the threshold (42.76%), its impact on extreme positive wholesale electricity price volatility is not significant. Once the proportion of renewable energy generation exceeds the threshold, its ability to impact extreme positive wholesale electricity price volatility strengthens and becomes significant. Renewable energy sources, such as wind and solar, are dispatched first due to their near-zero marginal costs. This leads to the exit of higher-cost traditional generation methods from the market, thereby reducing overall wholesale electricity prices. This effect is particularly significant when the proportion of renewable energy is high, reducing extremely positive price volatility. When the proportion of renewable energy is high, as technology matures and market rules improve, the system usually adopts more measures to balance intermittent supply. This includes increasing storage facilities and demand response capabilities, thereby improving the overall stability of the power system and reducing extremely positive price volatility. Additionally, the proportions of wind, solar, biomass, and other renewable energy generation exceeding their respective thresholds, compared to being below their thresholds (Table 7 column (2) (3) (4) (5)), all exhibit characteristics of reducing extreme positive wholesale electricity price volatility without significant changes in nature. This may be due to the low marginal cost of these renewable energy sources. For example, a study found that wind power in Germany and Denmark lowered electricity prices but increased price volatility due to the instability of wind power generation (Rintamäki et al., 2017). In Australia, studies found that wind and solar power significantly reduced electricity prices (Csereklyei et al., 2019). While reducing unexpected extreme positive price volatility, they only increased the expected price volatility for electricity producers and retailers. In contrast, although hydropower has the same low marginal cost characteristics as the four renewable energy sources mentioned above (Table 7(1)), note that its threshold must exceed 41.36% to exhibit its ability to reduce extreme positive price volatility. The main reason is that countries dominated by hydropower often face threats from dry and rainy seasons. In rainy seasons, the likelihood of extreme positive price volatility is naturally offset by the low marginal cost of wholesale electricity. However, in dry seasons, mainstream renewable energy sources (Hydro, Wind, and Solar) with increasing proportions and technological maturity mainly undertake the role of reducing extreme negative price volatility, revealing the risk of extreme positive price volatility. The most typical case is New Zealand, where, in 2022, wholesale electricity prices surged

Table 7
Dynamic Panel threshold regression results (VaG).

	(1) Hydro	(2) Wind	(3) Solar	(4) Bioenergy	(5) Other	(6) Whole
Renewable ($q_{it} \leq \lambda$)	−0.09446*** (0. 01271)	−0.07370*** (0. 00915)	−0.05995 *** (0.00765)	−0.06592 *** (0.01167)	−0. 05773 *** (0. 01064)	0.01226 (0.01385)
	$q_{it} \leq 41.36\%$	$q_{it} \leq 4.90\%$	$q_{it} \leq 0.42\%$	$q_{it} \leq 0.54\%$	$q_{it} \leq 0.40\%$	$q_{it} \leq 42.76\%$
Renewable ($q_{it} > \lambda$)	−0.02258 (0.01528)	−0. 05889*** (0. 00826)	−0.06162 *** (0.00830)	−0.08774 *** (0.01046)	−0. 12776 *** (0. 04318)	−0.02834 *** (0.01106)
	$q_{it} > \rangle$ 41.36%	$q_{it} > \rangle$ 4.90%	$q_{it} > \rangle$ 0.42%	$q_{it} > \rangle$ 0.54%	$q_{it} > \rangle$ 0.40%	$q_{it} > \rangle$ 42.76%
Control Variables	YES	YES	YES	YES	YES	YES
Obs.	256	256	256	256	256	256
AR (1)	−2.0003**	−2.4321**	−2.1687**	−1.4169	−3.09440***	−2.0328 **
AR (2)	−1.8484*	0.2670	0.2874	0.0201	−1.2647	10.2300
Sargan test	25.3145*	28.6812*	28.76262*	27.7839*	27.5732*	27.8581*
Year	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES

Note: Robust standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.

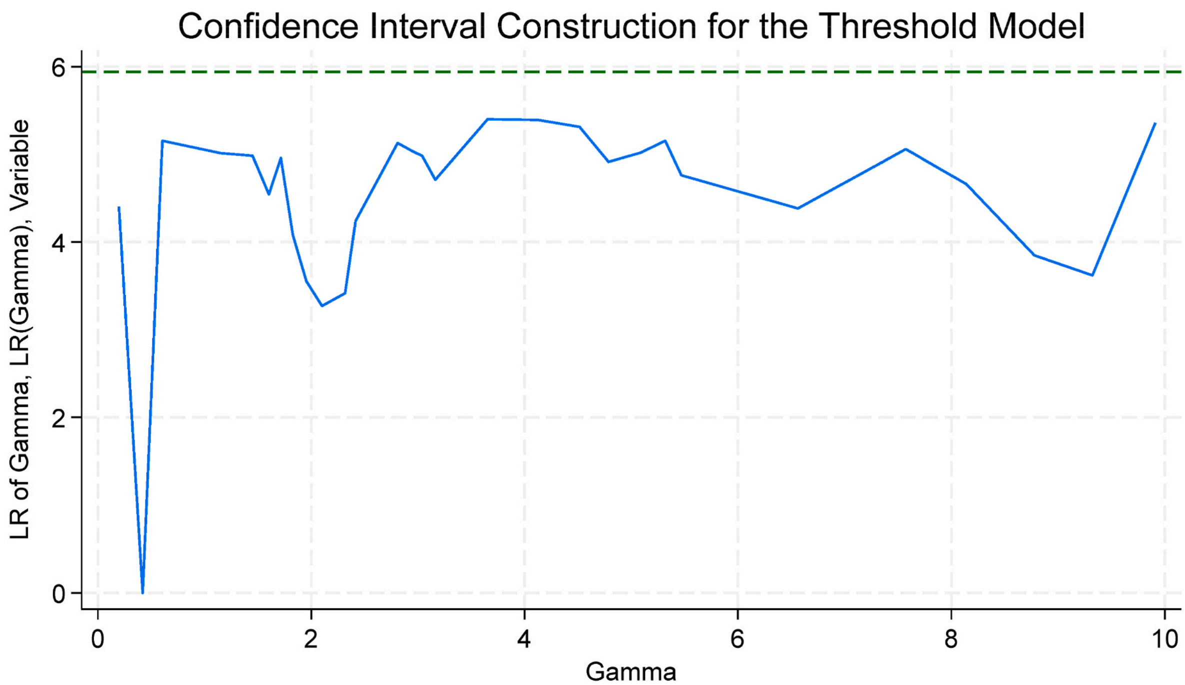

Fig. 4. Estimated value and confidence intervals of Solar energy (VaR).

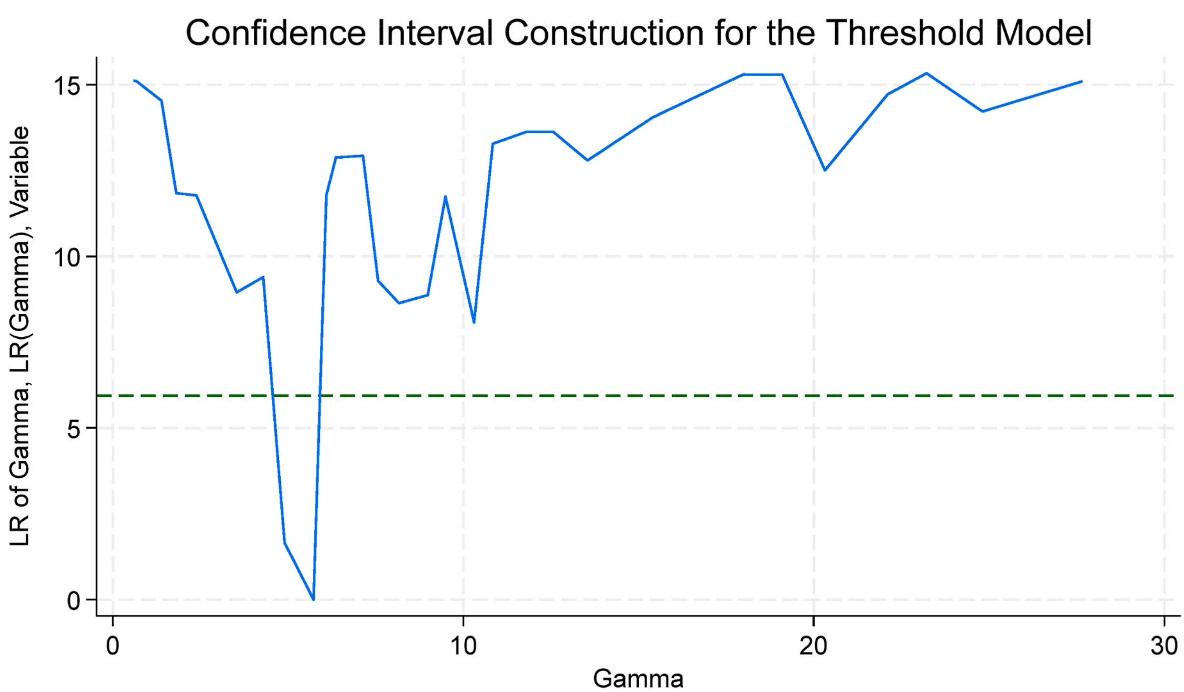

Fig. 5. Estimated value and confidence intervals of Wind energy (VaR).

within a day due to blockages in hydropower stations. Finally, in Table 3, we find that almost all renewable energy sources seem to promote extreme positive price volatility in electricity prices. However, combining the results of this chapter, we can conclude that all types of renewable energy need to reach a certain proportion in the grid to exert their ability to suppress extreme positive price volatility.

As previously mentioned, we employed dynamic panel threshold regression to investigate the nonlinear relationship between the share of renewable energy in the grid and extreme electricity price volatility. In our study, we selected the total amount of renewable energy, including hydropower, wind power, solar power, bioenergy, and other renewable energy sources, as the threshold variable and conducted threshold validity tests. The likelihood ratio function graphs in Figs. 4–15 respectively indicate threshold evidence for total renewable energy, other renewable energy sources, wind power, and solar power. However, in the regressions presented in Tables 6 and 7, some of the AR (2) and Sargan test results are borderline. Therefore, further research seems necessary to explore the robustness of the threshold effects of these two types of renewable energy on wholesale electricity price volatility.

This analytical approach allows us to dissect the complex dynamics of how renewable energy impacts electricity price volatility. By delineating these threshold levels, our study elucidates the conditions under

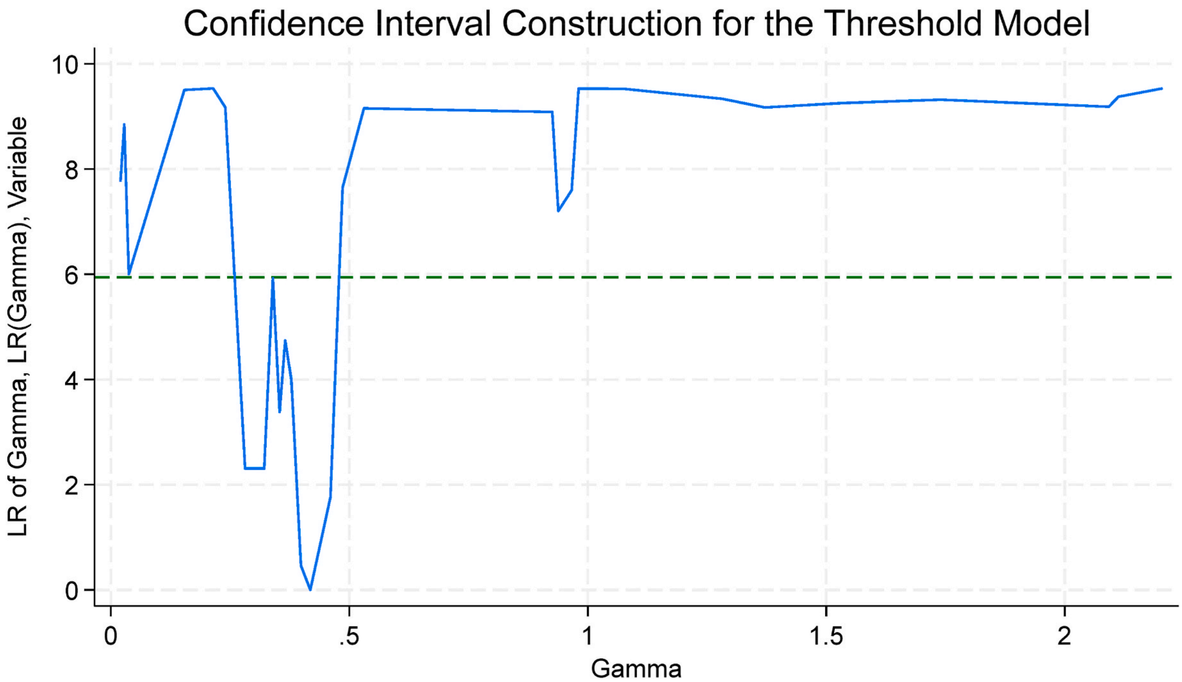

Fig. 6. Estimated value and confidence intervals of Other renewable energy (VaR).

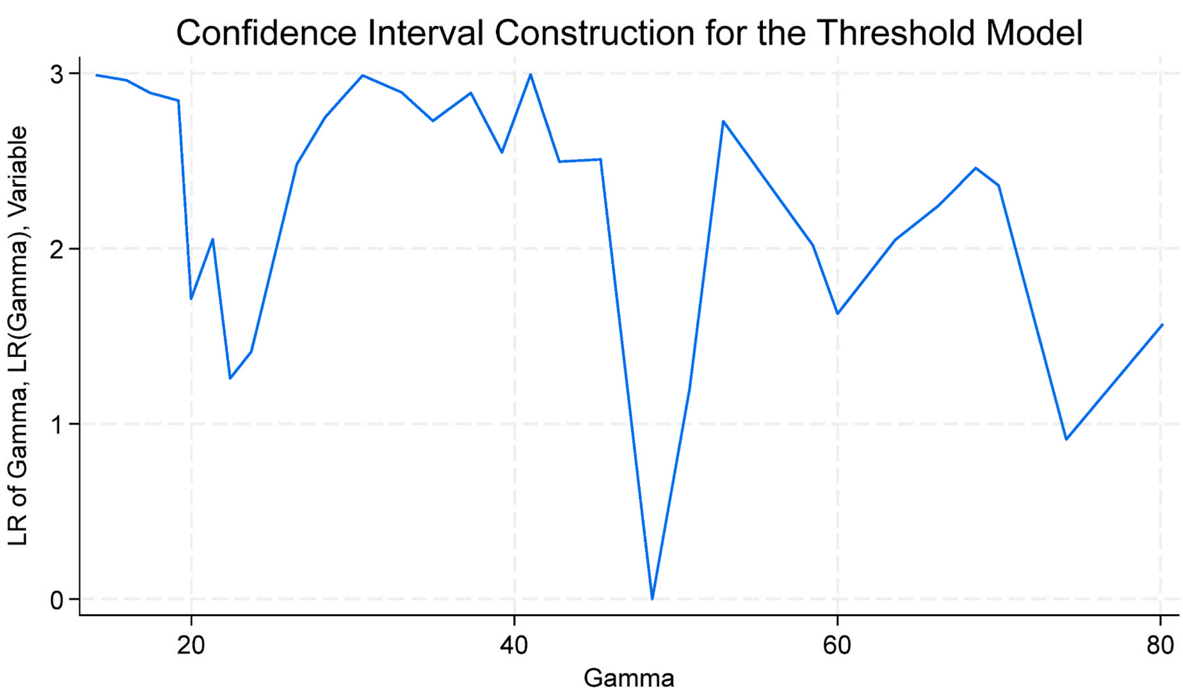

Fig. 7. Estimated value and confidence intervals of whole Renewable energy (VaR).

which renewable energy contributions significantly alter price stability. This nuanced understanding is crucial for policymakers and stakeholders in the energy sector as it highlights the varying impacts of different renewable energy sources on the balance of the power market. Moreover, the application of guided sampling enhances the robustness of our threshold validity tests, ensuring that the identified thresholds are not merely statistical artifacts but represent true inflection points in the relationship between renewable energy penetration and price stability.

3.3.4. *Robustness test*

In our previous analysis, threshold testing identified the threshold values for hydropower, wind power, other renewable energies, and total renewable energy as threshold variables. To further explore the impacts that dynamic panel threshold regression might overlook and to test the robustness of its results, we conducted a more in-depth study using the PSTR model. The outcomes of the PSTR model, as depicted in Figs. 16–21 and detailed in Appendix H, reveal the threshold effects of hydropower and biomass energy previously suspected of bias, as well as the transition from linear to nonlinear trends in other renewable energies. In the previous text, we aimed to confirm whether some threshold values and trends that were stuck at critical points in the dynamic threshold regression model were significant. In this chapter, the

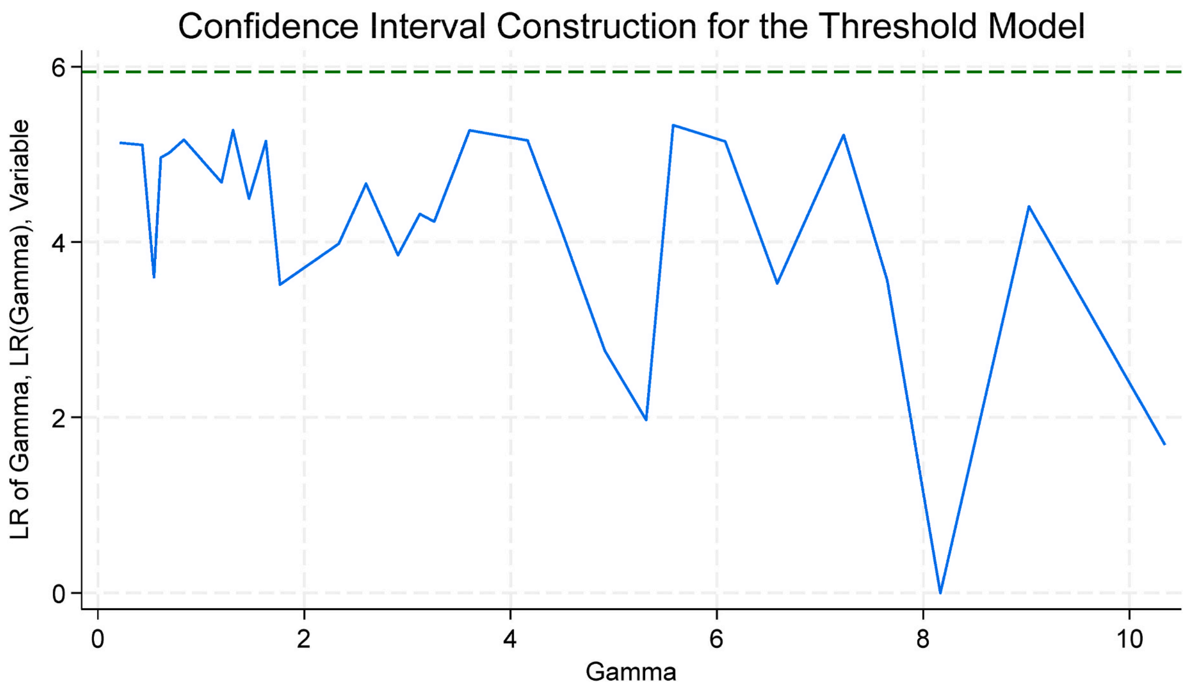

Fig. 8. Estimated value and confidence intervals of bioenergy (VaR).

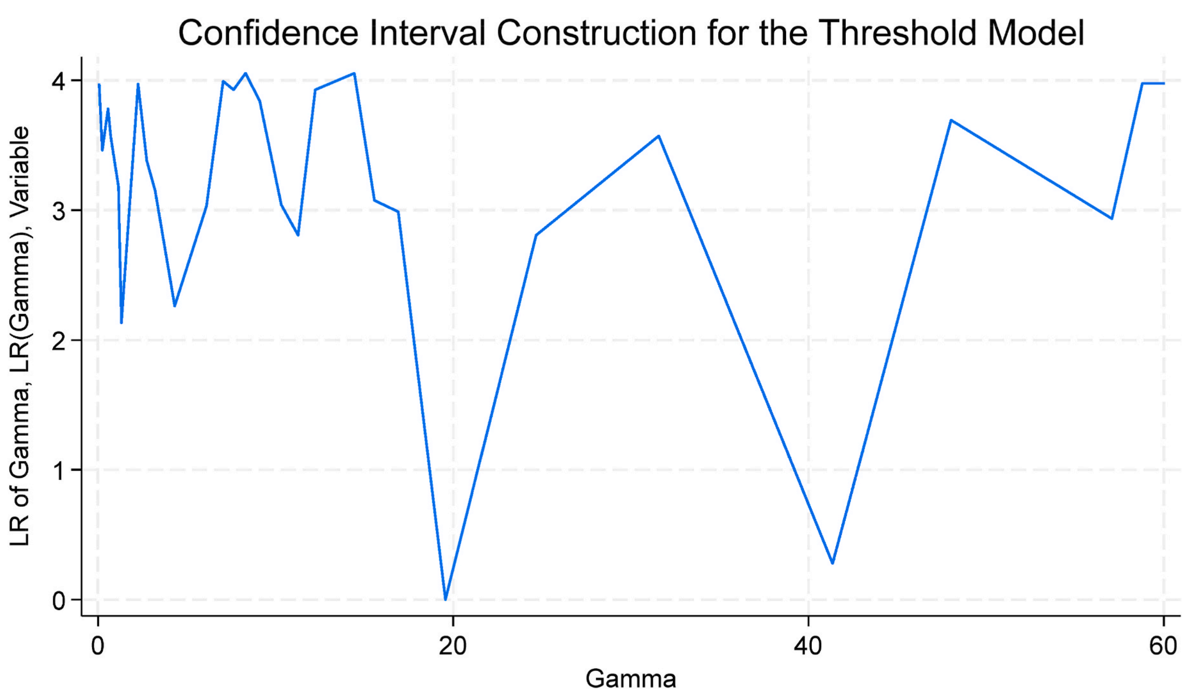

Fig. 9. Estimated value and confidence intervals of hydro (VaR).

performance trends of solar power, wind power, hydropower, other renewable energies, and total renewable energies as threshold variables in the PSTR model are very similar to the results presented in Tables 5 and 6 Although the specific threshold values differ slightly, the overall growth trends, as well as the sign and significance of the coefficients, show no significant differences. The conclusions of this chapter further consolidate the conclusions obtained through the dynamic threshold regression model, enhancing their reliability and robustness. The consistency in the trends and threshold ranges between the two methods provides a solid foundation for our conclusions.

4. Conclusion

Our analysis, employing dynamic panel threshold regression, reveals the significant impact of renewable energy on wholesale electricity price volatility, emphasizing the critical role of the renewable energy generation ratio as a threshold variable. This nuanced understanding underscores the importance of renewable energy sources such as hydropower, wind, solar, and bioenergy in mitigating extreme electricity price fluctuations.

Regarding extreme negative wholesale electricity price volatility, when the proportion of renewable energy generation is below a specific

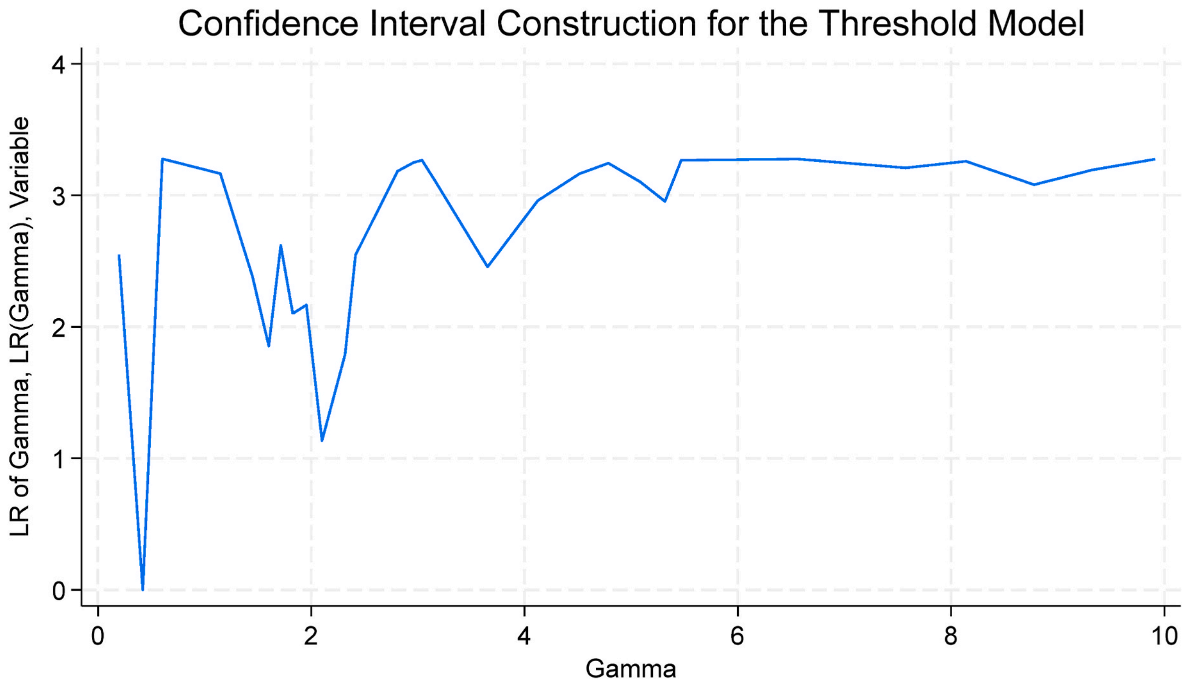

Fig. 10. Estimated value and confidence intervals of Solar energy (VaG).

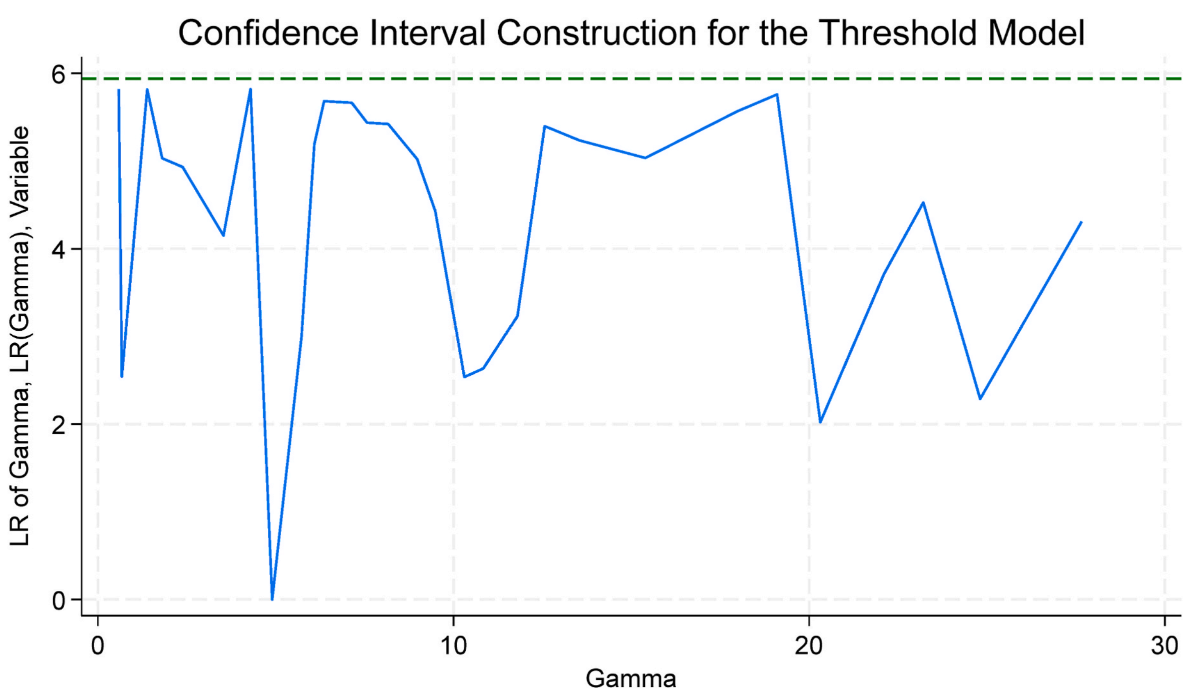

Fig. 11. Estimated value and confidence intervals of Wind energy (VaG).

threshold, its impact on extreme negative price volatility is not significant. This is primarily due to their lower marginal costs compared to fossil fuels, which stabilize market prices through the merit order effect. However, the intermittency and unpredictability of renewable energy, especially at lower penetration levels, pose challenges as the grid adapts to these fluctuations. Technological immaturity and imperfect market policies can lead to unstable power supply, increasing the likelihood of extreme negative price volatility. Yet, surpassing certain generation ratio thresholds, technological advancements, scale expansion, and reduced reliance on fossil fuels not only sustain but enhance the ability of renewable energy to reduce price volatility. Once the threshold is exceeded, the capacity of renewable energy to curb extreme negative price volatility becomes significant and enhanced. This is largely because low marginal cost renewables like wind and solar displace more expensive fossil fuel generation through the merit order effect, gradually reducing the number of inflexible, high-cost fossil fuel plants, shifting their role from primary to auxiliary generators. Analyzing specific types of renewable energy, hydropower, wind, and solar significantly reduces extreme negative price volatility once they reach certain proportions. In contrast, geothermal and bioenergy can stabilize prices at lower proportions but are surpassed in influence by mainstream renewables at higher proportions. This is possibly because the costs and outputs of

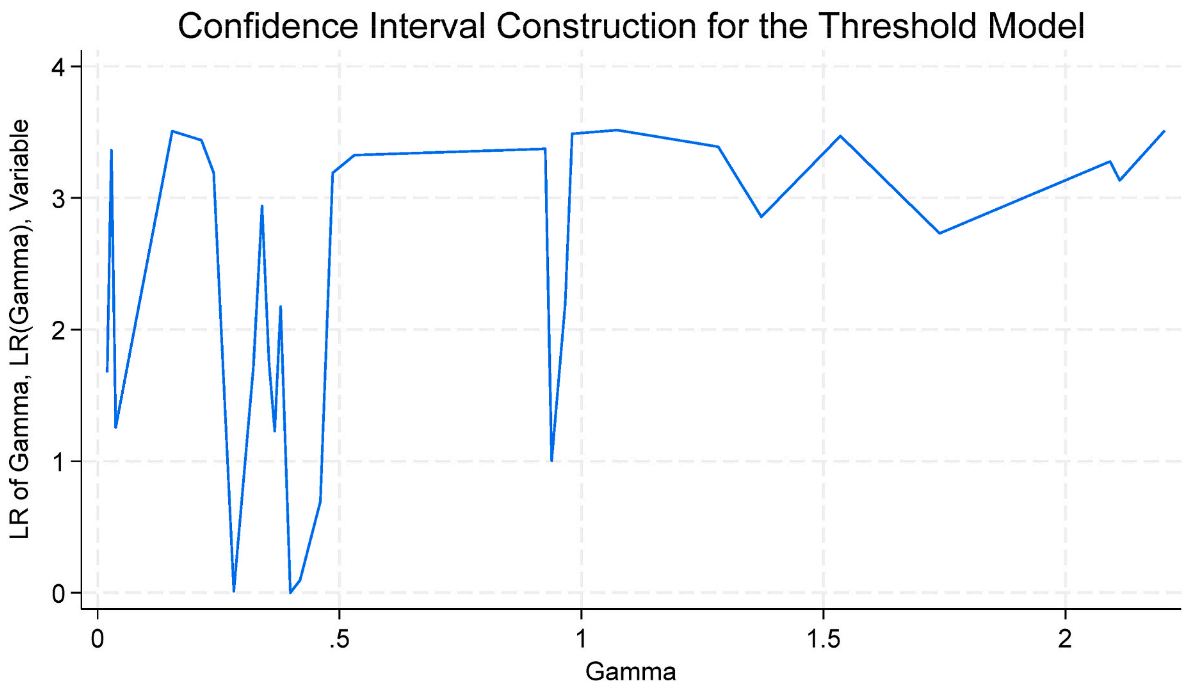

Fig. 12. Estimated value and confidence intervals of Other renewable energy (VaG).

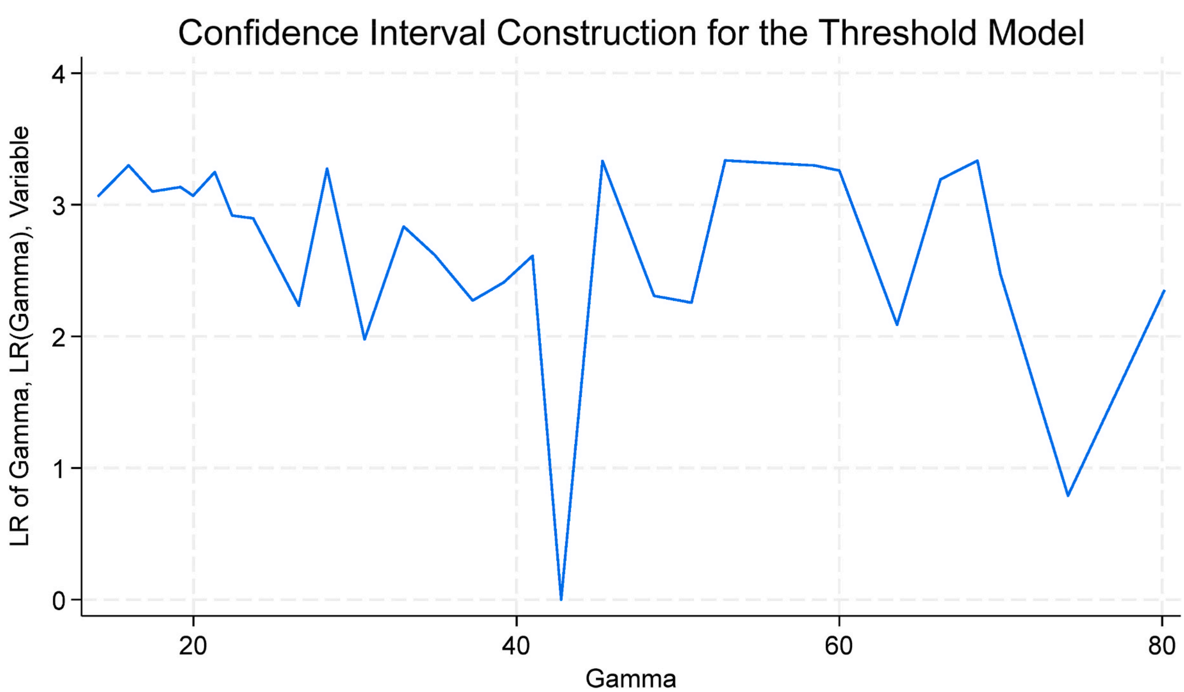

Fig. 13. Estimated value and confidence intervals of whole Renewable energy (VaG).

bioenergy and other renewables (mainly geothermal) are relatively fixed, less affected by technological immaturity, thus providing market stability. At higher proportions, the technological maturity and scale of mainstream renewables like hydropower, wind, and solar make their role in reducing price volatility more prominent. In contrast, the relative influence of bioenergy and other renewables diminishes due to their smaller share in generation.

Regarding extreme positive wholesale electricity price volatility, similarly, when the renewable energy generation ratio is below a certain threshold, its impact is not significant. However, once the threshold is surpassed, the ability of renewables to reduce extreme positive price volatility significantly enhances. Renewable energy sources, with near-zero marginal costs, are prioritized, leading to the exit of traditional generation methods affected by fossil fuel price volatility, thereby reducing overall price instability caused by geopolitical risks, extreme weather, and storage risks, lowering the likelihood of extreme positive price volatility. For each renewables' impact on positive extreme volatility, we find that when the proportion of hydropower exceeds a specific threshold, its ability to reduce extreme positive price volatility is not significant. This may be due to the influence of dry and wet seasons in hydropower-dominated markets, where reliance on fossil fuels during dry seasons increases the risk of extreme positive price volatility. During

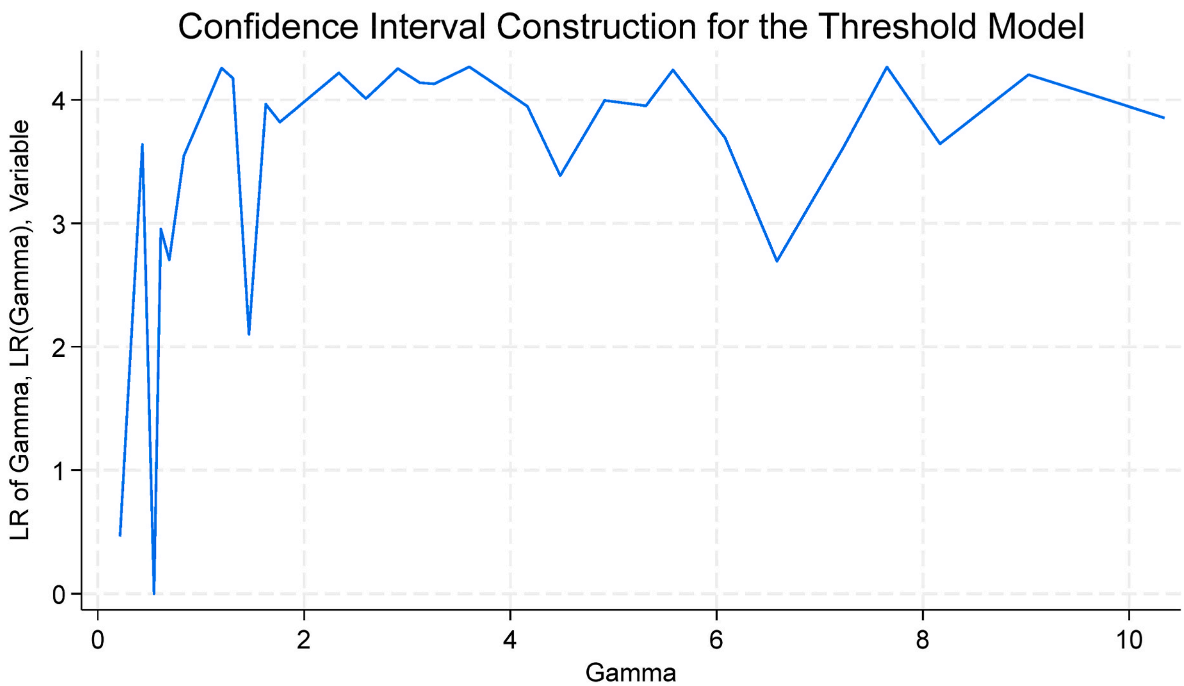

Fig. 14. Estimated value and confidence intervals of bioenergy (VaG).

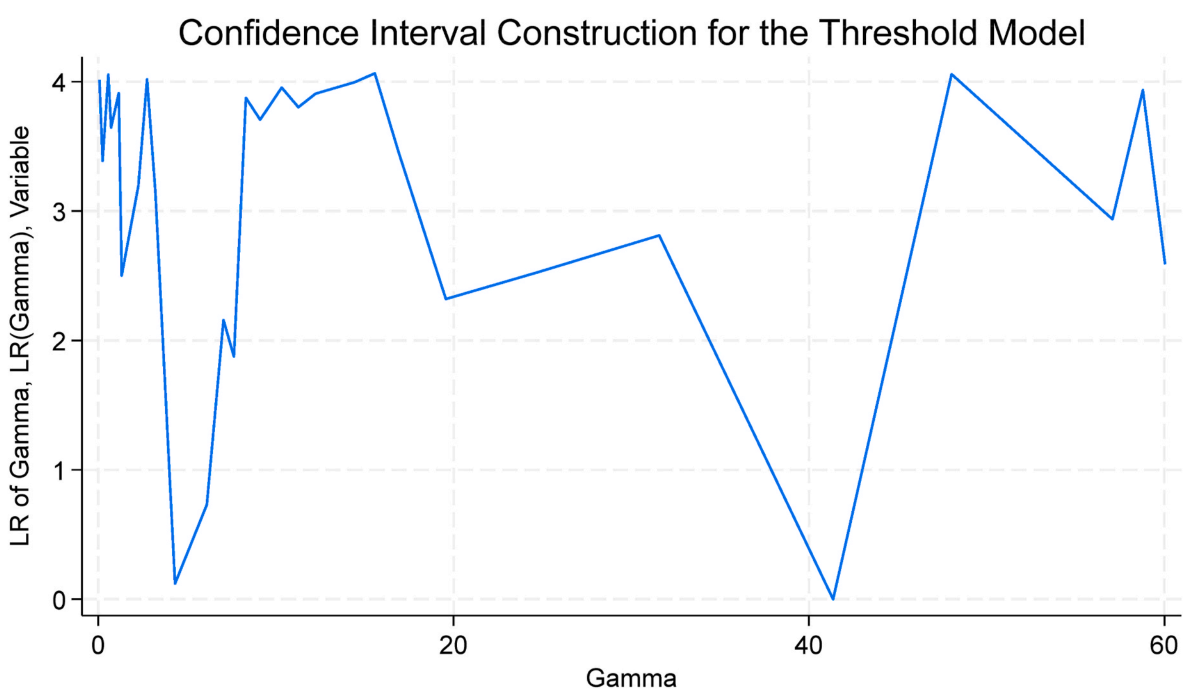

Fig. 15. Estimated value and confidence intervals of hydro (VaG).

wet seasons, the low marginal cost of hydropower effectively reduces extreme positive price volatility. For wind, solar, bioenergy, and other renewables (mainly geothermal), exceeding their respective thresholds helps reduce extreme positive price volatility. The low marginal cost characteristic of these renewables allows them to be prioritized, reducing overall wholesale electricity prices. Wind and solar, with near-zero marginal costs, lead to the exit of high-cost traditional generation methods, reducing extreme positive price volatility. Bioenergy and other renewables (mainly geothermal) significantly impact positive price volatility at lower proportions, but their stabilizing effect decreases after exceeding the threshold, primarily because mainstream renewables' technological maturity and scale make them the main price stabilizers.

Based on our analysis, several policy recommendations and future research directions are proposed to address the impact of renewable energy on wholesale electricity price volatility. First, given the intermittency and unpredictability of renewable energy, especially at lower penetration levels, the grid needs to adapt to these fluctuations. Therefore, governments should actively encourage and fund the development of energy storage technologies, such as battery storage, pumped hydro storage, and AI technologies (Nyangon, 2024) to balance supply and demand and reduce power supply instability. Additionally, by referencing wholesale electricity market policies from countries with higher

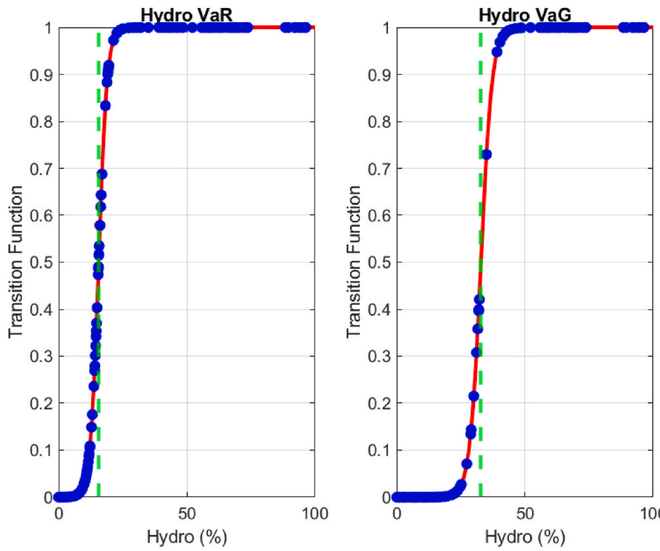

Fig. 16. PSTR result for hydro energy (VaR and VaG).

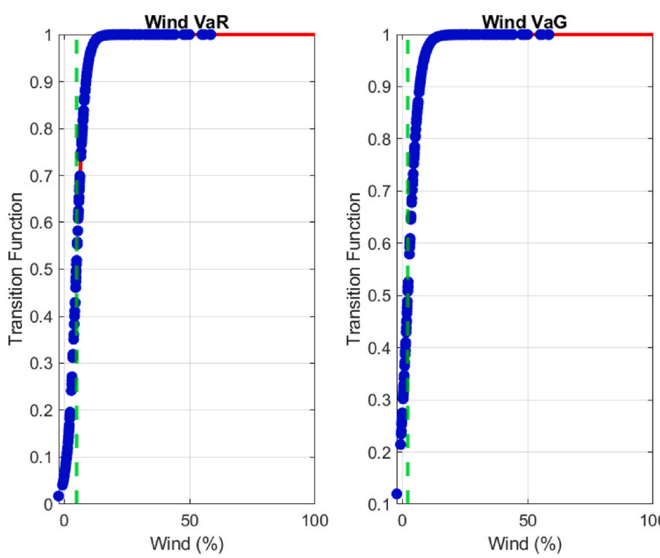

Fig. 17. PSTR result for wind energy (VaR and VaG).

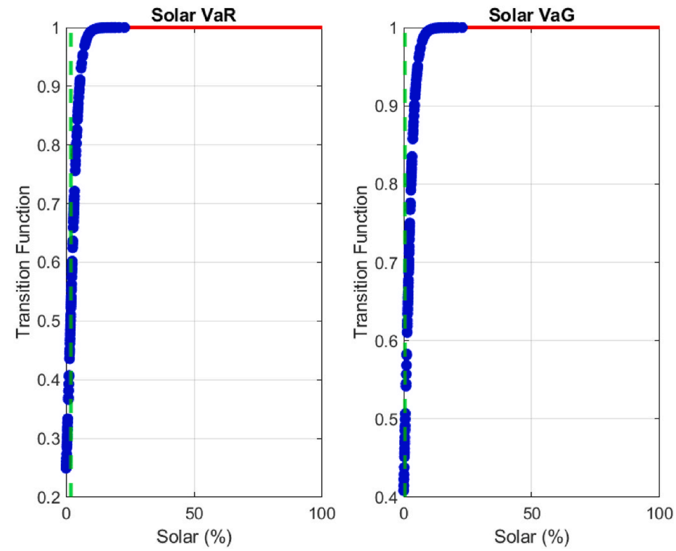

Fig. 18. PSTR result for solar energy (VaR and VaG).

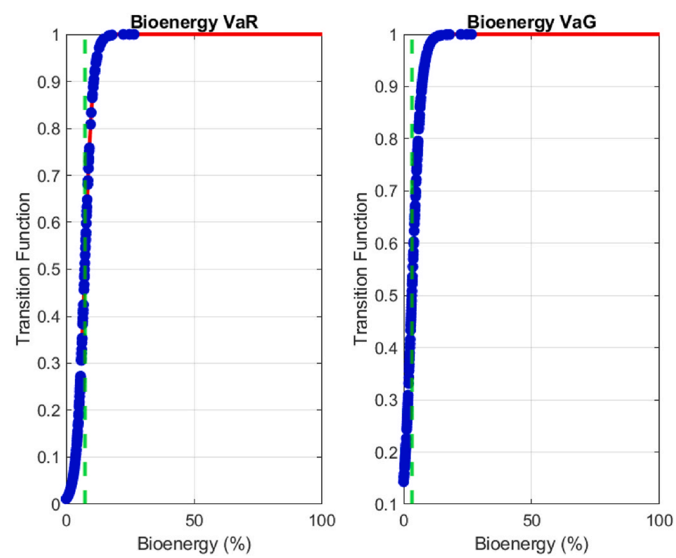

Fig. 19. PSTR result for bioenergy energy (VaR and VaG).

renewable energy penetration, we can avoid negative prices caused by oversupply during non-peak periods, thereby reducing extreme risks faced by domestic market participants. Secondly, in terms of power technology, efforts must be intensified to build modern grid infrastructure, enhancing its resilience and adaptability to integrate high proportions of renewable energy effectively. The promotion of smart grid technology helps monitor and manage electricity flow in real time, thereby improving overall system stability. Furthermore, the government should support the development of diverse renewable energy sources through policy incentives to reduce reliance on a single type of energy, optimize the energy structure, and mitigate the risks of supply and price volatility caused by extreme weather. Policy incentives should include subsidies, tax incentives, and supportive tariffs to encourage investment in renewable energy infrastructure and technologies. Importantly, the government should accelerate the transition of inflexible fossil fuel power plants from primary generation roles to auxiliary roles, learning from countries with higher renewable energy usage to find the balance between fossil and renewable energy, ensuring a smooth transition of the national grid from fossil fuels to renewable energy. While our study provides significant insights, it is limited by the reliance on historical data, modelling assumptions, and external factors such as geopolitical events and policy changes that may not be fully accounted for. These limitations could affect the generalizability and robustness of our conclusions, suggesting the need for cautious interpretation and further research.

Future research should focus on the long-term impacts of renewable energy integration on electricity markets and grid stability, evaluating the effectiveness of various energy storage technologies, and exploring the scalability of renewable energy solutions in different geographic and socio-economic contexts. Additionally, investigating the role of policy frameworks and market mechanisms in supporting renewable energy adoption and integration will provide valuable insights for policymakers and stakeholders. Research should also address the socio-economic benefits and challenges of transitioning to a renewable-dominant energy system, including job creation, energy security, and environmental impacts, ensuring the comprehensiveness and sustainability of the energy transition. In conclusion, as the proportion of renewable energy generation increases, particularly beyond specific thresholds, its ability to mitigate extreme price volatility is significantly enhanced. Policymakers should prioritize further development and integration of

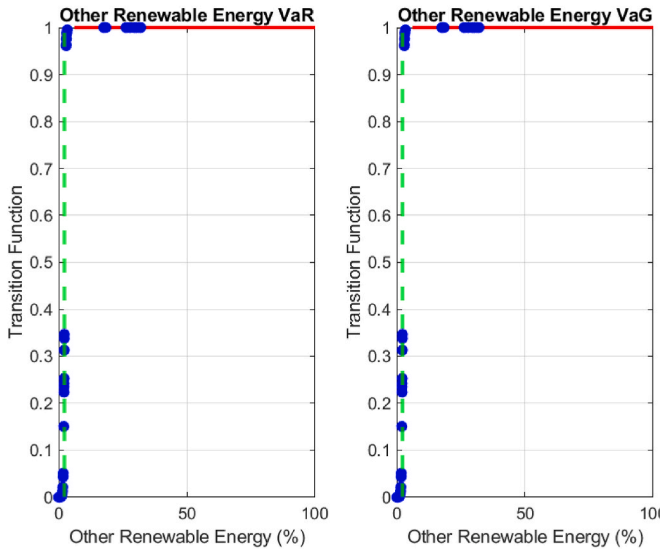

Fig. 20. PSTR result about other renewable energy (VaR and VaG).

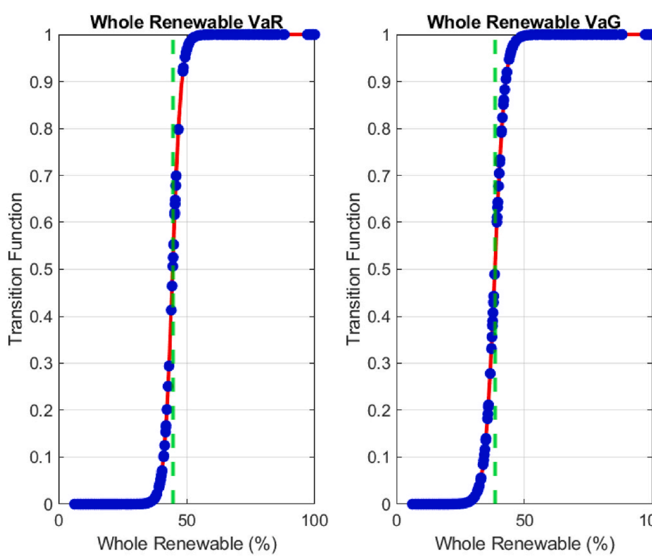

Fig. 21. PSTR result for Whole Renewable energy (VaR and VaG).

renewable energy through comprehensive policies and technical measures, promoting its effective application in electricity markets, enhancing system stability, and reducing extreme price volatility, thereby laying the foundation for a more sustainable energy future.

CRediT authorship contribution statement

Guanghao Wang: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Erwann Sbai:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Le Wen:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Mingyue Selena Sheng:** Writing – review & editing, Supervision, Methodology, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2024.144343.

Data availability

Data will be made available on request.

References

Abban, A.R., Hasan, M.Z., 2021. Solar energy penetration and volatility transmission to electricity markets—an Australian perspective. Econ. Anal. Pol. 69, 434–449. https://doi.org/10.1016/j.eap.2020.12.022.

Abbasi, K., Abbas, J., Tufail, M., 2021. Revisiting electricity consumption, price, and real GDP: a modified sectoral level analysis from Pakistan. Energy Pol. 149, 112087. https://doi.org/10.1016/J.ENPOL.2020.112087.

Alam, M., 2021. Accessing the effect of renewables on the wholesale power market. Int. J. Energy Econ. Pol. 11, 341–360. https://doi.org/10.32479/IJEEP.10756.

Alam, M.M., Aktar, M.A., Idris, N.D.M., Al-Amin, A.Q., 2023. World energy economics and geopolitics amid COVID-19 and post-COVID-19 policy direction. World Development Sustainability 2, 100048. https://doi.org/10.1016/j.wds.2023.100048.

Ballester, C., Furió, D., 2015. Effects of renewables on the stylized facts of electricity prices. Renewable Sustainable Energy Rev. 52, 1596–1609. https://doi.org/10.1016/J.RSER.2015.07.168.

Boroumand, R.H., 2009. Les fournisseurs non intégrés d'électricité: l'echec d'un modèle organisationnel. Rev. Energ. 590. http://pascal-francis.inist.fr/vibad/index.php?action=getRecordDetail&idt=21979597.

Boroumand, R.H., 2015. Electricity markets and oligopolistic behaviors: the impact of a multimarket structure. Res. Int. Bus. Finance 33, 319–333. https://doi.org/10.1016/j.ribaf.2014.04.004.

Boroumand, R.H., Zachmann, G., 2012. Retailers' risk management and vertical arrangements in electricity markets. Energy Pol. 40, 465–472. https://doi.org/10.1016/j.enpol.2011.10.041.

Boroumand, R.H., Goutte, S., Porcher, S., Porcher, T., 2015. Hedging strategies in energy markets: the case of electricity retailers. Energy Econ. 51, 503–509. https://doi.org/10.1016/j.eneco.2015.06.021.

Breuer, M., Dehaan, E., 2023. Using and interpreting fixed effects models. J. Account. Res. https://doi.org/10.1111/1475-679X.12559.

Bushnell, J.B., Mansur, E.T., Saravia, C., 2008. Vertical arrangements, market structure, and competition: an analysis of restructured US electricity markets. Am. Econ. Rev. 98 (1), 237–266. https://doi.org/10.1257/aer.98.1.237.

Cevik, S., Ninomiya, K., 2023. Chasing the sun and catching the wind: energy transition and electricity prices in Europe. J. Econ. Finance 1–24. https://doi.org/10.1007/s12197-023-09626-x.

Chan, K., Gray, P., 2006. Using extreme value theory to measure value-at-risk for daily electricity spot prices. Int. J. Forecast. 22, 283–300. https://doi.org/10.1016/J.IJFORECAST.2005.10.002.

Ciarreta, A., Pizarro-Irizar, C., Zarraga, A., 2020. Renewable energy regulation and structural breaks: an empirical analysis of Spanish electricity price volatility. Energy Econ. 88, 104749. https://doi.org/10.1016/j.eneco.2020.104749.

Dong, S., Li, H., Wallin, F., Avelin, A., Zhang, Q., Yu, Z., 2019. Volatility of electricity price in Denmark and Sweden. Energy Proc. https://doi.org/10.1016/J.EGYPRO.2019.01.788.

Dzyuba, A., Solovyeva, I., 2020. PRICE-BASED demand-side management model for industrial and large electricity consumers. Int. J. Energy Econ. Pol. https://doi.org/10.32479/ijeep.8982.

Elzaki, R., 2023. Impact of financial development shocks on renewable energy consumption in Saudi arabia. Sustainability. https://doi.org/10.20944/preprints202310.0093.v1.

Ember, 2023. Global electricity review 2023. https://ember-climate.org/insights/research/global-electricity-review-2023/.

Ember, 2024a. Data tools. https://ember-climate.org/data/.

Ember, 2024b. Nuclear. From. https://ember-climate.org/topics/nuclear/.

Fok, D., Van Dijk, D., Franses, P.H., 2005. A multi-level panel STAR model for US manufacturing sectors. J. Appl. Econom. 20 (6), 811–827. https://doi.org/10.1002/jae.822.

Forrest, S., MacGill, I., 2013. Assessing the impact of wind generation on wholesale prices and generator dispatch in the Australian National Electricity Market. Energy Pol. 59, 120–132. https://doi.org/10.1016/j.enpol.2013.02.026.

Gonzalez, A., Teräsvirta, T., van Dijk, D., Yang, Y., 2017. Panel Smooth Transition Regression Models. Retrieved from. https://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-332277.

Hirth, L., 2013. The market value of variable renewables the effect of solar and wind power variability on their relative price. Energy Econ. 38, 218–236. https://doi.org/10.1016/J.ENECO.2013.02.004.

Huisman, R., Kyritsis, E., Ştefǎ, C., 2020. Fat tails due to variable renewables and insufficient flexibility: evidence from Germany. Energy J. 43, 231–247. https://doi.org/10.5547/01956574.43.5.rhui.

IEA, 2023. World Energy Outlook 2023. IEA, Paris. https://www.iea.org/reports/world-energy-outlook-2023.

Johnson, E., Oliver, M., 2019. Renewable generation capacity and wholesale electricity price variance. Energy J. 40, 143–168. https://doi.org/10.5547/01956574.40.5.ejoh.

Karandikar, R.G., Deshpande, N.R., Khaparde, S.A., Kulkarni, S.V., 2009. Modelling volatility clustering in electricity price return series for forecasting value at risk. Eur. Trans. Electr. Power 19 (1), 15–38. https://doi.org/10.1002/etep.205.

Keeley, A., Matsumoto, K., 2018. Investors' perspective on determinants of foreign direct investment in wind and solar energy in developing economies – review and expert opinions. J. Clean. Prod. 179, 132–142. https://doi.org/10.1016/J.JCLEPRO.2017.12.154.

Keeley, A., Matsumoto, K., Tanaka, K., Sugiawan, Y., Managi, S., 2020. The impact of renewable energy generation on the spot market price in Germany: ex-post analysis using boosting method. Energy J. 41, 119–140. https://doi.org/10.5547/01956574.41.SI1.akee.

Ketterer, J.C., 2014. The impact of wind power generation on the electricity price in Germany. Energy Econ. 44, 270–280. https://doi.org/10.1016/j.eneco.2014.04.003.

Kremer, S., Bick, A., Nautz, D., 2013. Inflation and growth: new evidence from a dynamic panel threshold analysis. Empir. Econ. 44, 861–878. https://doi.org/10.1007/s00181-012-0553-9.

Loi, T., Jindal, G., 2019. Electricity market deregulation in Singapore – Initial assessment of wholesale prices. Energy Pol. https://doi.org/10.1016/J.ENPOL.2018.11.043.

Ma, M., Tang, J., 2023. Nonlinear impact and spatial effect of tourism urbanization on human settlement environment: evidence from the Yellow River Basin, China. J. Clean. Prod. 428, 139432. https://doi.org/10.1016/j.jclepro.2023.139432.

Maciejowska, K., 2020. Assessing the impact of renewable energy sources on the electricity price level and variability–A quantile regression approach. Energy Econ. 85, 104532. https://doi.org/10.1016/j.eneco.2019.104532.

Mauritzen, J., 2010. What happens when it's windy in Denmark? An empirical analysis of wind power on price volatility in the Nordic electricity market. An Empirical Analysis of Wind Power on Price Volatility in the Nordic Electricity Market (December 28, 2010). *NHH Dept. Of Finance & Management Science Discussion Paper*. https://doi.org/10.2139/ssrn.1754931, 2010/18).

Mays, J., Jenkins, J., 2023. Financial risk and resource adequacy in markets with high renewable penetration. IEEE Transactions on Energy Markets, Policy and Regulation 1, 523–535. https://doi.org/10.1109/TEMPR.2023.3322531.

Mills, A., Millstein, D., Wiser, R., Seel, J., Carvallo, J., Jeong, S., Gorman, W., 2019. Impact of wind, solar, and other factors on wholesale power prices: an historical analysis—2008 through 2017. https://doi.org/10.2172/1574352.

Mohan, A., Mannor, S., Kizilkale, AC., 2020. Price volatility in electricity markets: a stochastic control perspective. Cornell University. https://arxiv.org/pdf/2002.06808.

Moya, D., Aldas, C., Kaparaju, P., 2018. Geothermal energy: power plant technology and direct heat applications. Renew. Sustain. Energy Rev. https://doi.org/10.1016/J.RSER.2018.06.047.

Mwampashi, M.M., Sklibosios Nikitopoulos, C., 2023. Beyond the Mean: Examining Electricity Spot Price Distribution in Australia. Available at SSRN: https://ssrn.com/abstract=4540077. or. https://doi.org/10.2139/ssrn.4540077. Available at: SSRN 4540077.

Mwampashi, M.M., Nikitopoulos, C.S., Konstandatos, O., Rai, A., 2021. Wind generation and the dynamics of electricity prices in Australia. Energy Econ. 103, 105547. https://doi.org/10.1016/j.eneco.2021.105547.

Mwampashi, M.M., Nikitopoulos, C.S., Rai, A., Konstandatos, O., 2022. Large-scale and rooftop solar generation in the NEM: a tale of two renewables strategies. Energy Econ. 115, 106372. https://doi.org/10.1016/j.eneco.2022.106372.

Newbery, D., 2023. Efficient renewable electricity support: designing an incentive-compatible support scheme. Energy J. 44, 1–22. https://doi.org/10.5547/01956574.44.3.dnew.

Nicolosi, M., 2010. Wind power integration and power system flexibility–An empirical analysis of extreme events in Germany under the new negative price regime. Energy Pol. 38, 7257–7268. https://doi.org/10.1016/J.ENPOL.2010.08.002.

Nyangon, J., 2024. Climate-proofing critical energy infrastructure: smart grids, artificial intelligence, and machine learning for power system resilience against extreme weather events. J. Infrastruct. Syst. 30 (1), 03124001. https://doi.org/10.1061/JITSE4.ISENG-2375.

Nyangon, J., Akintunde, R., 2024. Principal component analysis of day-ahead electricity price forecasting in CAISO and its implications for highly integrated renewable energy markets. Wiley Interdisciplinary Reviews: Energy Environ. 13 (1), e504. https://doi.org/10.1002/wene.504.

Nyangon, J., Byrne, J., 2023. Estimating the impacts of natural gas power generation growth on solar electricity development: PJM's evolving resource mix and ramping capability. Wiley Interdisciplinary Reviews: Energy Environ. 12 (1), e454. https://doi.org/10.1002/wene.454.

Prete, C., Blumsack, S., 2023. Enhancing the reliability of bulk power systems against the threat of extreme weather: lessons from the 2021 Texas electricity crisis. Economics of Energy & Environmental Policy. https://doi.org/10.5547/2160-5890.12.2.clop.

Qiao, H., Zhang, Z., Su, Q., 2021. The optimal hourly electricity price considering wind electricity uncertainty based on conditional value at risk. Int. J. Green Energy 18 (5), 512–524. https://doi.org/10.1080/15435075.2020.1865372.

Rai, A., Nunn, O., 2020. On the impact of increasing penetration of variable renewables on electricity spot price extremes in Australia. Econ. Anal. Pol. 67, 67–86. https://doi.org/10.1016/j.eap.2020.06.001.

Rintamäki, T., Siddiqui, A.S., Salo, A., 2017. Does renewable energy generation decrease the volatility of electricity prices? An analysis of Denmark and Germany. Energy Econ. 62, 270–282. https://doi.org/10.1016/j.eneco.2016.12.019.

Schneider, N., 2021. Population growth, electricity demand and environmental sustainability in Nigeria: insights from a vector auto-regressive approach. Int. J. Environ. Stud. 79, 149–176. https://doi.org/10.1080/00207233.2021.1905317.

Seel, J., Mills, A., Wiser, R., Deb, S., Asokkumar, A., Hassanzadeh, M., Aarabali, A., 2018. Impacts of high variable renewable energy futures on wholesale electricity prices, and on electric-sector decision making. https://doi.org/10.2172/1437006.

Silva, P., Horta, P., 2018. The effect of variable renewable energy sources on electricity price volatility: the case of the iberian market. Sustainability & Economics eJournal. https://doi.org/10.2139/ssrn.3256259.

Singh, A.K., Pal, B.C., 2019. Rate of change of frequency estimation for power systems using interpolated DFT and Kalman filter. IEEE Trans. Power Syst. 34 (4), 2509–2517. https://doi.org/10.1109/TPWRS.2018.2881151.

Tao, M., Poletti, S., Wen, L., Sheng, M.S., Wang, J., Wang, G., Zheng, Y., 2023. Appraising the role of the digital economy in global decarbonization: a spatial non-linear perspective on globalization. J. Environ. Manag. 347, 119170. https://doi.org/10.1016/j.jenvman.2023.119170.

Wang, X., Chu, B., Ding, H., Chiu, A.S., 2023. Impacts of heterogeneous environmental regulation on green transformation of China's iron and steel industry: evidence from dynamic panel threshold regression. J. Clean. Prod. 382, 135214. https://doi.org/10.1016/j.jclepro.2022.135214.

Wang, G., Liu, C., Sbai, E., Sheng, M.S., Hu, J., Tao, M., 2024. Interrelations between bitcoin market sentiment, crude oil, gold, and the stock market with bitcoin prices: vision from the hedging market. Stud. Econ. Finance. https://doi.org/10.1108/SEF-03-2024-0137.

Wen, L., Sharp, B., Sbai, E., 2020. Spatial effects of wind generation and its implication for wind farm investment decisions in New Zealand. Energy J. 41 (2). https://doi.org/10.5547/01956574.41.2.lwen.

Wen, L., Suomalainen, K., Sharp, B., Yi, M., Sheng, M.S., 2022. Impact of wind-hydro dynamics on electricity price: a seasonal spatial econometric analysis. Energy 238, 122076. https://doi.org/10.1016/j.energy.2021.122076.

Wu, J., Yang, C., Chen, L., 2024. Examining the non-linear effects of monetary policy on carbon emissions. Energy Econ. 131, 107206. https://doi.org/10.1016/j.eneco.2023.107206.

Yang, Y., Zhao, Q., Liang, D., Qin, Z., Zhang, Y., Guo, H., 2023. Value-at-Risk measurement and case analysis of electricity consumption. In: 2023 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia), pp. 102–107. https://doi.org/10.1109/ICPSAsia58343.2023.10294810.