International Journal of World Economic Research
ISSN: 3080-9886 (Print), ISSN: 3080-9894 (Online) | Vol. 1, No. 1, 2026

Research on the Volatility Spillover Effects among Carbon Market, Energy Market, and Stock Market

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Abstract: With the advancement of China's "dual carbon" goals and the operation of the national carbon market, the linkages among the carbon market, energy market, and stock market have become increasingly close. Based on the TVP-VAR-DY model, this paper investigates the characteristics and asymmetry of volatility spillovers among these three markets from both static and dynamic perspectives. The findings reveal significant and time-varying volatility spillover effects among the three markets, with asymmetry observed in both static and dynamic contexts. Major external events significantly enhance cross-market volatility spillovers and amplify this asymmetry. This study provides theoretical and empirical support for understanding volatility spillovers among the carbon, energy, and stock markets, offering insights for investor asset allocation and financial regulation.

Keywords: Volatility spillover; Asymmetry; TVP-VAR-DY model.

1. Introduction

The ecological and environmental challenges triggered by global warming have become increasingly prominent, emerging as a global issue critical to human sustainable development. As the worlds largest energy consumer and carbon emitter, China actively shoulders global climate governance responsibilities. In 2020, it explicitly proposed the "dual carbon" goals of achieving peak carbon emissions before 2030 and carbon neutrality before 2060. The formal launch of the national carbon emissions trading market in July 2021 marked Chinas transition from regional pilot programs to a unified national development phase. This market has become the worlds largest carbon market in terms of greenhouse gas emissions coverage. As trading volumes expand and market mechanisms mature, its financial attributes continue to strengthen, with increasingly close links to energy markets and stock markets.

The carbon market maintains significant interconnections with the energy market. Fossil fuel combustion constitutes the primary source of greenhouse gas emissions, and fluctuations in energy prices directly influence corporate energy consumption structures and carbon emission demands, subsequently impacting the carbon market. Conversely, carbon price volatility can also exert reverse effects on the supply-demand dynamics of the energy market through cost constraint mechanisms. As a barometer of the macroeconomy, stock market volatility influences energy and carbon markets through channels such as investor expectations and capital flows. Conversely, shifts in carbon and energy markets also impact the valuation and returns of relevant stock market sectors. In recent years, major unforeseen events such as global geopolitical conflicts and public health crises have triggered sharp fluctuations in energy market prices, significantly impacting both carbon and stock markets. Cross-market volatility spillover effects have intensified, potentially amplifying systemic financial risks through contagion and posing challenges to the steady advancement of the "dual carbon" goals. Therefore, in-depth exploration of the volatility spillover effects between carbon markets, energy markets, and stock markets, along with their time-varying and asymmetric characteristics, holds significant theoretical value and practical relevance.

2. Literature Review

With the development of carbon markets and the increasing integration of financial markets, the interlinked volatility relationships among carbon, energy, and stock markets have become a hot topic in academic research. Scholars have engaged in extensive discussions on intermarket volatility spillover effects, asymmetric characteristics, and measurement methods, laying a crucial theoretical foundation for this study.

In core research on cross-market spillover effects, the interlinkages among different carbon markets have been extensively validated. Bidirectional asymmetric spillover effects exist between EU Allowances and Certified Emission Reductions, with EUA dominating risk spillover[26]. Similarly, bidirectional risk spillovers exist between Chinas carbon market and the EU carbon market, though the EU market exerts a stronger spillover effect on Chinas market[21]. Meanwhile, Chinas regional carb on markets exhibit differentiated risk transmission patterns: the Beijing, Tianjin, and Hubei pilot markets act as risk "exporters", while other pilots primarily function as risk recipients[27].The volatility correlation between carbon and energy markets exhibits distinct dynamic characteristics. Traditional energy market fluctuations provide strong predictive power for carbon markets, and persistent long-term volatility spillover effects exist between carbon markets and crude oil, coal, and natural gas markets[6][17]. Risk transmission between the European carbon market and energy markets exhibits distinct time-varying patterns[2]. Domestic research indicates that the volatility transmission mechanism between Chinas Shenzhen carbon market and energy markets remains underdeveloped, though linkage potential is gradually emerging[20].Crude oil price fluctuations exert the most pronounced impact on Chinas pilot carbon markets [25]. Overall, Chinas carbon and energy markets exhibit bidirectional volatility spillovers, with risk spillover effects from energy market turbulence being more pronounced on the carbon market[28].The correlation between the coking coal market and the carbon market exhibits persistence, with spillover intensity showing heterogeneity depending on the direction of transmission[18].

Volatility spillovers between carbon and stock markets also exhibit multifaceted characteristics. The EU carbon market maintains strong volatility risk and information transmission links with financial markets, with this relationship dynamically varying across development stages and external risk contexts[20]. Significant information interdependence exists between carbon price returns and power stock returns, with carbon markets predominantly absorbing information spillovers from power companies as information receivers[14]. Chinas carbon market generally functions as a net risk absorber for the stock market, with macroeconomic shifts further amplifying dynamic volatility in intermarket risk spillovers[24]. Compared to the European carbon market, Chinas carbon trading syst em still has considerable room for marketization improvement[7], and extreme risk events exert significant impacts on the relationship between carbon emissions trading markets and power sector stock markets, as well as risk spillovers[23]. The volatility linkage between energy markets and stock markets exhibits phased evolution characteristics. In the early stages, fluctuations in international crude oil prices did not form significant volatility transmission with the Chinese stock market[15], but after 2007, the volatility spillover effects between the two gradually strengthened[19]; International crude oil prices showed no significant volatility transmission to UK and US stock markets[8], while both the Beijing carbon market and clean energy market exhibited pronounced spillover effects on coal markets[16]. Volatility spillovers between Chinas domestic energy markets and stock markets exhibit significant time-varying characteristics, with extreme event shocks further amplifying spillover intensity[13]. Both intra-market and cross-market time-varying volatility spillovers exist within and across segments of international energy and stock markets, with cross-market spillovers constituting a key component of the overall systems total time-varying spillover[22].

Regarding market asymmetry and methodological research, the core manifestation of market asymmetry is that negative news triggers significantly greater volatility than positive news. Significant volatility asymmetry has been confirmed in the Chinese stock market[9][10].Barunik et al.(2016) pioneered the incorporation of realized semivariances into spillover index frameworks, distinguishing between positive and negative volatility and confirming the existence of volatility spillover asymmetry[3]. Subsequent refinements developed analytical frameworks incorporating bidirectional spillovers[4]. The evolution of econometric methods has provided more precise tools for volatility spillover research. Early studies predominantly employed ARCH and GARCH family models to characterize market volatility[12][5]. However, such models struggle to directly reveal intermarket volatility transmission mechanisms and cannot quantify the magnitude of volatility spillovers. Diebold and Yilmaz (2012) introduced the DY spillover index model, enabling quantitative measurement and dynamic analysis of volatility spillovers[11]. However, this model suffers from estimation efficiency issues influenced by window width. Antonakakis and Gabauer (2020)[1] proposed the TVP-VAR-DY model, which incorporates time-varying parameters to effectively overcome limitations of traditional models[1]. This approach yields high-frequency dynamic spillover results without requiring rolling windows, significantly enhancing estimation efficiency and accuracy.

Overall, existing research has yielded substantial results, yet notable shortcomings persist: most studies focus on bilateral market linkages, failing to comprehensively capture multi-market coordinated risk transmission pathways; attention to Chinas national unified carbon market remains insufficient, with research predominantly centered on regional pilots or mature markets in Europe and the US; characterization of volatility spillover asymmetry is inadequate, with analyses primarily centered on total volatility rather than detailed exploration of heterogeneous spillovers between positive and negative volatility Certain methodological approaches exhibit limitations, hindering precise capture of the time-varying characteristics of volatility spillovers. Based on these considerations, this paper integrates carbon, energy, and equity markets into a unified analytical framework, employing a TVP-VAR-DY model to investigate the time-varying and asymmetric features of their volatility spillovers.

3. Model Construction and Data Sources

(1) Volatility Model

This study employs Glosten et al. (1993)s methodology, utilizing the GJR-GARCH model to estimate market volatility.

$$r_{i,t} = \mu_i + \sqrt{x_{i,t}} z_{i,t}, \; z_{i,t} \sim t_v(0,1) \tag{1}$$

$$x_{i,t} = \omega_i + (\alpha_i + \gamma_i I_{[z_{i,t-1}<0]})(r_{i,t} - \mu_i)^2 + \beta_i x_{i,t-1} \tag{2}$$

Where $r_{i,t}$ denotes the market return i at time t , μ_i represents the mean return, $x_{i,t}$ signifies the conditional variance representing volatility, ω_i is the intercept, α_i is the ARCH coefficient, β_i is the GARCH coefficient, γ_i is the leverage coefficient capturing volatility asymmetry (corresponding to positive and negative shocks), and $I_{[z_{i,t-1}<0]}$ is the indicator function satisfying

$$I_{[z_{i,t-1}<0]} = \begin{cases} 0, & z_{i,t-1} \geq 0 \\ 1, & z_{i,t-1} < 0 \end{cases} \tag{3}$$

This study follows BenSaida (2019) in decomposing total volatility into good and bad volatility corresponding to positive and negative shocks, respectively, to measure volatility asymmetry. Good and bad volatility are defined as:

$$x_{i,t}^{+} = x_{i,t} I_{[z_{i,t-1} \geq 0]} \tag{4}$$

$$x_{i,t}^{-} = x_{i,t} I_{[z_{i,t-1} < 0]} \tag{5}$$

(2) Construction of the Volatility Spillover Index Model

Following the methodology of Antonakakis and Gabauer (2020), this paper constructs a TVP-VAR-DY model. This model avoids the need for rolling windows, effectively prevents loss of observations, and more accurately captures the dynamic characteristics of volatility spillovers.

First, define a TVP-VAR model with a lag of 1:

$$y_t = A_t y_{t-1} + \varepsilon_t \quad \varepsilon_t | \Omega_{t-1} \sim N(0, \Sigma_t) \tag{6}$$

$$vec(A_t) = vec(A_{t-1}) + \xi_t \quad \xi_t | \Omega_{t-1} \sim N(0, \Xi_t) \tag{7}$$

Ω_{t-1} denotes all known information at time $t-1$, y_t and ε_t represent market volatility and disturbance terms, respectively. A_t and Σ_t denote the time-varying autoregressive coefficient matrix and time-varying variance-covariance matrix, respectively. $vec(A_t)$ and ξ_t represent the vectorized form of A_t and the disturbance term, respectively. Ξ_t is the time-varying variance-covariance matrix.

The TVP-VAR model is transformed into TVP-VMA form using the Wold representation theorem:

$$y_t = \sum_{j=0}^{\infty} B_{jt} \varepsilon_{t-j} \tag{8}$$

where B_{jt} is the $m \times m$ -dimensional time-varying moving average coefficient matrix, and ε_{t-j} is the m -dimensional vector representing the disturbance term.

Next, extract the TVP-VMA model coefficients to further compute the generalized impulse response function (GIRF) and generalized forecast error variance decomposition (GFEVD). Here, GIRFs($\Psi_{ij,t}(H)$) represents variable js response after variable i experiences an external shock, i.e., the difference between the forecast result when variable i receives a shock at period H and when it does not. The calculation formula is:

$$\Psi^g_{ij,t}(H) = \sum\nolimits_{jj,t}^{-\frac{1}{2}} B_{H,t}\,\Sigma_t e_j \tag{9}$$

where H denotes the number of periods for the prediction error variance decomposition, and e_j is an n-dimensional column vector with the jth element equal to 1 and all other elements equal to 0.

GFEVD($\widetilde{\Phi^g_{ij,t}}(H)$)This represents the contribution share of variable js disturbance to the variance of the H -period forecast error for variable is total fluctuat ion. After normalization, the formula becomes:

$$\widetilde{\Phi^g_{ij,t}}(H) = \frac{\sum_{t=1}^{H-1} \Psi^2_{ij,t}}{\sum_{j=1}^{m}\sum_{t=1}^{H-1} \Psi^2_{ij,t}} \tag{10}$$

where$\sum_{j=1}^{m} \widetilde{\Phi^g_{ij,t}}(H) = 1$, and$\sum_{i,j=1}^{m} \widetilde{\Phi^g_{ij,t}}(H) = m$, meaning the sum of all variables can explain 100% of the variance in the forecast error of variable i.

The Total Contribution Index (TCI) formula based on GFEVD is:

$$C^g_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \widetilde{\Phi^g_{ij,t}}(H)}{m} \times 100 \tag{11}$$

The Total Outflow Index (TO) represents the spillover effects from market i to all other markets j following a shock. The Total Inflow Index (FROM) represents the inflow effects received by market i from all other markets j. The Net Outflow Index (NET) is calculated as the Total Outflow Index minus the Total Inflow Index, expressed as:

$$TO = C^g_{i\rightarrow\cdot,t}(H) = \frac{\sum_{j=1,i\neq j}^{m} \widetilde{\Phi^g_{ji,t}}(H)}{\sum_{j=1}^{m} \widetilde{\Phi^g_{ji,t}}(H)} \times 100 \tag{12}$$

$$FROM = C^g_{i\leftarrow\cdot,t}(H) = \frac{\sum_{i=1,i\neq j}^{m} \widetilde{\Phi^g_{ij,t}}(H)}{\sum_{i=1}^{m} \widetilde{\Phi^g_{ij,t}}(H)} \times 100 \tag{13}$$

$$NET = NC^g_{i,t}(H) = C^g_{i\rightarrow\cdot,t} - C^g_{i\leftarrow\cdot,t}(H) \tag{14}$$

(3) Variable Selection and Data Sources

This study focuses on the carbon market, energy market, and stock market, analyzing their volatility spillover effects. The carbon market is represented by the China National Carbon Emission Trading Market (CEA), which officially launched in July 2021. Its price effectively reflects the overall trading conditions of Chinas carbon market. The energy market is divided into two categories: the new energy market and the traditional energy market. The research samples are the New Energy Index (NEW), the Crude Oil Continuous Main Contract Index (SCM), the Coal Index (COAL), and the Natural Gas Index (GAS), respectively. The stock market employs the Shanghai Composite Index (SCI), which offers broad sector coverage and strong representativeness, to comprehensively reflect the overall trend of Chinas capital market. The sample period spans from July 16, 2021, to February 25, 2025, utilizing daily data. New energy market data is sourced from the CSMAR database, while all other variables are obtained from the Choice database. To ensure data stationarity, each series underwent log transformation and first-order differencing, ultimately yielding stationary return series. Descriptive statistics and test results for the sample data are presented in Table 1.

Table 1. Descriptive Statistics and Test Results for Market Price Returns

	CEA	NEW	SCM	COAL	GAS	SCI
Average	0.0007	-0.0009	0.0003	0.0004	-0.0001	0.0005
Maximum	0.0939	0.1158	0.1011	0.0615	0.0776	0.0703
Minimum	-0.1030	-0.1229	-0.1413	-0.0871	-0.0685	-0.0869
Standard Deviation	0.0179	0.0204	0.0232	0.0208	0.0103	0.0148
Skewness	0.2898	0.5396	-0.3401	-0.1709	0.0582	-0.1963
Kurtosis	9.4617	7.2943	6.2269	4.7065	10.7152	6.8786
ADF Test	-34.7585***	-28.8808***	-31.4695***	-30.4134***	-28.1089***	-30.6859***
JB Inspection	1515.2177***	705.8012***	391.5121***	109.0349***	2143.3722***	547.1239***

Note: "*, **, ***" indicate significance at the 10%, 5%, and 1% levels, respectively.

4. Empirical Analysis

(1) Static Spillover Analysis

Table 2 presents the static total volatility spillover indices for each market. The overall static volatility spillover index stands at 32.60%, indicating that cross-market volatility contagion constitutes a significant component of systemic risk across the three market categories. Beyond market-specific volatility, 32.60% of fluctuations can be explained by volatility in other markets, reflecting a pronounced interdependence among the carbon market, energy market, and stock market.

Examining individual markets, the carbon market exhibits the highest internal spillover index, indicating strong autocorrelation where its volatility is primarily determined by historical fluctuations within the market itself, with relatively minor external influences. This aligns with Chinas carbon market being in its developmental phase, where market mechanisms are still evolving. The internal spillover indices for the new energy, coal, and natural gas markets are lower at 61.58%, 58.88%, and 59.79%, respectively, indicating these three markets are more susceptible to external market fluctuations.

Regarding net spillover indices, the natural gas market and stock market are net spillover sources, acting as primary contributors of volatility risk within the system. Among these, the stock market exhibits significantly higher net spillover levels than other markets, positioning it as the core risk source. Conversely, the carbon market, new energy market, crude oil market, and coal market are net recipients, with the new energy market demonstrating the highest net reception level and thus being most significantly impacted by external market fluctuations.

The spillover effects between pairs of markets reveal bidirectional volatility spillovers. Traditional energy markets exhibit strong internal linkage, with crude oil markets dominating volatility spillovers to coal markets. Carbon markets and new energy markets show bidirectional volatility spillovers, with new energy markets being net spillover sources to carbon markets. Volatility spillovers between energy markets and stock markets display non-equilibrium characteristics, with stock markets exerting more significant spillover effects on energy markets.

Table 2. Static Total Volatility Spillover Index (%) for Each Market

Receiver Exporter	CEA	NEW	SCM	COAL	GAS	SCI	From Others
CEA	80.73	2.74	2.54	2.55	3.18	8.25	19.27
NEW	2.07	61.58	3.01	6.21	14.19	12.94	38.42
SCM	1.95	2.99	71.21	4.60	7.81	11.45	28.79
COAL	2.45	6.21	4.68	58.88	10.49	17.28	41.12
GAS	1.05	3.17	3.04	12.98	59.79	19.97	40.21
SCI	2.26	8.76	2.84	6.25	7.65	72.23	27.77
To Others	9.78	23.88	16.12	32.59	43.32	69.89	Total: 32.60
NET	-9.49	-14.54	-12.67	-8.52	3.11	42.12	

To investigate the asymmetry of volatility spillovers, this paper further calculates the static spillover indices for positive and negative volatility, with results shown in Tables 3 and 4. Overall, the total positive volatility spillover index stands at 32.59%, while the total negative volatility spillover index is 31.59%. Positive volatility spillover slightly exceeds negative volatility spillover, indicating that positive shocks induce slightly stronger volatility transmission than negative shocks in static conditions. This closely aligns with the policy-driven nature of Chinas carbon market, where positive policy signals exert stronger guiding effects on the market than the impact of negative information.

By market segment, positive volatility spillover exceeded negative spillover in the carbon, coal, and natural gas markets, while negative spillover surpassed positive spillover in the new energy, crude oil, and stock markets. This indicates significant differences in how various markets respond to positive and negative shocks. In terms of net spillover, the stock market is the only one exhibiting net spillover under both positive and negative volatility, reflecting its high-risk nature. The crude oil and coal markets are net recipients under both positive and negative volatility, demonstrating heightened sensitivity to external market fluctuations. Volatility inflow also exhibits asymmetry across markets: only the crude oil market shows greater negative volatility inflow than positive volatility inflow, while all other markets exhibit higher positive volatility inflow.

Table 3. Static Positive Fluctuation Spillover Index (%) for Positive Shocks Across Markets

Receiver Exporter	CEA	NEW	SCM	COAL	GAS	SCI	From Others
CEA	84.16	2.10	2.39	2.86	3.32	5.16	15.84
NEW	3.12	62.37	3.60	6.73	6.67	17.50	37.63
SCM	2.17	2.56	79.27	4.38	6.93	4.70	20.73
COAL	1.58	8.75	3.93	64.42	11.93	9.40	35.58
GAS	2.16	7.20	4.35	10.43	58.74	17.11	41.26
SCI	4.61	15.04	3.38	7.06	14.38	55.52	44.48
To Others	13.64	35.66	17.66	31.45	43.23	53.87	Total: 32.59
NET	-2.20	-1.97	-3.07	-4.13	1.98	9.39	

Table 4. Static Bad Volatility Spillover Index (%) for Negative Shocks Across Markets

Receiver Exporter	CEA	NEW	SCM	COAL	GAS	SCI	From Others
CEA	87.59	2.53	1.99	1.57	2.25	4.08	12.41
NEW	3.65	62.60	4.08	5.16	8.57	15.94	37.40
SCM	1.97	5.84	74.23	5.98	8.30	3.67	25.77
COAL	1.50	7.97	4.78	66.83	12.19	6.73	33.17
GAS	1.53	7.29	5.97	11.66	61.70	11.85	38.30
SCI	3.96	16.70	3.95	5.94	11.97	57.49	42.51
To Others	12.61	40.33	20.77	30.30	43.28	42.26	Total: 31.59
NET	0.20	2.93	-5.00	-2.86	4.99	-0.25	

(2) Dynamic Spillover Analysis

Figure 1 shows the trend of the dynamic total spillover index for overall volatility, exhibiting significant time-varying characteristics. The dynamic spillover index fluctuates within the 40%–80% range, substantially higher than the static spillover index. This indicates that volatility spillover levels between markets fluctuate significantly with changes in the external environment, and extreme events substantially amplify the intensity of cross-market volatility spillovers.

From a temporal perspective: From 2023 to 2024, as the impact of these events gradually subsided and domestic economic policies proved effective, market expectations stabilized, causing the dynamic total spillover index to retreat to a steady level. From late 2024 to 2025, the dynamic total spillover index rose again, primarily influenced by global monetary policy adjustments and the deepening transformation of Chinas energy structure, which once more amplified the transmission of volatility across markets. These characteristics indicate that volatility spillovers across the three markets exhibit distinct event-driven patterns, with extreme external shocks significantly amplifying systemic risk.

Figure 2 and Figure 3 display the dynamic total spillover indices for positive and negative volatility. Both exhibit time-varying characteristics, with the negative volatility spillover index consistently and significantly higher than the positive volatility index for the majority of the period. This indicates that negative shocks trigger volatility transmission with greater intensity, speed, and persistence than positive shocks, confirming the behavioral pattern in financial markets that fear spreads faster than greed.

Under extreme event shocks, this asymmetry becomes more pronounced: Following the outbreak of the Russia-Ukraine conflict in 2022, the bad volatility spillover index rapidly climbed to nearly 40%, while the good volatility spillover index rose only to 35%. Moreover, the bad volatility spillover index declined more slowly and exhibited greater persistence, indicating that negative shocks have stickier cross-market contagion effects, requiring longer market recovery periods. Since late 2024, the Bad Volatility Spillover Index has again surged significantly while the Good Volatility Spillover Index remains relatively stable, further confirming the dominance of bad volatility spillover. This outcome indicates that market participants react more sensitively to negative news, with panic triggered by such news rapidly transmitting across markets and amplifying systemic financial risks.

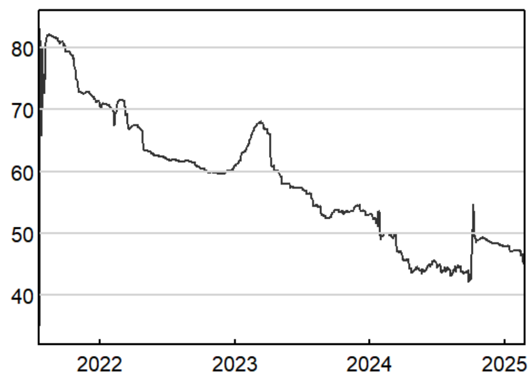

Figure 1. Dynamic Total Volatility Spillover Index

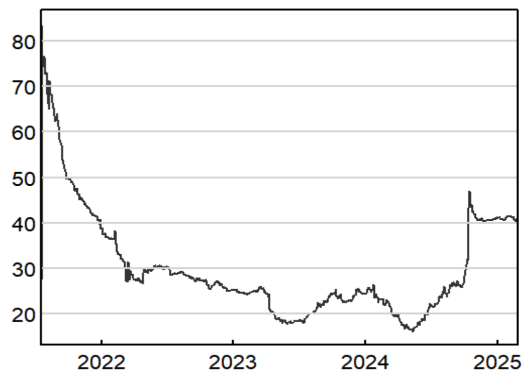

Figure 2. Dynamic Total Positive Volatility Spillover Index

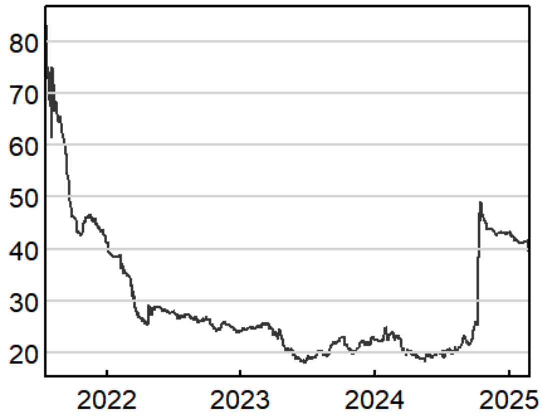

Figure 3. Dynamic Total Negative Volatility Spillover Index

Figure 4 net Volatility Spillover Index reveals that each markets net risk role exhibits significant time-varying characteristics rather than remaining static. The carbon markets role transition is particularly pivotal: from 2022 to 2023, its net spillover values were predominantly negative, primarily acting as a net risk absorber. Starting late 2023, it trended upward and maintained positive values, marking a shift from passive absorber to net exporter—closely aligned with the deepening development of the national carbon market. Traditional energy markets exhibit heightened sensitivity to major events. Following the Russia-Ukraine conflict in 2022, the net spillover indices for crude oil and natural gas markets surged in a pulse-like manner, transforming these markets into net risk exporters. Subsequently, as the impact of the event was absorbed, the indices gradually declined. The net spillover index for the new energy market remained negative for the majority of the period, consistently acting as a net risk absorber. The stock market exhibited a pattern of high early on followed by a decline. It was a significant net exporter during the 2022 conflict period, but its net spillover level decreased in 2024-2025 and turned negative on multiple occasions, reflecting a relative weakening of its capacity to export risks externally.

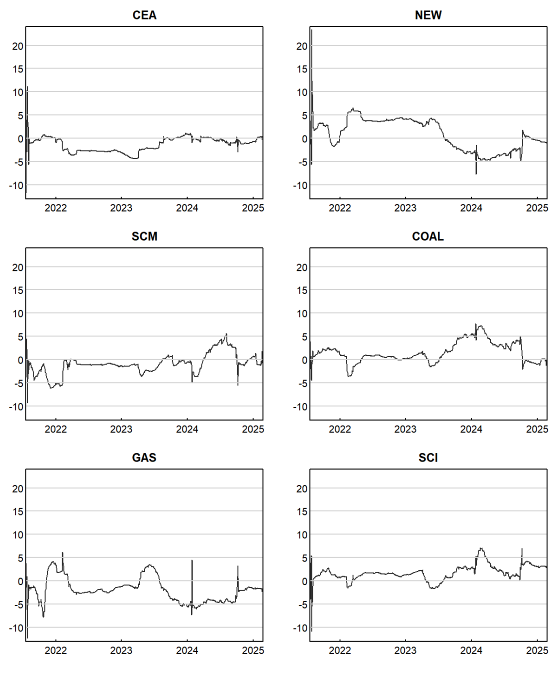

Figure 4. Total Net Volatility Spillover Index by Market

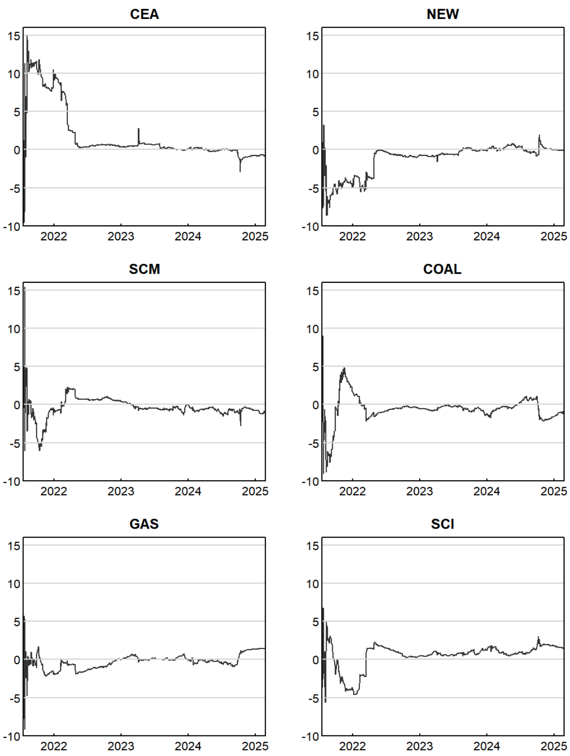

Figure 5. Net Volatility Spillover Index for Good Volatility Across Markets

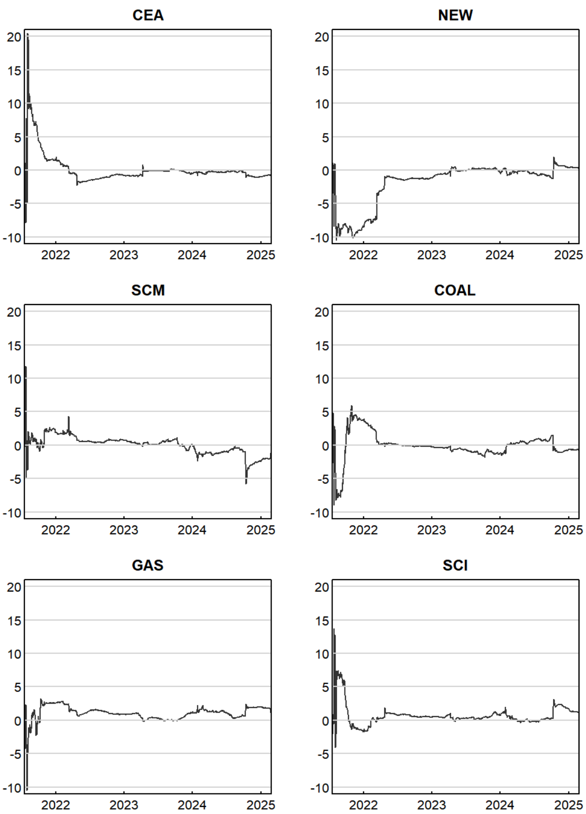

Figure 6. Net Volatility Spillover Index for Bad Volatility Across Markets

Comparing the net volatility spillover index for positive and negative volatility, as shown in Figure 5 and Figure 6, reveals a widespread and significant asymmetry in the volatility spillover effects across Chinas carbon, energy, and equity markets. The cross-market contagion intensity of negative volatility is markedly higher than that of positive volatility.

In terms of spillover intensity, both the volatility amplitude and extreme values of the net spillover index for bad volatility significantly exceed those of good volatility. For instance, during the Russia-Ukraine conflict in 2022, the net spillover of bad volatility in crude oil and natural gas markets exhibited sharp, pulsed surges, while good volatility responded relatively smoothly. This indicates that cross-market chain reactions triggered by equivalent negative information are markedly stronger than those induced by positive information. Regarding market roles, different markets exhibit distinct positions in transmitting both types of volatility: The carbon market displays a bidirectionally amplified asymmetric characteristic, becoming a net exporter of both positive and negative volatility in the later stages of the sample period. However, the volatility of negative volatility net outflows is more pronounced, reflecting the markets more intense and uncertain reaction to negative news. Crude oil and natural gas markets are predominantly negative volatility-dominated exporters. The new energy and coal markets function as stable net absorbers, continuously absorbing both positive and negative volatility. However, their absorption intensity and persistence for negative volatility are significantly higher than for positive volatility, highlighting their vulnerability to external negative shocks. The stock market exhibits role switching, acting as a net exporter of positive volatility most of the time, but potentially becoming a net absorber of negative volatility during market turbulence. At the extreme event response level, asymmetric characteristics are equally pronounced: major external events simultaneously boost net outflows of both volatility types, but the uplift effect for bad volatility is instantaneous and intense, while the impact on good volatility is relatively delayed and mild. Moreover, after crises, the decline in net outflow of bad volatility lags behind that of good volatility, indicating that the contagion effect of negative shocks is more persistent and market recovery cycles are longer.

5. Conclusions and Recommendations

This study integrates carbon, energy, and equity markets into a unified analytical framework. Using daily data from July 16, 2021, to February 25, 2025, and employing GJR-GARCH and TVP-VAR-DY models, it analyzes volatility spillover effects across the three markets from both static and dynamic perspectives. Key findings include: Significant and time-varying volatility spillover effects exist among the three markets. The static total spillover index is 32.60%, while the dynamic spillover index fluctuates between 40% and 80%. The carbon market exhibits strong autocorrelation (internal spillover accounts for 80.73%). historically acting as net volatility recipients, while natural gas and equity markets predominantly function as primary net emitters. New energy and crude oil markets primarily serve as net recipients. Volatility spillover exhibits pronounced asymmetry: static analysis reveals marked differences across submarkets, and dynamic analysis shows adverse volatility spreads significantly faster, more intensely, and with greater persistence than positive volatility. Major external events intensify cross-market volatility spillovers and asymmetry. Following events like the 2022 Russia-Ukraine conflict, traditional energy markets and stock markets briefly became primary volatility emitters, while renewable energy and coal markets exhibited vulnerability. As financialization increases, the carbon markets capacity to export external risks grows, and under extreme shocks, the asymmetry of negative volatility spillovers is significantly amplified.

Based on these findings, the following recommendations are proposed: Investors should optimize cross-market asset allocation by leveraging the interlinked volatility characteristics across three market segments to diversify risk. Investment proportions should be flexibly adjusted in response to policy dynamics and market shifts, while enhancing risk identification and assessment capabilities. Rapid response mechanisms for major events should be established, alongside event-driven risk management strategies. At the policy formulation and financial regulatory levels, precise differentiated interventions are needed to protect vulnerable industries like new energy, guide the positive transmission of "good volatility" in stock markets, establish cross-departmental collaborative regulatory frameworks, strengthen compliance and security oversight of carbon markets, create risk early-warning mechanisms, improve cross-market information-sharing platforms, encourage the development of carbon financial products, channel capital toward low-carbon sectors, and advance the construction of green financial systems to achieve the "dual carbon" goals.

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