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Cross-market spillover effects of energy risks: from the perspective of GARCH-CQR-based CoVaR model

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ABSTRACT

This study quantifies risk spillover effects from multi-dimensional energy markets to China's Guangdong carbon market by constructing an EGARCH-CQR-based CoVaR model, which integrates the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) framework to capture volatility leverage effects and clustering, combined with quantile regression for precise characterization of cross-market tail dependencies. Empirical analysis reveals significant structural heterogeneity in energy-to-carbon risk spillovers: traditional energy markets, such as oil and coke, exhibit 'high-intensity, high-volatility' shock patterns that transmit abrupt short-term risks during global crises like the COVID-19 outbreak, whereas new energy markets, including new energy vehicles and wind power, demonstrate 'low-intensity, persistent' spillover dynamics reflecting stronger market resilience. Additionally, China's 'Dual Carbon' policy reinforcement is identified as a critical policy transmission channel that significantly intensifies risk linkages between high-carbon energy sectors and the carbon market, with model validation confirming the robustness and coverage capability of the proposed GARCH-CQR-CoVaR framework.

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Risk spillover; energy market; GARCH-CQR-based CoVaR model

1. Introduction

The pervasive interconnectedness of the contemporary global economic system renders cross-market risk spillovers a critical determinant of financial stability and economic prosperity. Within the energy sector, pronounced price volatility poses a dual threat: it directly impinges upon the operational costs of economic agents and, through intricate transmission mechanisms, can precipitate systemic financial risks. Consequently, the accurate quantification of energy market risks and the elucidation of their spillover dynamics are paramount for the development of robust risk management frameworks, the safeguarding of financial market resilience, and the optimization of resource allocation. Current research trajectories in risk spillovers are fostering interdisciplinary scholarly engagement across finance, economics, and energy economics, effectively integrating theoretical discourse with empirical applications. Methodologically, risk linkages between energy-related financial assets are

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often elucidated through the analysis of co-movements in their returns or volatilities. In the energy domain, extrapolating potential price risks from historical data for commodities such as crude oil and natural gas, and subsequently assessing their transmission across diverse exchanges and geographical regions, carries profound practical implications for investors, corporations, and policymakers. The recent history of the global energy market has been punctuated by transformative shocks, including geopolitical disruptions, extreme meteorological events, and swift alterations in global economic policy, which have profoundly amplified energy price volatility, thereby elevating cross-market risk spillover to an urgent research imperative.

Current risk models often fail to delineate the specific transmission pathways and intensity of risk spillovers across different market entities. Furthermore, while much of the existing literature has focussed on modelling linear interdependencies between different energy markets, it frequently overlooks the pervasive nonlinearities and heterogeneous contagion patterns inherent in risk spillover dynamics. This gap is particularly salient in energy markets, where risk transmission between countries and exchanges tends to be highly asymmetric and tail-dependent. For instance, a significant supply disruption in a major oil-producing country would likely induce significant price increases across interconnected markets, potentially through complex transmission mechanisms that go beyond simple linear causality. Thus, there is a clear need to develop measurement approaches capable of more accurately capturing nonlinear and asymmetric tail risk spillovers.

To comprehensively assess cross-market risk spillover effects in energy markets, this study adopts the Conditional Value at Risk (CoVaR) framework to quantify risk transmission across different energy segments. At its core, CoVaR quantifies the magnitude of potential losses in a given energy institution, market, or system conditional upon another experiencing a state of severe distress or extreme risk exposure. To improve the accuracy and robustness of estimation in complex energy market environments, we integrate the volatility modelling strengths of the GARCH model with the capacity of Quantile Regression (QR) to characterize nonlinear tail dependence, thereby constructing a hybrid GARCH-CQR approach. Building on this foundation, we further develop a GARCH-CQR-based CoVaR measure. This integrated model simultaneously portrays the conditional volatility of energy market prices and precisely quantifies the level of risk faced by linked markets when a specific energy market encounters a severe negative shock. Using this novel empirical framework, the study aims to deeply investigate risk spillover dynamics between China's carbon trading market and major global energy markets, such as crude oil and natural gas, thereby providing theoretical and empirical support for the construction of a more resilient risk management architecture in the energy sector.

2. Literature review

This study is connected to three major research streams: (i) the evolution of risk measurement methods from traditional VaR to cross-market CoVaR; (ii) the progression of risk spillover mechanisms from macro-level measurement to micro-level transmission analysis; and (iii) the characteristics and driving factors of risk spillovers between carbon and energy markets as an emerging interdisciplinary field. This literature review will systematically examine relevant research findings in these areas.

Traditional risk measures mainly included Value at Risk (Engle, 1982) and Expected Shortfall (Artzner et al., 1999), with the primary focus of risk measure being extreme risks within individual markets. For instance, Mi and Zhang (2011) employed Extreme Value Theory (EVT) to quantify VaR for EUA futures prices, while Zhang et al. (2020) explored carbon market VaR determinants using Vine Copula models. Although effective in characterizing isolated extreme risks, these approaches exhibit inherent limitations in capturing increasingly significant risk spillover effects across interconnected energy markets. As economic and energy markets become increasingly integrated, the interconnections and cross-market transmission of risks have emerged as a significant research area. To explore the issue of cross-market risk spillover, Adrian and Brunnermeier (2016) proposed Conditional Value at Risk (CoVaR), designed to measure a single market's contribution to systemic risk. Building on this, scholars began integrating CoVaR with Copula methods to analyze complex cross-market risk structures. Ji et al. (2019) captured dynamic changes in dependence relationships using six time-varying Copula models, subsequently proposing upside and downside CoVaR. To reflect the asymmetric responses, recapitalization effects, and structural shifts observed during the global financial crisis, López-Espinosa et al. (2012) introduced an asymmetric version of CoVaR. Subsequent research has focussed more on improving the accuracy and relevance of risk measurement. For instance, Cao (2013) proposed multi-CoVaR to more precisely quantify an individual energy market's contribution to systemic risk. Additionally, to address challenges posed by high-dimensional data, Xu et al. (2019) incorporated the LASSO method into this framework. Furthermore, Fan et al. (2018) proposed a high-dimensional CoVaR estimation approach that combines a semiparametric single-index model with variable selection techniques.

Upon reaching a clear understanding of the evolution and growing relevance of risk spillover measure methods, academic focus has naturally shifted from macro-level measure techniques toward a micro-level analysis of cross-market transmission mechanisms. The fundamental cause of this transition lies in the widely recognized consensus that financial risks do not exist in isolation; instead, they spread across different markets. As a result, substantial research attention has been directed toward examining risk spillovers between energy-related commodities and energy markets. For instance, Yuan and Yang (2020) applied a GAS-DCS-copula model to study asymmetric risk spillovers from stock and crude oil market uncertainties to the carbon market. Similarly, Sun et al. (2020) used a GARCH-Copula-CoVaR framework to address ongoing debates about the transmission of extreme risks from commodity markets to maritime markets. Expanding on this approach, Zhao et al. (2023) employed a GARCH-EVT-Copula-CoVaR model to analyze the risk spillover effects from international oil prices to various sector-specific stock markets in China. From another perspective, Zheng et al. (2024) applied the Tail-Event driven NETwork methodology to examine high dimensional CoVaR-based spillover networks within energy and other strategic commodity markets.

Given its foundational role in the global economic system and the broad transmission of its price signals across industries, the energy market has long been a focal point of risk spillover research. In recent years, however, the growing urgency of global climate mitigation and the widespread adoption and refinement of carbon emission trading systems worldwide have made risk spillovers between carbon and energy markets increasingly evident. This interconnected domain is rapidly emerging as a central subject of academic investigation. Scholars have actively explored this developing area. For instance, Mansanet-Bataller et al. (2011) identified a significant correlation between EU carbon prices and energy prices. Subsequently, Ren et al. (2022) applied quantile Granger causality tests to uncover complex interdependencies in international carbon-oil dynamics. Su et al. (2023) further employed a network approach based on quantile vector autoregression (Q-VAR) to analyze risk spillover effects under different market conditions. Focussing on China, Tang et al. (2024) constructed a risk transmission network for the country's carbon energy system, revealing right tail risk contagion within this integrated framework. Complementing these studies on market linkages and contagion, Chang et al. (2019) used the DCC-GARCH model to examine dynamic conditional correlations. Further research by Wang and Guo (2018), applying the Diebold-Yilmaz methodology (Diebold & Yilmaz, 2009), pointed to relatively weak market linkages and highlighted a notable susceptibility to policy-induced shocks.

Existing literature has focussed on CoVaR measurement and risk spillover effects within energy markets. Prior research overlooks the complex and distinctive interaction mechanisms between China's carbon and energy markets. This limitation has resulted in superficial interpretations of cross-market risk interdependencies. Extant studies on carbon market risk spillovers largely rely on pre-pandemic or pre-stabilization datasets, which fail to capture current market dynamics characterized by post-COVID recovery and policy evolution. Different from previous studies, we investigate the risk spillover effects from multi-dimensional energy markets to the carbon trading market and quantify the spillover intensity using the EGARCH-CQR model. Contributions are listed in the following.

- An integrated EGARCH-CQR-CoVaR framework is developed that combines asymmetric volatility modelling with quantile regression, improving the measurement accuracy of tail-risk spillovers between energy and carbon markets.
- We uncover a structural heterogeneity in risk spillovers between traditional and new energy sources, showing that traditional energy markets transmit high-intensity, high-volatility shocks, while new energy sectors exhibit low-intensity but persistent spillover dynamics.
- China's 'Dual Carbon' policy is a key transmission channel, significantly amplifying risk linkages between high-carbon energy sectors and the carbon market and highlighting the role of regulatory shocks in cross-market risk contagion.

The rest of this paper is organized as follows. In Section 3, we introduce and discuss the statistical characteristics and significant effects observed in the yield data from both the energy market and the carbon trading market. In Section 4, we establish the EGARCH-CQR based model, and explain the rationale for model selection. In Section 5, we demonstrate the risk spillover effect from energy markets to carbon trading markets through data, and analyze the changes in spillover intensity. Our conclusions are presented in Section 6.

3. Statistical characteristics and ARCH effect

This study constructs a comprehensive analytical framework that spans the core chain of energy transition and global connections. This study selects new energy indices (SSE NEV, NEV Battery, Wind) and traditional energy indices (Coke, Oil, USA Oil) for analysis. We select the Guangdong carbon trading market as a study case. It leads China's regional carbon markets in trading volume and liquidity, covers major energy-intensive industries consistent with the national market, has a complete policy evolution path, and provides high-quality, continuous public data. These merits make it an ideal sample for analyzing risk spillovers between energy and carbon markets. We aim to disentangle the three-dimensional risk contagion chain that connects energy structure transition, fossil fuel pricing, and carbon asset

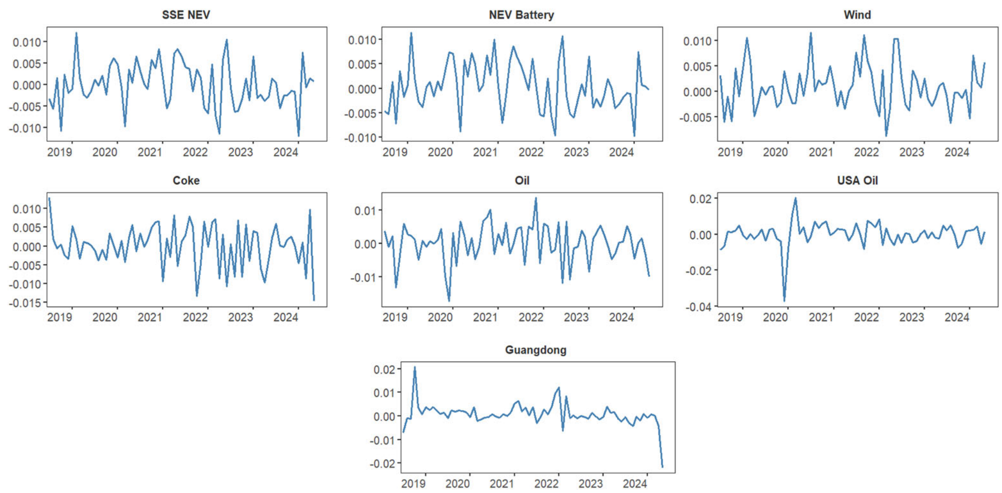


Figure 1. Regional energy trends (aggregated weekly).

volatility in a sequential manner. Specifically, new energy indices reflect the driving effect of clean substitution on decarbonization, while coal and oil indices capture the fundamental impact of traditional energy price fluctuations on carbon cost pass through and the influence of exogenous energy shocks.

We investigate the risk spillovers between the carbon trading market and energy markets, characterized by distinct time-series properties. This study utilizes daily industry index data from July 2018 to May 2024, employing logarithmic returns as the primary empirical metric. To capture these characteristics, we define $r_{\mathrm{gd},t}$ as the logarithmic return of the Guangdong carbon trading market at time t, and $r_{e_i,t}$ as the logarithmic return of the ith energy sub-market (where $i = 1, 2, 3, \ldots, n$) at time t. The logarithmic return is defined as $r_t = 100 \times \ln P_t - \ln P_{t-1}$.

Figure 1 depicts the returns of energy market indices and carbon trading market prices during the analysis period. With the occurrence of the COVID-19 pandemic, the global energy crisis, and the deepening of China's 'dual carbon' policies, distinct markets exhibited similar patterns of volatility clustering. However, over the period, their responses to extreme shocks diverged. These differing characteristics present an opportunity to explore the risk spillover effects from various energy markets to the carbon trading market.

The relationships between individual energy assets and the carbon trading market (see Figure 2) are characterized by significant dynamic volatility and strong heterogeneity. Short-term correlations display a time-varying strength pattern, with coefficients between all energy assets and the Guangdong carbon trading market fluctuating markedly within $[-0.4, 0.4]$. Moreover, inter-market differences are pronounced: new energy segments show wider correlation fluctuations, whereas traditional energy sources exhibit relatively stable directional influences. This observation underscores divergent cross-market linkage mechanisms across energy commodities and carbon trading. Subsequent analysis should therefore focus on examining risk spillover effects from distinct energy segments to the carbon market, enabling quantitative assessment of cross-category risk transmission intensity and identification of its time-varying drivers.

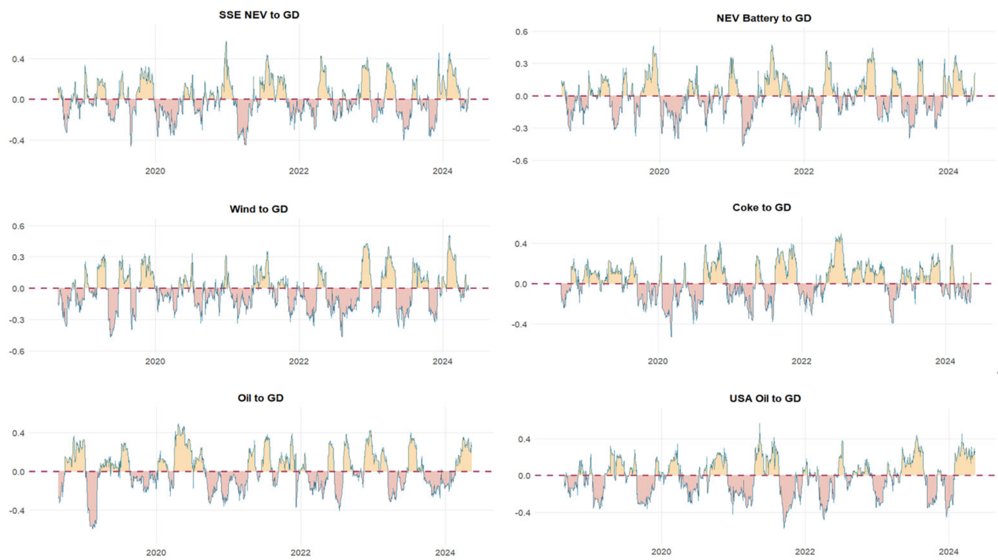


Figure 2. Rolling correlation (window = 30 obs).

Table 1. Time series feature testing methods.

Test	Hypothesis	Test statistic
J-B Test	$H_0 : S = 0$ and $K = 3$ $H_1 : S \neq 0$ or $K = 3$	$J_B = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$
ADF Test	$H_0 : \rho = 1$ $H_1 : \rho < 1$	$t = \frac{\hat{\phi}}{SE(\hat{\phi})}$
ARCH Test	$H_0 : \alpha_1 = \alpha_2 = \cdots = \alpha_q = 0$ $H_1 : \exists \alpha_i \neq 0\ (i = 1, 2, \ldots, q)$	$\mathrm{LM} = T \cdot R^2$

Before beginning a detailed analysis of these market return data, it is essential to examine their statistical characteristics (Table 1), determining whether they adhere to the standard normal distribution hypothesis, whether unit roots exist (via unit root tests), and whether volatility clustering is evident. The Jarque-Bera (J-B) test assesses whether datasets conform to a normal distribution. The Augmented Dickey-Fuller (ADF) test examines unit root presence in time series data to determine stationarity. The Autoregressive Conditional Heteroskedasticity (ARCH) test evaluates heteroskedasticity in time series. These test outcomes will provide a critical foundation for subsequent model specification and empirical analysis.

Table 2 summarizes descriptive statistics of daily returns, revealing distinct differences across market sectors: the new energy battery index, wind energy index, and Guangdong carbon market exhibit relatively higher returns, whereas traditional energy sectors such as the coke index and the oil index show lower returns. In terms of distributional shape, all markets display left skewness, with the coke index demonstrating the most pronounced skewness. The J-B test rejects the normal distribution hypothesis at the 1% significance level, particularly given kurtosis values of 10.51 for the USA oil index and 5.46 for the Guangdong carbon market, confirming fat-tailed risks in returns. The ADF test verifies stationarity across all series, and significant ARCH effects underscore the widespread volatility clustering phenomenon.

Table 2. Descriptive statistics of daily log-returns.

	SSE NEV	NEV Battery	Wind	Coke	Oil	USA Oil	Guangdong
Mean	0.00022	0.00036	0.00082	0.00016	0.00007	0.00054	0.00104
SD	0.02100	0.02119	0.01925	0.02291	0.02713	0.03020	0.02387
Skew	0.03979	0.14300	0.16152	−0.48730	−0.26077	0.03942	0.25956
Kurt	1.29635	1.28027	2.43337	1.99294	3.19596	10.5111	5.45993
J-B	100.175	102.173	356.729	291.339	620.277	6524.11	1777.47
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	20.3528	31.1208	11.7221	24.5374	37.1559	107.725	263.528
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF	−36.5361	−36.3402	−37.7147	−38.4307	−38.8959	−35.9104	−42.5453
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)

[a]This table describes the basic characteristics of daily return time series data.

Table 3. Comparison of AIC and BIC values between GARCH and EGARCH models.

	AIC		BIC	
	GARCH	EGARCH	GARCH	EGARCH
SSE NEV	−4.9617	−4.9700	−4.9393	−4.9402
NEV Battery	−4.9593	−4.9786	−4.9370	−4.9489
Wind	−5.1585	−5.1958	−5.1362	−5.1660
Coke	−4.8294	−4.8882	−4.8071	−4.8585
Oil	−4.4943	−4.5874	−4.4720	−4.5576
USA Oil	−4.5731	−4.6729	−4.5507	−4.6431
Guangdong	−5.1056	−5.2652	−5.0833	−5.2354

These features (i.e., asymmetric distributions, peakedness with fat tails, and volatility clustering) support the use of skewed t-distribution, GARCH family models, and Copula methods to capture the nonlinear risk transmission across markets.

4. Model fitting and testing

Among various risk measure approaches, the GARCH model has garnered attention for its ability to capture time-varying tail dependence in volatility. However, this model has proven less effective in predicting market tail risk. To better characterize risks, this paper employs the EGARCH model (Exponential Generalized Autoregressive Conditional Heteroskedasticity), whose core advantage lies in its more precise characterization of risk transmission when markets are subjected to adverse shocks.

Based on the comparison of AIC and BIC values between GARCH and EGARCH models for seven markets (see Table 3), the EGARCH model consistently yields smaller AIC and BIC values across all markets. This indicates that the EGARCH model outperforms the standard GARCH model in fitting the volatility of these energy and commodity markets, as it effectively captures the asymmetric leverage effect of volatility, a key characteristic of such markets. Therefore, the EGARCH model is deemed the most appropriate choice for volatility modelling of the markets.

To examine the risk spillovers from different sectors in the energy market to the carbon trading market, we define the selected market vector as $\mathbf{M} \triangleq [M_1, M_2, M_3, \dots, M_n]^\top$, where M_i is the ith selected energy-related industry market. Let $\mathbf{X} \triangleq [X_1, X_2, X_3, \dots, X_n]^\top$ represent a set of representative assets (or industry indices) from market $\mathbf{M}$. Then the return vector of $\mathbf{X}$ at time t, denoted by $\boldsymbol{R}_t$, can be written as

$$\boldsymbol{R}_t = \left[r_{e_1,t}, r_{e_2,t}, r_{e_3,t}, \dots, r_{e_m,t}\right]^\top,$$

where $r_{e_t,t}$ is the return of the X_i at time t. We need to perform univariate modelling for each market. Taking the return series $r_{e_i,t}$ of the ith market as an example, we assume the return consists of a predictable linear component and a random disturbance, leading to the following mean equation:

$$\begin{cases} r_{e_i,t} = \mu_{e_i} + \phi_{e_i,1} r_{e_i,t-1} + \varphi_{e_i,1} a_{e_i,t-1} + a_{e_i,t}, \\ a_{e_i,t} = \sigma_{e_i,t} \varepsilon_{e_i,t}, \end{cases} \tag{1}$$

where μ_{e_i} is the long term average return level, $a_{e_i,t}$ is the unpredictable component, $\sigma^2_{e_i,t}$ denotes the time varying conditional volatility, and $\varepsilon_{e_i,t}$ is an independently and identically distributed random innovation. $\phi_{e_i,1}$ and $\varphi_{e_i,1}$ are the persistence effect of past returns and the short term impact of prior shocks, respectively.

As stated earlier, the returns of energy-related assets have the typical characteristics including a left-skewed distribution, heavy tails, and volatility clustering. EGARCH model may capture these characteristics, and hence we employ the EGARCH model to describe the dynamic evolution of $\sigma^2_{e_i,t}$ in the following:

$$\ln\left(\sigma^2_{e_i,t}\right) = \omega_{e_i} + \alpha_{e_i}\varepsilon_{e_i,t-1} + \gamma_{e_i}\left(\left|\varepsilon_{e_i,t-1}\right| - E\left|\varepsilon_{e_i,t-1}\right|\right) + \beta_{e_i}\ln\left(\sigma^2_{e_i,t-1}\right), \tag{2}$$

where α_{e_i} is the long-term average level of volatility, γ_{e_i} is the asymmetric effect, and β_{e_i} is volatility persistence, indicating how strongly past volatility affects current volatility.

Table 4 reveals significant differences in return dynamics and volatility structures across markets through the ARMA-EGARCH(1,1) model parameter estimates, with the Guangdong carbon market being particularly evident. In the mean equation of the ARMA-EGARCH(1,1) model, its autoregressive coefficient ϕ_1 is 0.02081, indicating weak autocorrelation in the return series, a stark contrast to traditional energy markets like Coke and Oil, whose highly significant ϕ_1 values reach −0.80580 and −0.96247, respectively, reflecting pronounced lag-dependent characteristics. In the variance equation, Guangdong's volatility persistence coefficient β_1 (0.90817, the lowest among all markets) suggests relatively rapid decay of external shocks' impact on volatility. Its leverage effect coefficient γ_1 (0.68258) significantly exceeds other markets, highlighting an exceptionally strong amplification of volatility by negative news and reflecting high sensitivity to policy and sentiment shocks. Distributionally, Guangdong's skewness parameter ξ (1.06797) indicates positive skewness, while its degrees of freedom parameter ν (3.01842, the smallest across markets) confirms heavy-tailed returns. Overall, the market characteristics revealed by the parameter differences are summarized in Table 5. These results collectively validate the ARMA-EGARCH model's capability to meticulously capture structural differences in volatility mechanisms across diverse markets.

The test results for the ARMA-EGARCH(1,1) model across the seven markets in Table 6 comprehensively validate the effectiveness and robustness of the model specification. Taking the new energy vehicle (SSE NEV) market as an example, its log-likelihood value (LLF) is 3618.16, indicating a high overall goodness-of-fit; the Ljung-Box test shows p-values of 1.000 and 0.198 for the standardized residuals and their squared sequences, respectively, well above the 0.05 significance level, confirming that the model adequately captures autocorrelation and volatility clustering in the return series; the ARCH effect test p-value is 0.669, indicating no residual conditional heteroskedasticity; and the Pearson goodness-of-fit test p-value is 0.889, supporting the assumption of skewed t-distributed residuals. For the other markets, all indicators show similar results: Ljung-Box test p-values exceed 0.05, ARCH effect test p-values

Table 4. ARMA-EGARCH(1,1) model parameters.

Item	SSE NEV	NEV battery	Wind	Coke	Oil	USA oil	Guangdong
ϕ_1	−0.52126	−0.26055	−0.44259	−0.80580	−0.96247	−0.35320	0.02081
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.081)
φ_1	0.57522	0.30272	0.43116	0.81829	0.94522	0.36503	−0.29507
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ω	−0.16519	−0.08812	−0.18205	−0.18030	−0.33577	−0.25308	−0.70398
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_1	−0.01707	−0.05362	−0.01424	−0.00729	−0.04596	−0.09481	0.02959
	(0.280)	(0.430)	(0.466)	(0.718)	(0.048)	(0.000)	(0.467)
β_1	0.97864	0.98858	0.97728	0.97680	0.95393	0.96615	0.90817
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_1	0.15960	0.11616	0.19098	0.13962	0.21637	0.20190	0.68258
	(0.000)	(0.003)	(0.000)	(0.022)	(0.000)	(0.000)	(0.000)
ξ	1.05111	1.11527	1.03209	1.05505	0.89847	0.84191	1.06797
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ν	8.95059	7.24266	6.21245	6.94481	4.56797	5.23262	3.01842
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

[a]This table describes the model parameters of the ARMA-EGARCH(1,1) model.

Table 5. Comparative characteristics of different markets based on ARMA-EGARCH model estimates.

Market type	RA	VP	LEI	TRL
Traditional Energy (e.g., Coke, Oil, USA Oil)	+++	++	+	++
New Energy (e.g., SSE NEV, NEV Battery, Wind)	++	++	++	+
Guangdong Carbon Market	+	+	+++	+++

[a]RA, VP, LEI, and TRL denote Return Autocorrelation, Volatility Persistence, Leverage effect intensity, and Tail Risk Level, respectively. The strength of corresponding market characteristics across different markets is indicated by '+' for weak, '++' for moderate, and '+++' for strong characteristics.

Table 6. ARMA-EGARCH(1,1) model diagnostic tests.

Item	SSE NEV	NEV battery	Wind	Coke	Oil	USA oil	Guangdong
LLF	3618.16	3524.63	3701.03	3530.83	3250.35	3315.07	3741.89
L_j	0.5319	0.1802	1.7771	0.7533	1.2836	1.5110	1.6764
	(1.000)	(1.000)	(0.986)	(1.000)	(0.999)	(0.920)	(0.992)
$L_j{}^2$	4.4904	2.5865	3.1530	0.2374	2.3380	3.1100	3.0132
	(0.198)	(0.487)	(0.379)	(0.989)	(0.541)	(0.389)	(0.404)
Arch	0.1822	3.7626	3.5840	1.3180	2.0900	0.8782	2.7890
	(0.669)	(0.196)	(0.215)	(0.857)	(0.451)	(0.769)	(0.321)
Pearson	11.91	40.24	21.82	30.49	25.51	36.67	39.61
	(0.889)	(0.415)	(0.988)	(0.833)	(0.952)	(0.576)	(0.442)

[a]L_j and $L_j{}^2$ are Ljung-Box statistics, used to calculate the serial correlation of standard residuals and squared standard residuals at various lag orders. The ARCH test is used to examine whether the residual data exhibits ARCH effects. The Pearson test is used to check if the model residuals follow the selected distribution.

are above 0.1, and Pearson test p-values are insignificant. Overall, this demonstrates that the ARMA-EGARCH(1,1) model is structurally sound and consistently reliable for capturing the dynamic structure of return series across diverse markets, providing a robust foundation for further analysis.

Based on the model fitting described above, we obtain the volatility distribution for each market. The next step involves applying the probability integral transform to convert the marginal distributions into uniformly distributed variables, so as to link the different energy markets $v_{e_i} = F_{e_i}(r_{e_it})$ with the carbon market $u_{\mathrm{gd}} = F_{\mathrm{gd}}(r_{\mathrm{gd},t})$. Their joint distribution is linked by a Copula function:

$$H(r_{\mathrm{gd}}, r_{e_i}) = C\left(u_{\mathrm{gd}}, v_{e_i}; \delta\right). \tag{3}$$

To determine the most suitable form of the Copula function, this study compares the goodness-of-fit of several commonly used Copula families, including Gumbel, Clayton, and Student-t Copulas, evaluated based on the AIC and BIC. Due to numerical instability in the parameter estimation of the Frank Copula (manifested as a singular Hessian matrix), its AIC and BIC values could not be reliably computed and were therefore excluded from the final selection criteria.

As shown in Table 7, there are some variations in the AIC and BIC values across different pairings of energy markets and the carbon market, but the Gumbel Copula consistently exhibits stable and satisfactory fitting performance in all markets. So we select the Gumbel Copula family to model the joint distribution between the carbon market and each energy market, with the specific forms given in Equation (4).

$$\begin{cases} C_{\mathrm{Gumbel}}(u_{\mathrm{gd}}, v_{e_i}; \delta) = \exp\left(-\left[(-\ln(u_{\mathrm{gd}}))^{\delta} + (-\ln(v_{e_i}))^{\delta}\right]^{1/\delta}\right), \\ C_{\mathrm{Rot-Gumbel}}(u_{\mathrm{gd}}, v_{e_i}; \delta) = u_{\mathrm{gd}} + v_{e_i} - 1 + C_{\mathrm{Gumbel}}(1 - u_{\mathrm{gd}}, 1 - v_{e_i}; \delta). \end{cases} \tag{4}$$

Using a copula function to link the two assets, we aim to quantify the additional risk borne by the carbon trading market when a specific energy market is hit by an event shock. Given that the return of the X_i, $r_{e_i,t}$, reaches a specified level x, the probability that the return of the carbon trading market $r_{gd,t}$ attains level y can be written as

$$\tau = \Pr(r_{\mathrm{gd},t} \le y \mid r_{e_i,t} = x) = \frac{\partial C}{\partial u}\left(F_{r_{\mathrm{gd},t}}(x), F_{r_{e_i,t}}(y); \delta\right). \tag{5}$$

We adopt the Value-at-Risk (VaR) to characterize the extreme risk level of the $M_i, i = 1, 2, \ldots, n$. Specifically, the VaR of X_i at confidence level β, denoted by $\mathrm{VaR}^{e_i}_{\beta,t}$, can be computed from

$$\Pr\left(r_{e_i,t} \le \mathrm{VaR}^{e_i}_{\beta,t} \mid \mathcal{F}_{t-1}\right) = \beta. \tag{6}$$

From Equation (6), we get

$$\mathrm{VaR}^{e_i}_{\beta,t} = \mu_{e_i,t} + F^{-1}_{(v_{e_i},\lambda)}(\beta) \cdot \sigma_{e_i,t}.$$

By setting a small probability τ (e.g., 5%, representing an extreme scenario) and conditioning on $r_{e_i,t} = \mathrm{VaR}^{e_i}_{\beta,t}$, we can inversely solve for the carbon market's conditional risk y_τ, namely,

$$y_\tau = F^{-1}_{r_{e_i,t}}\left(C_1^{-1}\left(\tau \mid F_{r_{\mathrm{gd},t}}, \mathrm{VaR}^{ei}_{\beta,t}; \delta\right)\right) \triangleq \mathrm{CoVaR}^{\mathrm{gd}|ei}_{\tau|\beta,t}. \tag{7}$$

This value corresponds to the measure of interest $\mathrm{CoVaR}^{\mathrm{gd}|e_i}_{\tau|\beta,t}$ which represents the worst possible loss that the carbon market may face at probability τ when the M_i, $i = 1, 2, \ldots, n$. is in its own worst β-probability scenario. To capture the additional risk contributed by the energy market, we define the risk level borne by the carbon market when the energy market

Table 7. Comparison of AIC and BIC values among Copula models.

	AIC			BIC		
	Gumbel	Clayton	Student-*t*	Gumbel	Clayton	Student-*t*
SSE NEV	1.7299	1.9873	3.8219	6.9827	7.2400	14.3270
Wind	1.9367	1.9716	3.9443	7.1895	7.2244	14.4490
NEV Battery	2.0000	2.0689	2.3622	7.2527	7.3217	12.8670
Coke	1.8884	1.9655	2.1952	7.1411	7.4882	12.0000
Oil	2.0000	2.0553	3.9964	7.2527	7.8057	15.5019
USA Oil	1.7643	2.0753	2.8920	7.0170	7.3281	13.3970

is in a normal state ($\beta = 50\%$) as the baseline. Thus, the marginal risk spillover from market M_i to the carbon market is measured by

$$\Delta \mathrm{CoVaR}^{\mathrm{gd}|ei}_{\tau|\beta,t} = \mathrm{CoVaR}^{\mathrm{gd}|ei}_{\tau|\beta,t} - \mathrm{CoVaR}^{\mathrm{gd}|ei}_{\tau|0.5,t}. \tag{8}$$

A larger value of ΔCoVaR indicates a significant risk spillover effect from changes in the energy market to the industry indices of the carbon trading market. Subsequently, we can visualize the temporal evolution of the magnitude of risk spillovers, thereby providing a more intuitive representation of the extent of inter-market risk transmission.

5. Empirical analysis

This section quantifies the risk contributions of different markets to the carbon market and subsequently carries out validity tests on the estimation results to ensure the rationality of the model specification and the robustness of the conclusions. Through this dual examination of empirical findings and their reliability, it provides reliable empirical evidence for understanding the risk transmission mechanisms between energy and carbon markets.

5.1. Risk spillover effect

In this subsection, we examine risk contagion effects and transmission pathways from energy markets to carbon trading under varying market risk scenarios, analyzing spillover effects between six energy markets and one carbon trading market from July 2018 to May 2024.

Figure 3 illustrates risk spillover effects from energy markets to the carbon trading market. The red line indicates baseline CoVaR, representing regular risk transmission from energy markets to carbon trading under stable conditions. The black line denotes risk-state CoVaR, reflecting the intensity of spillovers during extreme fluctuations in energy markets. The green line (CoVaR) quantifies additional risk shocks to the carbon trading market by measuring the difference between risk-state and baseline CoVaR. A larger CoVaR signifies stronger contagion effects from energy market disruptions.

- **Risk spillover effects during periods of risk shocks.** The COVID-19 pandemic's impact on energy-to-carbon market risk spillovers exhibited significant sectoral heterogeneity in early 2020 (see the red-dashed interval in Figure 3). Oil and USA Oil markets manifested an acute short-term surge in spillover intensity due to pandemic-driven collapses in global demand and prices, transmitting abrupt shocks as a core traditional energy source. Conversely, spillovers from SSE NEV and NEV Battery markets demonstrated synchronized yet contained fluctuations; despite supply chain disruptions, robust long-term fundamentals maintained relatively stable incremental risk impacts on carbon markets. Similarly,

Table 8. Descriptive statistics of risk spillover effects.

	SSE NEV	NEV Battery	Wind	Coke	Oil	USA Oil
Max	0.0280	0.0256	0.0283	0.0363	0.0464	0.1319
Min	0.0114	0.0114	0.0102	0.0120	0.0146	0.0146

Coke and Wind markets exhibited marginal spillover deviations without extreme volatility; coke supply adapted flexibly to reduced industrial demand, while wind power proved resilient to transient disruptions. These differential responses underscore how exogenous shocks heterogeneously reconfigure energy-carbon market linkages, contingent on sector-specific demand elasticity and structural characteristics.

- **Risk spillover effects during policy adjustment periods.** In mid-2021, robust demand in the new energy vehicle, battery, and wind power markets driven by policy support and consumer adoption was partially offset by persistent supply chain disruptions such as semiconductor shortages, resulting in moderately elevated risk spillovers to the carbon market. Concurrently, tight domestic coal supplies combined with intensified energy consumption dual-control policies triggered sharp coke price fluctuations, causing significant spillover surges to the carbon market. Toward year-end, oil market spillovers rose sharply again under converging pressures: global economic recovery, OPEC+ production cuts, coordinated releases of strategic petroleum reserves by multiple nations, and peak winter energy demand. These patterns demonstrate that policy-driven events exert more direct impacts on risk linkages between high-carbon energy sectors and carbon markets, whereas stable market segments exhibit greater resilience to short-term disruptions.
- **Risk spillover gap among different markets.** As shown in Table 8, there are notable differences in the intensity of risk spillovers from various energy markets to the carbon trading market, reflecting distinct transmission characteristics and risk attributes. Traditional high-carbon energy markets exhibit high-intensity and high-volatility spillover features: the upper bound of risk spillover for USA Oil reaches 0.1319, the highest among all markets, and its fluctuation range is also the largest, indicating that its impact on the carbon market is particularly severe and unstable under sudden events. The maximum spillover values for Coke and Oil are 0.0363 and 0.0464, respectively, also reflecting strong risk transmission capacity. In contrast, the spillover values for new energy markets (SSE NEV, NEV Battery, Wind) are generally lower and more concentrated in distribution, especially the minimum value for Wind, which is only 0.0102, indicating steadier and more persistent risk transmission. Traditional energy sources bring ‘high intensity, high volatility’ impacts to the carbon market, while new energy sources present ‘low intensity, stable transmission’ characteristics.

As shown in Figure 4, the charts track the direct risk spillover intensity from energy markets to the carbon market across pre-pandemic, pandemic, and post-pandemic periods. The pandemic phase clearly strengthened risk transmission overall: Oil and USA Oil show the deepest red, indicating the strongest spillover, while other markets (Coke, SSE NEV, etc.) also reddened compared to pre- and post-pandemic levels. In the pre-pandemic phase, most markets appear in light shades, signaling weak spillovers. After the pandemic, new energy markets such as Wind turn light blue, reflecting diminished transmission, whereas traditional energy markets retain darker hues, suggesting more persistent spillover pathways. The trend chart confirms a common rise-then-fall pattern across markets, though the decline

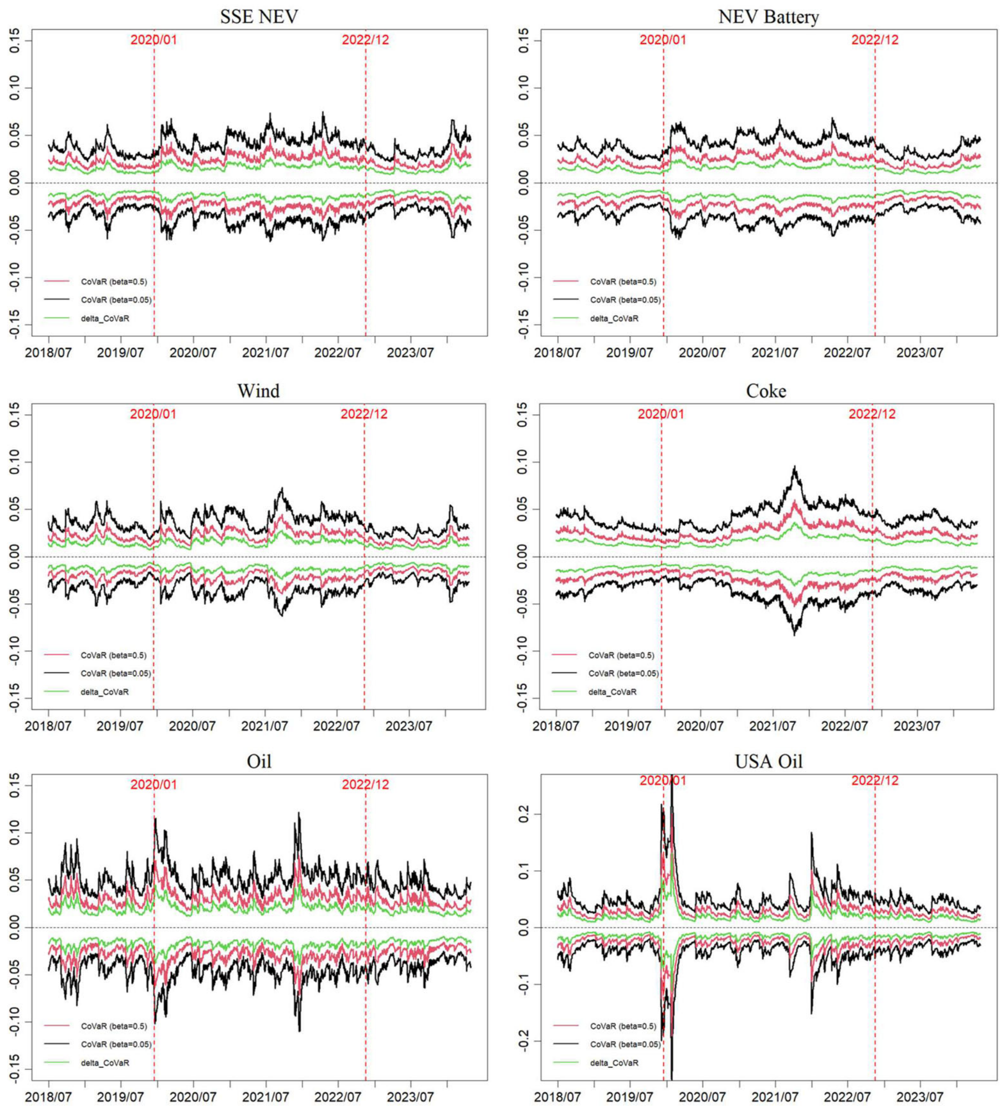
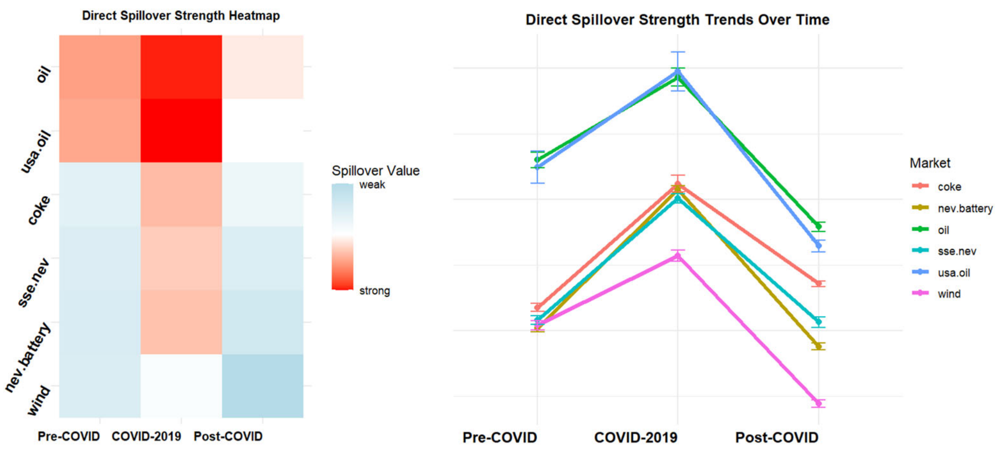


Figure 3. Spillover effects of risk from various markets to the Guangdong carbon trading market.

varies in speed and extent–pointing to differential recovery paces after the shock. Together, these patterns indicate that the pandemic shock broadly intensified transmission pathways, but traditional energy sources exhibited stronger and more lasting amplification, reshaping the post-shock spillover landscape in their favour.

Traditional energy markets (e.g., Oil, Coke), with low supply-demand elasticity, high policy sensitivity, strong liquidity, and a direct ‘production-emission-trading’ industrial chain, experience sharp price volatility under external shocks that directly spill over to carbon markets, forming a ‘high-volatility, high-impact’ risk pattern. In contrast, new energy markets (e.g., Wind) feature weaker demand rigidity, long-term policy incentives, lower liquidity, and an indirect ‘substitution-emission reduction-trading’ transmission chain, resulting in longer pathways and more friction that produce a ‘low-volatility, slow-release’ risk pattern. These



(a) direct spillover strength heatmap (b) direct spillover strength trend over time

Figure 4. Direct spillover strength. (a) direct spillover strength heatmap and (b) direct spillover strength trend over time.

Table 9. Structural breakpoints in risk spillovers from energy markets to the carbon market.

	Breakpoint				
	1	2	3	4	5
SSE NEV	2020/2/3	2020/4/17	2020/12/22	2022/11/30	2024/1/19
Wind	2020/7/16	2021/4/15	2021/9/1	2021/11/25	2022/11/18
NEV Battery	2019/7/11	2020/2/3	2020/4/20	2022/12/6	2024/1/22
Coke	2019/1/23	2020/12/17	2021/9/15	2021/12/10	2022/9/21
Oil	2019/12/27	2020/3/12	2021/12/2	2022/1/12	2023/2/22
USA Oil	2019/2/18	2020/3/3	2022/1/12	2022/2/17	2022/11/15

distinct risk transmission patterns between the two markets account for the heterogeneous spillover effects observed in Figure 3 and Table 8.

5.2. *Analysis of policy shocks*

Building on the analysis of risk spillover effects from each energy market to the Guangdong carbon market, this section further investigates whether policy timing constitutes a structural turning point in the aforementioned spillover relationships. To this end, the multiple structural break test proposed by Bai and Perron is employed to separately identify breakpoints in the ΔCoVaR series of the six representative markets with respect to the Guangdong carbon market. Table 9 summarizes the structural breakpoints detected for each series.

The structural breakpoints identified in the risk spillovers from each energy market to the Guangdong carbon market align closely with key policy windows, offering strong evidence that 'dual-carbon' policies act as structural turning points. The widespread breaks in early 2020 coincide with the COVID-19 outbreak, the global energy demand collapse, and subsequent emergency policy responses (e.g., U.S. rate cuts, China's fiscal stimulus), indicating that this exogenous shock fundamentally reshaped the energy-carbon risk transmission pathway.

Examining representative breaks: the SSE NEV break on December 22, 2020, corresponds to China's announcement of the '3060' dual-carbon goals; the NEV Battery break on July 11,

Table 10. CoVaR metrics and test results.

Metrics	SSE NEV	NEV battery	Wind	Coke	Oil	USA oil
5% CoVaR Coverage Rate	0.0531	0.0567	0.0694	0.0510	0.0347	0.0439
Kupiec Test p-value	0.5946	0.2606	0.0015	0.8647	0.0054	0.2840
95% CoVaR Coverage Rate	0.0581	0.0574	0.0644	0.0439	0.0319	0.0446
Kupiec Test p-value	0.1742	0.2142	0.0169	0.2840	0.0000	0.3449
CoVaR Quantile Loss	0.0359	0.0357	0.0326	0.0372	0.0446	0.0440

2019, aligns with the EV subsidy phase-down; the Coke break on December 10, 2021, matches new coal contract rules and the policy clarification of coal's role in energy security; and the USA Oil break on February 17, 2022, reflects the Ukraine crisis escalation. These findings demonstrate that both domestic climate policies and international geopolitical events induce structural changes in risk spillovers via energy-carbon linkages, validating policy timing as a critical structural turning point and providing key temporal anchors for understanding risk dynamics under the 'dual-carbon' transition.

5.3. Validity tests

To validate the reliability of the model estimation results presented earlier and ensure the accuracy of risk spillover effect measurement, this study conducts multi-dimensional validity tests based on the CoVaR framework.

Table 10 presents the CoVaR coverage rates, Kupiec test results, and quantile losses of six energy markets under different risk levels, systematically evaluating the degree of risk spillover from each market to the carbon trading market as well as the validity of the model. In terms of coverage rate, test data of wind energy shows the highest coverage at the 5% confidence level (0.0694) and remains the highest at the 95% level, indicating that it contributes the most significant actual risk to the carbon market. NEV Battery ranks second, while Oil consistently exhibits the lowest coverage, reflecting relatively weaker effective risk spillover. The p-values of the Kupiec test are generally above 0.05, suggesting that the CoVaR predictions for most markets are broadly consistent with actual risk exposure, supporting the feasibility of the model. Further analysis based on quantile loss shows that the oil-related markets (Oil and USA Oil) have the highest loss values (0.0446 and 0.0440, respectively), implying that they cause more extreme losses to the carbon trading market during tail risk events. In contrast, Wind has the lowest quantile loss (0.0326), indicating a relatively smaller contribution to losses under extreme conditions. These above results show that there are structural differences in risk spillover intensity and tail risk impact across different energy markets.

The accuracy of the estimated CoVaR is evaluated using the unconditional coverage (UC) test developed by Banulescu-Radu et al. Essentially, a type $\mathrm{CoVaR}_t^g(\beta,\alpha,\theta_0)$ violation is defined by condition $h_t(\alpha,\beta,\theta_0) = I((R_t^g \leq \mathrm{CoVaR}_t^g(\beta,\alpha,\theta_0)) \cap (R_t^{e_i} \leq \mathrm{VaR}_t^{e_i}(\alpha,\theta_0)))$, and a type $\mathrm{VaR}_t^{e_i}(\alpha,\theta_0)$ violation by condition $h_t(\bar{\alpha},\beta,\theta_0) = I((R_t^g \leq \mathrm{CoVaR}_t^g(\beta,\bar{\alpha},\theta_0)) \cap (R_t^{e_i} \leq \mathrm{VaR}_t^{e_i}(\bar{\alpha},\theta_0)))$, where $I_{\bullet}$ is an indicator function. Let α and $\bar{\alpha}$ denote the quantiles of the return distributions for the adverse energy market states ($\alpha = 0.05$)and normal energy market states($\bar{\alpha} = 0.5$), respectively. A violation is registered as one if the loss in the carbon trading market exceeds its CoVaR and, simultaneously, the loss in the energy market exceeds its VaR; otherwise, it is registered as zero.

Table 11. UC_ΔCoVaR values and *p*-values across different markets.

	SSE NEV	NEV Battery	Wind	Coke	Oil	USA Oil
UC_ΔCoVaR	1.5484 (0.4611)	2.6755 (0.2624)	15.7255 (0.0004)	0.4688 (0.7922)	3.1007 (0.2122)	2.0426 (0.2601)

Table 11 presents the model validity test results for risk spillovers from six energy markets to the carbon trading market. The test evaluates whether the model accurately captures systematic risk transmission under different market states–such as stress periods ($\alpha = 0.05$) and normal periods ($\bar{\alpha} = 0.05$) by comparing CoVaR predictions with actual risk coverage. Based on the test statistics UC_ΔCoVaR and the corresponding p-values, most markets passed the test (p-values are significantly greater than 0.05), indicating that the model exhibits good risk coverage capability in these markets. Specifically, the coke market shows the highest p-value (0.7922), reflecting the most robust model performance. The SSE NEV, NEV Battery, Oil, and USA Oil markets also have p-values greater than 0.05, demonstrating that the model effectively reflects actual risk conditions in these markets. In contrast, the Wind has a p-value of only 0.0004 and fails to pass the test, suggesting that its risk transmission mechanism may differ structurally from other markets or that the model has inadequate coverage for this market.

5.4. Robustness tests under extreme scenarios

To assess the robustness of the model under different types of extreme shocks, this section selects representative exogenous events that occurred during the sample period. For each event, the full sample is divided into pre-event and post-event subsamples, and the intensity of risk spillovers from each energy market to the carbon market is re-estimated and compared. The two representative exogenous events selected for this analysis are as follows.

- **Geopolitical conflict**: The Russia-Ukraine conflict broke out in February 2022, causing severe fluctuations in global energy prices. Using February 24, 2022, as the cutoff, the sample is split into a pre-conflict period (February 2021–February 2022) and a post-conflict period (March 2022–February 2023).
- **Major policy adjustment**: The national carbon emissions trading market was officially launched in July 2021, marking the transition of the carbon market from a pilot scheme to a unified national system. Taking July 16, 2021, as the cutoff, the sample is divided into a pre-policy period (July 2020–July 2021) and a post-policy period (August 2021–July 2022).

Table 12 reports the changes in the average ΔCoVaR (risk spillover from the carbon market to each energy market during downturns) before and after each event, along with the results of the Mann-Whitney U test.

The results reveal distinct patterns across events and market segments. During the Russia-Ukraine conflict, risk spillovers from new energy markets generally intensified, potentially reflecting heightened expectations for clean energy substitution amid geopolitical tensions. Traditional energy markets exhibit heterogeneous responses: Coke experiences increased risk spillovers due to supply concerns, while USA Oil faces downward pressure driven by anticipated production increases; domestic oil shows no significant effect, underscoring the

Table 12. Changes in risk spillovers before and after exogenous events.

Event	Market	Pre-mean	Post-mean	Change (%)	p-value
Russia-Ukraine Conflict	SSE NEV	−0.0417	−0.0391	6.18	0.0001
	NEV Battery	−0.0416	−0.0392	5.76	0.0001
	Wind	−0.0367	−0.0338	7.83	0.0036
	Coke	−0.0516	−0.0442	14.30	0.0000
	Oil	−0.0494	−0.0470	4.94	0.6563
	USA Oil	−0.0422	−0.0504	−19.57	0.0000
National Carbon Market Launch	SSE NEV	−0.0383	−0.0442	−15.47	0.0000
	NEV Battery	−0.0403	−0.0426	−5.79	0.0000
	Wind	−0.0356	−0.0398	−11.79	0.0000
	Coke	−0.0358	−0.0532	−48.52	0.0000
	Oil	−0.0456	−0.0521	−14.12	0.0000
	USA Oil	−0.0379	−0.0511	−34.77	0.0000

divergent sensitivities of different energy commodities to the same external shock. Following the launch of the national carbon market, risk spillovers across all markets decline significantly, with traditional energy markets experiencing the most pronounced reductions. This suggests that policy clarification helps mitigate the risk co-movements between regional markets and energy prices.

Collectively, the model consistently captures both the direction and magnitude of changes in risk spillovers under two fundamentally different types of shocks. The results align closely with the economic logic underlying each event, further validating the robustness and explanatory power of the EGARCH-CQR-CoVaR framework. These findings also provide reliable empirical evidence for understanding risk transmission mechanisms between energy and carbon markets in complex environments.

6. Conclusions and future work

In this paper, we adopt the EGARCH-CQR-CoVaR model to quantitatively analyzes the risk spillover effects from energy markets to China's carbon market. Empirical findings reveal significant heterogeneity in risk spillovers from energy markets to the carbon market: traditional energy markets, represented by Oil, exhibit 'high-intensity, high-volatility' shock characteristics, transmitting abrupt risks during extreme events such as the COVID-19 pandemic; whereas new energy markets, represented by new energy vehicles and wind power, demonstrate a 'low-intensity, stable' spillover pattern, indicating stronger market resilience. The study also verifies that policy events are key transmission nodes and shows that the constructed model has good risk coverage capability for most markets. For future work, extending the analysis to other pilot markets would help validate the generalizability of our findings. Furthermore, incorporating high-dimensional risk spillover network analysis, integrating quantitative macro-policy indicators, and utilizing high-frequency data can more precisely identify risk transmission pathways and driving factors, thereby providing support for building a more resilient risk management framework for the energy-carbon system.

Author contributions

CRediT: **Yarong Zhang:** Investigation, Visualization, Writing – original draft; **Sheng Zhu:** Methodology, Supervision, Writing – review & editing

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