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Spillover effect between oil prices, climate risks, and carbon prices in China: dynamic effects and key drivers

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Against the backdrop of escalating global climate change and volatile international oil markets, the interdependence among energy prices, climate-risk information, and carbon markets has become increasingly prominent. Clarifying their dynamic spillover patterns is important for climate governance, energy security, and carbon-market risk management. This study examines the dynamic interactions among decomposed oil price shocks, physical and transition climate-risk indices, and China's regional carbon price represented by the Guangdong pilot market. The research design is structured in three stages. First, oil price fluctuations are decomposed into supply, demand, and risk shocks following Ready (2018), and a time-varying parameter vector autoregressive (TVP-VAR) model is employed to capture evolving spillovers. Second, the Baruník–Křehlík (2018) frequency-domain spillover framework is used to distinguish short- and long-horizon connectedness. Third, the XGBoost–SHAP framework is used as a post-estimation predictive complement to identify nonlinear feature contributions to changes in spillover intensity; the resulting SHAP values are interpreted as feature-association evidence rather than structural causal estimates. The results show that: (1) oil price shocks, carbon prices, and climate risks exhibit substantial volatility spillovers, with short-term spillovers considerably stronger than long-term spillovers (baseline short-term TCI = 24.91 versus long-term TCI = 5.30, using a 1–10 trading-day short-term band); (2) physical and transition climate-risk information has strong bilateral spillover links with carbon prices, while oil-related risk shocks are more relevant in the short term and supply- and demand-related oil shocks display stronger long-horizon connections; and (3) SHAP-based variable-importance analysis indicates that exchange rate dynamics, China's economic policy uncertainty, and market liquidity are important predictors of time-varying spillover intensity. Robustness checks using the Hubei pilot carbon market, together with additional frequency-domain evidence under the baseline 1–10 trading-day partition, confirm that the main conclusions remain qualitatively stable. The findings should be interpreted in light of the fact that regional pilots differ from the national ETS in liquidity, sector coverage, and allowance fungibility, and that the climate-risk indices are constructed from global media sources.

KEYWORDS
carbon prices, climate risks, oil price shocks, spillover effects, TVP-VAR

1 Introduction

Climate change and the greenhouse effect have become critical global concerns. In response, governments around the world are implementing carbon-reduction policies and promoting transitions in their energy structures. China has introduced its "dual-carbon" targets, aiming to reach peak carbon emissions by 2030 and achieve carbon neutrality by 2060. As one of the key market-based tools for meeting these goals, carbon emissions trading plays a pivotal role, and fluctuations in carbon prices directly influence the overall progress of the dual-carbon strategy (Lin and Jia, 2019). Since firms are the primary actors responsible for realizing emission-reduction commitments, they typically evaluate abatement decisions through a cost–benefit lens, with the degree of emission reduction ultimately determined by prevailing carbon price levels. Consequently, examining the drivers of carbon price movements not only aids policymakers in improving the design and efficiency of carbon trading systems but also offers enterprises valuable guidance for setting scientifically grounded reduction plans (Adamolekun, 2024). As China's carbon market continues to expand and its mechanisms mature, the determinants of carbon prices have also shifted. Recent research further shows that sustainable environmental governance increasingly depends on institutional readiness for human-AI collaboration (Zhou, 2026), while China's green-transition resilience differs across regions and resource-based city types (Wang et al., 2026). The financial characteristics of traded emission allowances have become increasingly evident, making carbon prices more sensitive to external shocks such as international oil price volatility and climate-related risk factors (Li et al., 2023; Ready, 2018; Baruník–Křehlík, 2018).

As a major form of traditional fossil energy, oil plays a central role in the global energy consumption mix, and fluctuations in its price have far-reaching consequences for economic activity and social development (Mohaddes and Pesaran, 2017; Ready, 2018). Moreover, shifts in oil prices influence the production decisions and operating costs of energy-related enterprises, thereby affecting the overall supply and demand for carbon allowances. These changes subsequently transmit to the carbon market and contribute to volatility in carbon prices (Batten et al., 2021). From the perspective of their origins, oil price shocks can generally be divided into three categories: demand-driven shocks, supply-side shocks, and risk-related shocks. Prior research has shown that these different types of oil shocks produce heterogeneous effects across energy markets, financial markets, and other sectors (Cao et al., 2025). Therefore, a detailed examination of how each category of oil price shock interacts with the carbon market is crucial for understanding the substitution relationship between fossil energy and carbon trading, accurately interpreting carbon price movements, improving carbon market design, facilitating energy system transformation, and advancing long-term emission reduction objectives.

Beyond the spillover effects originating from fossil energy markets, climate risks may also induce volatility transmission to carbon prices. Climate risks are typically classified into two dimensions: the physical risk index (PRI) and the transition risk index (TRI) (Stroebel and Wurgler, 2021). Physical risks arise from direct manifestations of climate change, such as extreme weather events, natural disasters, or rising sea levels, which can disrupt production processes, supply chains, and broader economic systems. Transition risks, in contrast, stem from the policy, technological, and structural adjustments associated with the shift toward a low-carbon economy, including regulatory reforms, changes in consumer behavior, and innovation adoption (Bua et al., 2024). Behavioral responses to low-carbon policies are also shaped by normative perceptions and consumer expectations (Jiang et al., 2026), while AI-supported carbon-emission monitoring and dynamic trading mechanisms can further influence expectations about future carbon-market governance (Li et al., 2026). Both forms of climate risk may exert distinct influences on carbon price behavior (Ozturk et al., 2022). Given the accelerating pace of global climate change, analyzing the spillover effects of climate risks on carbon prices is essential for uncovering the underlying drivers of carbon price dynamics.

Although researchers have begun to examine the volatility spillover relationships among oil price shocks, climate risks, and the carbon market, current findings remain limited. Existing studies show that oil price shocks and climate policy uncertainty (CPU) can influence the supply–demand dynamics of carbon allowances and thereby generate notable volatility spillovers in carbon prices (Li et al., 2022; Li et al., 2023; Zhang Y et al., 2023). However, much of the literature concentrates on the overall impact of oil price fluctuations and climate risks, while paying insufficient attention to how different categories of oil price shocks and climate-risk indicators may exert differentiated spillover effects. At the same time, most studies focus predominantly on identifying volatility transmission channels, with relatively few efforts directed toward systematically analyzing the determinants of time-varying spillover intensity across variables. Although some research explores how individual variables affect the total connectedness index (TCI) within specific empirical frameworks (Huang et al., 2024; Lin and Gong, 2025; Zhang T et al., 2025), no existing study provides a comprehensive comparison of the relative importance of potential influencing factors using nonlinear machine learning approaches within a unified analytical setting. This gap limits a deeper understanding of the mechanisms underlying dynamic spillover behavior.

To address these shortcomings, the present study combines a time-varying parameter vector autoregressive (TVP-VAR) model with the frequency-domain spillover index framework developed by Baruník and Křehlík (2018) to construct a time–frequency risk spillover network linking various oil price shocks, carbon prices, and climate risks. Additionally, an XGBoost-SHAP model is used to uncover key predictors associated with time-varying connectedness intensity. Following Ready's (2018) approach, we first apply a structural vector autoregressive (SVAR) model to decompose oil price shocks into supply, demand, and risk components. These shock types, together with carbon prices, PRI, and TRI, are then incorporated into the TVP-VAR system to estimate their evolving interdependencies. The Baruník–Křehlík frequency-domain spillover index is subsequently employed to reveal how connectedness patterns differ across short- and long-term horizons. Finally, using total spillover intensity as the dependent variable, we construct a set of explanatory features reflecting macroeconomic conditions, uncertainty factors, and

financial market indicators. The XGBoost-SHAP method is applied to quantify the relative contribution of each feature to the dynamic spillover intensity, offering empirical insights and policy guidance for building an early-warning system for carbon market risks.

The marginal contributions of this study can be summarized in the following three dimensions:

First, this study advances the literature by explicitly identifying and disentangling the heterogeneous transmission mechanisms through which different types of oil price shocks and climate risks affect carbon price volatility. While a growing body of research employs spillover index models to examine the interlinkages among oil prices, carbon markets, and climate risks, most studies remain at an aggregate level and provide limited insights into the underlying sources and channels of these spillovers (Li et al., 2022; Li et al., 2023; Zhang X et al., 2023). In particular, the differentiated impacts of supply-driven, demand-driven, and risk-driven oil price shocks, as well as distinct dimensions of climate risks, are still underexplored. To address this gap, this study adopts a structural identification strategy to decompose oil price shocks and further distinguishes between physical climate risk and transition climate risk. This framework is also consistent with recent work emphasizing that carbon pricing can transmit volatility to green financial assets (He et al., 2025). By doing so, it provides a mechanism-based understanding of how heterogeneous shocks propagate across markets, thereby enriching the literature on carbon price determinants.

Second, this study contributes by uncovering the time-varying and frequency-dependent nature of connectedness among oil prices, climate risks, and carbon prices across both short-term and long-term horizons. Existing studies typically focus on a single time dimension, which limits their ability to capture the dynamic evolution of spillover effects. To overcome this limitation, this study integrates the TVP-VAR model with the Baruník and Křehlík (2018) frequency-domain spillover index, enabling a decomposition of connectedness across different time scales. This approach provides new empirical evidence on how market interdependencies evolve over time and across frequencies, offering a more nuanced understanding of the temporal structure of spillovers.

Third, this study adopts a nonlinear, data-driven framework to systematically evaluate the key drivers of dynamic market connectedness. The existing literature predominantly relies on linear models to examine the determinants of spillover effects (Huang et al., 2024; Lin et al., 2025; Zhang T. et al., 2025), potentially overlooking nonlinear interactions and complex dependencies among variables. In contrast, this study employs the XGBoost–SHAP framework to quantify the relative importance of macroeconomic and financial factors in shaping the intensity of connectedness among oil prices, climate risks, and carbon prices. By capturing nonlinearities and interaction effects within a multidimensional feature space, this approach provides deeper insights into the underlying forces driving market interconnectedness and offers a more comprehensive analytical perspective than traditional methods. The empirical contribution is therefore framed as evidence on dynamic connectedness and nonlinear feature association rather than as structural causal identification.

2 Literature review

2.1 The relationship between climate risks and carbon prices

With global temperatures rising and extreme weather events occurring more frequently, climate risks associated with climate change have begun to exert significant and far-reaching effects on economic activity and social development. From a governance perspective, AI adoption in environmental governance depends on institutional, technological, and behavioral conditions that support sustainable development (Zhou, 2026). As a key market-oriented tool for achieving emission-reduction goals, carbon emissions trading incorporates climate-related uncertainty into market pricing, meaning that fluctuations in carbon prices often mirror the market's assessment of climate risks. Consequently, examining how climate risks influence carbon price dynamics has become an important direction in recent academic research.

Climate risks can shape carbon prices through several mechanisms. First, climate change alters patterns of energy consumption and the generation structure of clean energy, thereby affecting actual emissions and the demand for carbon allowances. Second, CPU affects carbon prices via shifts in market expectations, investment sentiment, and firms' compliance strategies. Using a TVP-VAR framework, Yan, 2023 reported that both CPU and coal prices impose significant and time-varying influences on China's carbon prices. Chen, 2025 further showed that climate-related spillover effects on the carbon market display strong heterogeneity over time, with risk contagion intensifying during extreme climate events or following the introduction of major climate policies.

The literature commonly distinguishes between two categories of climate risks, each exerting differentiated impacts on carbon prices. PRI reflects uncertainties associated with extreme climate phenomena, such as persistent warming, intense rainfall, typhoons, and other natural hazards. TRI, by contrast, reflects uncertainties linked to policy adjustments, the restructuring of the energy system, and evolving market expectations (Bua et al., 2024; Stroebel and Wurgler, 2021). Low-carbon behavioral responses, including travel and consumption choices, provide an additional expectation channel through which transition policies can affect market sentiment (Jiang et al., 2026). Using a multivariate stochastic volatility model for EU ETS allowance prices, Ozturk et al. (2022) found that climate uncertainty is a major driver of carbon price volatility, with the effect of PRI-related natural-disaster information increasingly surpassing that of policy-related uncertainty in recent years. Overall, while PRI-related physical risk has received substantial scholarly attention due to its immediate influence on production and supply chains, TRI-related transition risk remains relatively underexplored, largely because the implementation strength of carbon policies is still insufficient.

2.2 The linkage between oil prices and carbon prices

Crude oil is widely recognized as a vital strategic resource and is often regarded as the "lifeblood" of modern economic and social

systems. As a dominant traditional energy source, the combustion of oil constitutes a major source of carbon dioxide emissions. Accordingly, fluctuations in oil prices can significantly influence both the demand for and supply of carbon emission allowances, generating notable spillover effects in carbon markets. Because oil prices also serve as an indicator of broader macroeconomic conditions, their movements can propagate across industries and produce complex linkage effects with carbon prices. The majority of existing studies have examined the aggregate influence of oil prices on carbon prices. For instance, Song et al. (2022) applied VAR and BEKK-MGARCH models to show clear spillover effects between China's carbon trading market and major energy markets. Li et al. (2022) adopted a TVP-VAR model to analyze the dynamic relationships among oil prices, green bonds, carbon prices, and carbon efficiency indicators, finding that oil price shocks exert negative impacts on carbon trading prices in both the short and medium term, suggesting a suppressive effect of rising oil prices on carbon allowance prices. Conversely, Li et al. (2023), using WTI crude oil futures as a proxy for oil price shocks and employing a TVP-VAR framework, reported that oil price shocks primarily influence China's carbon market in the short run, with positive oil shocks increasing carbon prices. This stands in contrast to earlier findings and underscores the possibility that the oil–carbon price relationship is sensitive to changing market structures and contextual conditions. He et al. (2025) further demonstrate that carbon-pricing spillovers can affect green asset price volatility, confirming the relevance of TVP-VAR/DY-type methods for carbon-related asset-pricing research. Charles (2025) also highlights the link between oil-price movements and exchange-rate adjustment, which is important because exchange-rate dynamics are identified below as a key predictor of spillover intensity. Extending this literature, Zhang T et al. (2025) used a TVP-DY spillover index to examine volatility transmission among oil prices, China's renewable energy market, and carbon prices. Their time-frequency approach captured dynamic spillover patterns across different horizons, shedding light on the distinct short- and long-term interactions among these markets. Taken together, the evolving and sometimes contradictory findings suggest that the relationship between oil prices and carbon prices is more intricate than previously assumed. Market conditions, policy shifts, and technological developments may all shape how these variables interact over time. Such complexity highlights the need for more advanced analytical frameworks capable of capturing dynamic, time-varying, and potentially asymmetric linkages between oil markets and carbon markets.

In addition, several scholars have sought to decompose oil price fluctuations in order to more precisely identify the underlying sources of volatility and to deepen the analysis of asymmetric interactions between the oil market and the carbon market. Building on the decomposition framework of Ready (2018), Zheng et al. (2021) separated oil price changes into supply shocks (SS), demand shocks (DS), and RS. Using a nonlinear autoregressive distributed lag model, they examined the asymmetric effects of these shocks on China's carbon emissions trading market, finding that oil shocks generate long-term asymmetric influences on carbon allowance prices. Using the same decomposition methodology proposed by Ready (2018), Ren et al. (2022) applied the quantile coherence approach to explore how different types of oil shocks interact with carbon market dynamics across various time horizons and distributional characteristics. Similarly, Cao et al. (2025) decomposed oil price movements into SS, DS, and RS and employed quantile regression techniques to investigate the heterogeneous impacts of structural oil shocks on carbon prices. Their empirical findings showed that both supply and DS exert negative effects on carbon prices, whereas RS consistently produce positive impacts across all quantiles.

Recent studies on maritime transportation and carbon-pricing regulation further support the view that carbon markets are embedded in broader energy, logistics, and macro-financial networks. Sun et al. (2024) show that the EU ETS changes the carbon-cost accounting and operating-speed decisions of liner shipping firms, implying that allowance prices can be transmitted to real production and transportation costs. Sun et al. (2025b) provide direct evidence that the inclusion of maritime emissions in the EU ETS strengthened return and volatility spillovers among crude oil, crude-oil maritime transportation, and the EU carbon market. Sun et al. (2025a) further demonstrate that freight-market volatility is closely linked to inflation and macroeconomic conditions. These findings are consistent with the present study's argument that oil-market shocks, climate-policy risks, and macro-financial factors jointly shape carbon-price connectedness.

2.3 Drivers of time-varying risk spillover intensity

The intensity of risk spillovers across financial asset prices reflects how closely different markets or variables are connected over time. It also partially reveals how systemic risk propagates and how its transmission strength evolves. Understanding the time-varying behavior of spillover intensity is therefore essential for uncovering the dynamic mechanisms of cross-market risk linkages and for supporting early-warning systems and regulatory policy design (Qin et al., 2024). Most existing research investigates this issue from a qualitative viewpoint, typically discussing how major events, such as global financial crises, the COVID-19 outbreak, or the Russia–Ukraine conflict, might influence risk spillover patterns (Luo et al., 2024; Zhang Y. et al., 2025; Zhang Z. et al., 2025). However, such descriptive analyses often fail to capture the precise dynamic evolution of spillover effects.

To ensure consistent terminology, this study uses 'spillover intensity' and 'connectedness' to refer to the magnitude of volatility transmission measured by the DY/BK spillover indices. 'Spillover intensity' emphasizes the size of the estimated transmission effect, whereas 'connectedness' emphasizes the overall network linkage implied by the same index system. The term 'correlation strength' is avoided because the empirical framework is based on forecast-error variance decomposition rather than simple correlation coefficients.

More recently, some scholars have shifted toward quantitative approaches, examining the determinants of spillover intensity from multiple angles, including macroeconomic conditions, policy uncertainty, market liquidity, exchange-rate volatility, and investor sentiment. These studies predominantly rely on linear empirical frameworks, such as linear regression and Granger causality analysis, to evaluate how individual factors shape the time-varying spillover structure. Recent research on nonlinear

dynamics and heterogeneous expectations also suggests that market interactions may display strategic and nonlinear adjustment patterns that cannot be fully captured by conventional linear models (Tian et al., 2026). For example, Lin and Gong, 2025 combined a modified Diebold–Yilmaz connectedness framework with a TVP-VAR-SV model to measure systemic linkages between energy and non-energy commodities. Their results show that public climate attention significantly influences transmission from energy to non-energy markets: physical climate-related attention suppresses spillover, while transitional climate attention amplifies it and acts as the primary propagation channel. Huang et al. (2024), using a multi-scale R^2-based connectedness method, found that economic policy uncertainty (EPU) strongly predicts long-horizon spillovers between climate risk and high-carbon asset prices, whereas financial stress predominantly shapes short-term spillover dynamics. Similarly, Zhang, Li, et al. (2025) applied the Baruník and Křehlík (2018) frequency-domain spillover index together with linear regression to analyze how CPU affects inter-industry volatility spillovers in China, revealing that CPU suppresses cross-industry risk transmission.

Despite these advances, research adopting nonlinear perspectives on the determinants of spillover intensity remains limited, and existing studies generally continue to focus on single-factor effects. Qin et al. (2024), using a semi-parametric framework, reported that market liquidity has a U-shaped nonlinear influence on total spillover intensity. Hu et al. (2025) employed a random forest model and showed that public climate attention exhibits complex nonlinear patterns, such as M-shaped relationships, with spillover dynamics in the energy futures market.

2.4 Research gap

Although prior research has advanced our understanding of the interconnectedness among oil prices, climate risks, and carbon prices, several important limitations remain.

First, most studies treat oil price shocks as a single aggregate variable, neglecting the heterogeneity of effects stemming from different types of oil price shocks on carbon prices (Li et al., 2022; Li et al., 2023; Zhang T et al., 2025). In practice, oil price fluctuations arise from multiple sources, including supply, demand, and risk factors, and each type of shock may influence the carbon market through distinct transmission channels. By examining the dynamic impacts of three categories of oil price shocks alongside two types of climate risks within a unified framework, this study provides a more comprehensive understanding of the heterogeneous mechanisms through which climate risk and oil price shocks propagate to carbon prices.

Second, most existing literature emphasizes the transmission relationships among variables themselves, offering limited insights into the underlying drivers of connectedness or the characteristics of time-varying spillovers. While a few studies have applied linear methods, such as regression analysis, to assess the influence of individual factors on dynamic spillover intensity, they lack a systematic evaluation of multi-dimensional determinants within a cohesive analytical framework. The recent development of machine learning techniques offers new opportunities to identify and interpret key drivers of complex interactions (Cao et al., 2023; Wang et al., 2024; Zhang Y et al., 2023). Building on this, the present study employs an XGBoost-SHAP approach to quantify the relative importance of macroeconomic, policy, and financial market factors in shaping time-varying spillover intensity. This approach provides more robust empirical evidence for uncovering new risk transmission channels and sources of systemic risk. In addition, related ETS studies in transportation and shipping markets suggest that carbon-cost pass-through, fuel-price changes, and regulatory expectations may jointly reshape cross-market volatility; this provides a useful conceptual reference for interpreting how carbon-pricing mechanisms interact with energy-price shocks and broader macro-financial conditions.

2.5 Theoretical framework and research hypotheses

To address the concern that the empirical design should be theory-guided rather than purely data-driven, this study clarifies the conceptual framework before the empirical analysis. The interaction among oil shocks, climate risks, and carbon prices can be understood through three related channels: an energy-cost channel, a policy-expectation channel, and a financial risk-pricing channel. Oil supply, demand, and risk shocks affect firms' production costs, energy-substitution incentives, and investor risk appetite. Climate-risk information affects expectations about physical disruptions, transition-policy tightening, allowance allocation, and future compliance costs. Carbon prices, as market prices of emission allowances, therefore respond not only to allowance supply and demand but also to energy-market shocks, policy uncertainty, liquidity conditions, and climate-risk expectations.

Based on this framework, four testable hypotheses are proposed. H1: Oil price shocks and climate-risk information generate time-varying volatility spillovers to China's regional carbon market. H2: The spillover effects are heterogeneous across oil supply shocks, oil demand shocks, oil risk shocks, physical climate risk, and transition climate risk. H3: Spillover effects are stronger over short horizons than over long horizons because high-frequency market repricing is more sensitive to information shocks, liquidity changes, and policy expectations. H4: Macro-financial variables, including exchange rates, liquidity indicators, and economic policy uncertainty, provide nonlinear predictive information for the time-varying spillover intensity, although these post-estimation predictors should not be interpreted as structural causal factors.

3 Data sources and empirical methodology

3.1 Data sources and descriptions

This study examines the volatility spillover effects among oil price shocks, climate risks, and carbon prices using daily-frequency data from October 2014 to May 2024. A defining feature of China's carbon market is the coexistence of the national ETS and regional pilot markets. The national ETS began trading in July 2021, while the Guangdong pilot has operated continuously since the early pilot period and provides a longer and more liquid daily price series covering the full sample. Because the TVP-VAR and frequency-

domain connectedness frameworks require a continuous long-span series to trace evolving spillovers, Guangdong carbon prices are used as the baseline proxy for China's regional carbon-market conditions.

This proxy choice does not imply that Guangdong is institutionally identical to the national ETS. Regional pilots differ from the national system in several important respects: lower average liquidity, narrower sector coverage (often dominated by local power and industrial entities), and non-fungible allowances. These institutional differences may limit the generalizability of pilot-market results to China's unified national carbon pricing system. The use of Guangdong therefore reflects a pragmatic trade-off between representativeness and data continuity. Guangdong is one of China's most active pilot ETS markets, with comparatively mature trading rules, sectoral coverage, and compliance mechanisms. Recent policy research also emphasizes that local carbon markets continue to perform important functions within China's dual-track carbon-market framework (Dai and Pollitt, 2025). To test whether the baseline findings are driven by Guangdong-specific features, this study further replaces Guangdong carbon prices with Hubei carbon prices in the robustness analysis reported in Section 4.5; Supplementary Appendix B. Evidence on regional heterogeneity in transport-sector carbon mitigation also suggests that carbon-reduction performance and policy responsiveness may differ across regions and sectors (Liu and Zhou, 2026).

Hubei is selected as the alternative proxy because it is also a major regional pilot market with relatively active trading and a different industrial structure from Guangdong. Consistent findings across Guangdong and Hubei therefore provide a cross-pilot check on the external validity of the main conclusions; they do not, however, constitute validation against the national ETS. Carbon trading price data are obtained from official datasets of the carbon exchanges.

For climate-risk measures, this study employs the text-based physical (PRI) and transition (TRI) climate-risk indices developed by Bua et al. (2024). These indices are constructed from global English-language news sources, including Reuters, and capture daily changes in two dimensions of climate-related uncertainty. China's carbon pricing is heavily steered by domestic central planning (e.g., NDRC/MEE directives and provincial allocation plans). A global media-based proxy may therefore miss high-frequency domestic regulatory policy swings.

Although the PRI and TRI are based on global media information, they are relevant to China's regional carbon market through three transmission channels. First, global climate-risk news affects investor sentiment and risk appetite, which can be rapidly internalized into traded carbon allowances as their financial attributes strengthen. Second, global transition-risk information changes expectations regarding future climate-policy tightening, allowance allocation, and compliance costs, thereby influencing the pricing of domestic emission allowances. Third, global physical-risk information may affect China through energy-demand pressure, international supply-chain disruptions, oil-price movements, and exchange-rate channels.

Accordingly, the estimated climate-risk spillovers should be interpreted as the effect of global climate-risk information and expectation shocks on regional carbon-price formation, rather than as evidence that every global physical event directly changes Guangdong's (or Hubei's) emissions fundamentals. The scarcity of high-frequency, China-specific climate-risk indices covering the full 2014–2024 sample is acknowledged as a limitation; future research would benefit from domestic regulatory-news or policy-intensity indices once continuous daily series become available.

Domestic regulatory policies remain a key determinant of China's carbon prices. However, under increasing carbon-market financialization and global policy coordination, external climate information can still influence regional carbon prices through expectation formation, information diffusion, oil-market linkages, and macro-financial conditions. Including PRI and TRI therefore provides an additional perspective for examining how climate-related information shocks are associated with carbon-market dynamics.

We plotted time-series graphs for the original series of all variables and conducted the Augmented Dickey-Fuller (ADF) test. The results indicate that all original series of oil supply shock (SS), oil demand shock (DS), oil risk shock (RS), climate physical risk (PRI), and climate transition risk (TRI) are stationary at the 1% significance level according to the ADF unit root test.

By contrast, the carbon price series is non-stationary in levels but becomes stationary after first-order differencing, which is used in the subsequent empirical analysis, with detailed results presented in Supplementary Appendix A.

3.2 Decomposition of oil price shocks

In addition to Ready's (2018) method, common approaches to decomposing oil price shocks include those by Kilian (2009). Compared with Kilian (2009), this study adopts Ready (2018) mainly due to its better suitability for high-frequency (daily) data and its ability to incorporate forward-looking market information. Kilian's structural VAR framework is typically implemented using low-frequency macroeconomic data (e.g., monthly), which limits its effectiveness in capturing short-term dynamics and rapid information transmission in financial markets. In contrast, Ready (2018) constructs oil price shocks based on futures market data, which are available at a daily frequency and embed investors' expectations and real-time market sentiment. This forward-looking feature allows for a more precise identification of shocks in a financialized setting, particularly when analyzing volatility spillovers among oil prices, climate risks, and carbon prices. Therefore, the Ready (2018) approach not only aligns with the data frequency used in this study but also enhances the economic relevance of the identified shocks by better capturing expectation-driven and market-based dynamics. Oil price shocks originating from different sources can have heterogeneous effects on other variables, including carbon prices. Based on the structural restrictions proposed by Ready (2018), the identified innovations are interpreted as supply, demand, and risk shocks. These restrictions allow the model to distinguish whether oil-price fluctuations originate from changes in oil supply conditions, global demand conditions, or oil-market-specific uncertainty. Decomposing oil price shocks according to their sources allows for a more nuanced analysis of the interactions between petroleum and carbon markets, which in turn supports the design of targeted risk management strategies and informed investment decisions. Ready (2018) proposes a model to distinguish between oil

demand and SS, addressing several limitations of the decomposition approach introduced by Kilian (2009). In Ready's framework, DS are defined as the portion of returns on a global stock index of oil-producing firms that is orthogonal to innovations in the VIX. Here, VIX innovations capture aggregate changes in market discount rates that affect the stock returns of oil-producing firms, serving as a proxy for RS. SS are then identified as the residual component of oil price changes that is orthogonal to both demand and RS. The Ready (2018) model can be expressed in the following matrix form:

The identification of oil price shocks follows Ready's (2018) recursive and orthogonal decomposition rather than a narrative identification design or an external-instrument SVAR. Specifically, innovations in the VIX are treated as risk shocks (RS); demand shocks (DS) are identified from the residual variation in oil-producer equity returns after orthogonalizing with respect to RS; and supply shocks (SS) are identified from the residual variation in oil-price changes after orthogonalizing with respect to both RS and DS.

Orthogonality among SS, DS, and RS is imposed through the covariance restrictions in Ready's decomposition, as summarized below. This procedure reduces the endogeneity concern that would arise if raw oil-price changes were used directly, but it does not eliminate broader macro-financial endogeneity. The subsequent spillover analysis remains a reduced-form exercise based on forecast-error variance decompositions.

$$X_t = \mathrm{A}Z_t \tag{1}$$

Let $X_t = [\Delta, o_t, R_t^{\mathrm{prod}}\ \xi_t^{\mathrm{VIX}}]'$ be the 3×1 vector of observables, where Δo_t is the change in the oil price, R_t^{prod} is the return on a global stock index of oil-producing firms, and ξ_t^{VIX} denotes the VIX innovation (obtained from an ARMA (1,1) filter). Let $Z_t = [S, S_t, DS_t\ RS_t]'$ be the 3×1 vector of structural oil shocks, where SS_t, DS_t, and RS_t denote the oil supply, demand, and risk shocks, respectively. The mapping from structural shocks to observables is $X_t = AZ_t$, where A is a 3×3 coefficient matrix defined as follows:

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{2}$$

To ensure orthogonality, Ready (2018) requires that the structural shocks in Z_t be mutually uncorrelated and that A and the covariance matrix of X_t satisfy:

$$A^{-1} \sum_{X} \left(A^{-1}\right)^{T} = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \tag{3}$$

Here, Σ_X denotes the covariance matrix of the observable vector X_t, while σ_s^2, σ_d^2, and σ_v^2 represent the variances of the supply shock SS_t, the demand shock DS_t, and the risk shock RS_t, respectively. Equation 3 is a renormalized form of the standard orthogonalization used to recover structural shocks. Unlike a unit-variance normalization, this renormalization ensures that the sum of the decomposed shocks is consistent with the observed oil-price change. Using this model, oil-price fluctuations are decomposed into mutually orthogonal supply, demand, and risk components.

Following this methodology, the study collects WTI crude oil futures prices, the Dow Jones US Select Oil Exploration and Production Index, and the VIX index to serve as measures of oil prices, oil-producer equity returns, and market risk, respectively. These variables are then input into the decomposition model to generate three distinct shock series: oil SS, oil DS, and oil RS.

3.3 Volatility spillover index methodology

To investigate the time–frequency spillover effects among climate risks, the international crude oil market, and China's carbon market, this study adopts a three-step approach. First, the Diebold–Yilmaz spillover index based on a TVP-VAR is used to measure time-varying connectedness. Second, the Baruník–Křehlík frequency-domain decomposition separates short- and long-horizon spillovers. Third, an XGBoost–SHAP post-estimation analysis identifies nonlinear predictors of spillover intensity. The TVP-VAR–BK connectedness measures quantify the intensity, direction, and frequency profile of volatility transmission. They are reduced-form representations of forecast-error variance shares and do not identify structural causal channels of corporate abatement behavior or trading-desk pass-through mechanisms.

The joint use of TVP-VAR and frequency-domain decomposition is intended to answer two different empirical questions rather than to duplicate the same function. The TVP-VAR component captures how the overall spillover structure evolves over calendar time, allowing the strength and direction of connectedness to change with market conditions. The BK frequency-domain component further decomposes the forecast-error variance contributions into short- and long-horizon components, thereby identifying whether the connectedness is mainly associated with short-lived information shocks or more persistent fundamental adjustments.

This methodological separation is important for carbon-market risk analysis because policy news, climate-risk sentiment, and liquidity shocks may be rapidly reflected in short-horizon spillovers, whereas energy-structure adjustment, industrial demand, and compliance-cost expectations may operate over longer horizons. Therefore, the frequency decomposition provides incremental interpretation beyond the time variation captured by TVP-VAR alone. To examine the robustness of the empirical findings, the analysis considers an alternative carbon-market proxy and provides additional frequency-domain evidence under the baseline 1–10 trading-day partition. The detailed formulations of the decomposed oil-price shocks, the climate-risk measure and the spillover indices are given in Equations 1, 2, and 5–30.

3.3.1 Time-domain (DY) spillover index

To analyze the temporal spillovers among climate risks, international crude oil prices, and China's carbon market, this study employs the spillover index framework developed by Diebold and Yilmaz (2012), which is based on generalized forecast error variance decomposition (GFEVD). First, we estimate a -order vector autoregression (VAR) model for the variables as follows:

Specifically, the SVAR framework identifies oil-market innovations by separating unexpected oil price movements into three economically distinct components: supply-side shocks, demand-side shocks, and oil-specific risk shocks.

$$X_t = \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \tag{4}$$

where y_t is an N-dimensional column vector consisting of climate-risk indicators, oil price shocks, and China's carbon-market variables; $\Phi_t(L)$ denotes the time-varying coefficient matrix; and ε_t represents the random error term with covariance matrix Σ_t. The model can be rewritten in moving-average form as $y_t = \sum_{h=0}^{\infty} A_{t,h}\varepsilon_{t-h}$, where $A_{t,h}$ is the MA coefficient matrix at horizon h.

$$(\theta_{\mathrm{H}})_{\mathrm{j,k}} = \frac{\sigma_{\mathrm{kk}}^{-1}\sum_{\mathrm{h=0}}^{\mathrm{H-1}}\left((\mathrm{A_h}\sum)_{\mathrm{j,k}}\right)^2}{\sum_{\mathrm{h=0}}^{\mathrm{H}}\left(\mathrm{A_h}\sum\mathrm{A_h'}\right)}, \tag{5}$$

where Σ_t is the covariance matrix of the error vector ε_t. The generalized forecast-error variance shares can be row-normalized as:

$$\left(\tilde{\theta}_{\mathrm{H}}\right)_{\mathrm{j,k}} = \frac{(\theta_{\mathrm{H}})_{\mathrm{j,k}}}{\sum_{\mathrm{k=1}}^{\mathrm{N}}(\theta_{\mathrm{H}})_{\mathrm{j,k}}}, \tag{6}$$

where $\sum_{j=1}^{N}(\tilde{\theta}_H)_{j,k} = 1$, $\sum_{i,j=1}^{N}(\tilde{\theta}_H)_{j,k} = N$.

Accordingly, the total spillover index TCI, the directional spillover indices FROM and TO, and the net spillover index NET can be calculated as follows:

$$\mathrm{S^H} = \frac{\sum_{\mathrm{k,j=1;k\neq j}}^{\mathrm{N}}\left(\tilde{\theta}_{\mathrm{H}}\right)_{\mathrm{j,k}}}{\mathrm{N}} \times 100, \tag{7}$$

$$C_{j\cdot}^{H} = \sum_{k=1;k\neq j}^{N}\left(\tilde{\theta}_H\right)_{j,k} \times 100 \tag{8}$$

$$C_{\cdot j}^{H} = \sum_{k=1;k\neq j}^{N}\left(\tilde{\theta}_H\right)_{k,j} \times 100 \tag{9}$$

$$C_{j,\mathrm{net}}^{H} = C_{\cdot j}^{H} - C_{j\cdot}^{H} \tag{10}$$

In the empirical implementation, the TVP-VAR model is estimated using Bayesian recursive updating with forgetting factors. The lag length is set to nlag = 12, which captures approximately two trading weeks of information transmission while avoiding excessive parameter proliferation. The forecast horizon is set to nfore = 200, following the connectedness literature and ensuring that the generalized forecast-error variance decomposition captures persistent volatility responses. The forgetting factors are set to kappa1 = 0.99 and kappa2 = 0.99, implying gradual parameter updating and allowing the model to reflect structural changes without overreacting to short-lived noise.

These parameter settings correspond to an exponentially weighted dynamic updating mechanism: recent observations receive higher weights, while the influence of earlier information decays gradually. The same TVP-VAR parameter settings are used in the baseline and robustness specifications to ensure comparability across carbon-market proxies and frequency partitions.

3.3.2 Frequency domain (BK) spillover index

To analyze spillover effects across different frequency bands, this study adopts the approach of Baruník and Křehlík (2018), representing the spectral properties of the series y_t using a frequency response function:

$$A(e^{-\mathrm{i}\omega}) = \sum_{h} e^{-\mathrm{i}\omega\mathrm{h}}A_h \tag{11}$$

In the frequency domain ω, the spectral density of X_t is:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E\left(x_t x_{t-h}'\right)e^{-\mathrm{i}\omega\mathrm{h}} = A(e^{-\mathrm{i}\omega})\sum A'(e^{+\mathrm{i}\omega}) \tag{12}$$

where the Fourier transform of A_h yields $A(e^{-iw}), i = \sqrt{-1}$. Therefore, when the frequency domain is ω, the generalized causal spectrum is:

$$(\xi(\omega))_{j,k} \equiv \frac{\sigma_{\mathrm{kk}}^{-1}\left|\left(A(e^{-\mathrm{i}\omega})\sum\right)_{j,k}\right|^2}{(A(e^{-\mathrm{i}\omega}))\sum A'(e^{+\mathrm{i}\omega})_{j,j}} \tag{13}$$

where $(\xi(\omega))_{j,k}$ represents the portion of the variation in variable j at frequency ω that is caused by the impact of variable k. Thus, the weighting function is:

$$\Gamma_{\mathrm{j}}(\omega) = \frac{\left(\mathrm{A}(\mathrm{e}^{-\mathrm{i}\omega})\sum\mathrm{A}'(\mathrm{e}^{+\mathrm{i}\omega})\right)_{\mathrm{j,j}}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left[\mathrm{A}(\mathrm{e}^{-\mathrm{i}\lambda})\sum\mathrm{A}'(\mathrm{e}^{+\mathrm{i}\lambda})\right]_{\mathrm{j,j}}\mathrm{d}\lambda} \tag{14}$$

where $\Gamma_j(\omega)$ denotes the power of variable j at frequency ω. Thus, the contribution of variable k to the variance of prediction error for variable j in the frequency band $d = (a, b), a, b \in (-\pi, \pi), a < b$ is:

$$(\theta_{\mathrm{d}})_{\mathrm{j,k}} = \frac{1}{2\pi}\int_{\mathrm{d}}\Gamma_{\mathrm{j}}(\omega)[\xi(\omega)]_{\mathrm{j,k}}\,\mathrm{d}\omega, \tag{15}$$

Where $(\theta_\infty)_{j,k} = \frac{1}{2\pi}\int_{-\pi}^{\pi}\Gamma_j(\omega)[\xi(\omega)]_{j,k}\,\mathrm{d}\omega$ equals $(\theta_H)_{j,k}$ at $H \to \infty$ in the time domain. Normalizing $(\theta_d)_{j,k}$:

$$\left(\tilde{\theta}_{\mathrm{d}}\right)_{\mathrm{j,k}} = \frac{(\theta_{\mathrm{d}})_{\mathrm{j,k}}}{\sum_{\mathrm{k}}(\theta_{\infty})_{\mathrm{j,k}}}, \tag{16}$$

where $(\tilde{\theta}_d)_{j,k}$ measures the level of spillover effect from variable k to variable j in the frequency band d.

Accordingly, within the frequency band d, the total spillover index (S^d), the directional spillover indices ($C_{j\cdot}^d$ and $C_{\cdot j}^d$), and the net spillover index ($C_{j,\mathrm{net}}^d$) are defined as follows:

$$\mathrm{S^d} = \frac{\sum_{\mathrm{k,j=1;k\neq j}}^{\mathrm{N}}\left(\tilde{\theta}_{\mathrm{d}}\right)_{\mathrm{j,k}}}{\mathrm{N}} \times 100, \tag{17}$$

$$C_{j\cdot}^{d} = \sum_{k=1;k\neq j}^{N}\left(\tilde{\theta}_d\right)_{j,k} \times 100 \tag{18}$$

$$C_{\cdot j}^{d} = \sum_{k=1;k\neq j}^{N}\left(\tilde{\theta}_d\right)_{k,j} \times 100 \tag{19}$$

$$C_{j,\mathrm{net}}^{d} = C_{\cdot j}^{H} - C_{j\cdot}^{H} \tag{20}$$

The frequency-domain spillover framework extends the time-domain connectedness measure by decomposing overall spillovers into different investment horizons. Specifically, it identifies whether volatility transmission mainly occurs in the short term or persists over longer horizons.

For the baseline frequency-domain decomposition, the short-term band is defined as 1–10 trading days and the long-term band as fluctuations beyond 10 trading days (i.e., >10 days). This setting corresponds approximately to one trading week and is consistent with the logic of separating high-frequency market noise and short-lived information shocks from lower-frequency trend components (Baruník and Křehlík, 2018; Rostan and Rostan, 2018; Wang et al., 2017). The legend of Figure 1 is aligned with this baseline definition

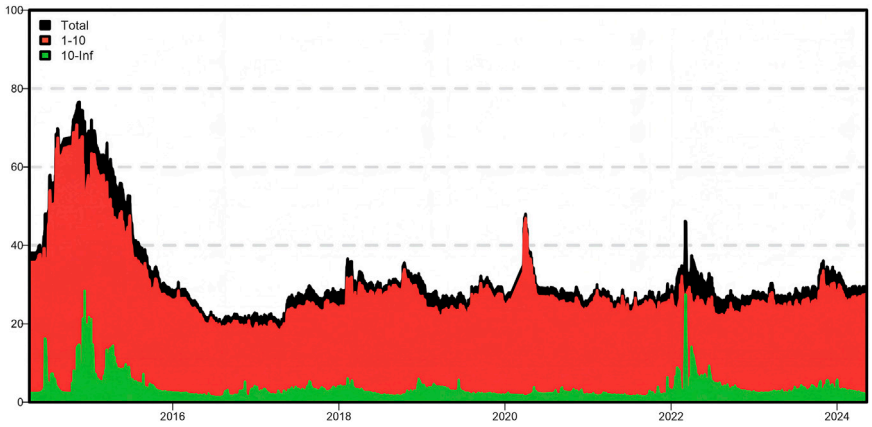


FIGURE 1
Dynamic total spillover index.

(1–10 and >10). To examine the robustness of the frequency-domain results, additional evidence based on alternative frequency specifications is reported in Supplementary Appendix C. The alternative partition produces the same central pattern: short-term spillovers remain dominant, climate-risk variables remain important transmitters, and carbon prices continue to behave mainly as risk receivers. The detailed comparison is reported in Supplementary Appendix C.

3.4 XGBoost and SHAP value analysis

3.4.1 Principles of the XGBoost model

The XGBoost algorithm uses CART decision trees as base learners (Chen and Guestrin, 2016). By employing a boosting mechanism, multiple weak learners are sequentially combined to form a high-accuracy strong learner. Each weak learner is added iteratively using a greedy strategy, with the model progressively minimizing the prediction residuals of previous iterations. The predicted value $\hat{y}_i$ for the i th sample generated by the XGBoost model can be expressed as:

$$\hat{y}_i = \sum_{m=1}^{M} f_m(x_i) \tag{21}$$

Here, f_k denotes the prediction of the k-th weak learner for the i-th sample, while $\hat{y}_i$ represents the final ensemble prediction obtained by summing the outputs of all weak learners. All base learners are optimized with respect to an objective function L, which consists of a loss function $l(y_i, \hat{y}_i)$ and a regularization term $\Omega(f_m)$. The loss function quantifies the discrepancy between the true target value y_i and the predicted value $\hat{y}_i$, while the regularization term penalizes model complexity to prevent overfitting. The objective function and the regularization term $\Omega(f_m)$ can be expressed as:

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{m=1}^{M} \Omega(f_m) \tag{22}$$

$$\Omega(f_m) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{23}$$

Here, T denotes the number of leaf nodes in the tree, w_j represents the weight of the j-th leaf node, and γ and λ are regularization parameters that control the penalty strength of the regularization term., w_j represents the weight of the j -th leaf node, and γ and λ are regularization parameters that control the penalty strength of the regularization term.

After incorporating the first m weak learners, the objective function can be expressed as:

$$L^m = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{m-1} + f_m(x_i)) + \Omega(f_m) \tag{24}$$

Unlike a conventional VAR model with fixed coefficients, the TVP-VAR framework allows the transmission relationship among variables to evolve over time, which is suitable for capturing changing spillover patterns under different market conditions.

By applying a second-order Taylor expansion to Equation 4 to approximate the loss function, the objective function can be rewritten as:

$$L^m = \sum_{i=1}^{n} \left[g_i f_m(x_i) + \frac{1}{2} h_i f_m(x_i)^2 \right] + \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \left(w_j^m\right)^2 \tag{25}$$

$$g_i = \frac{\partial l(y_i, \hat{y}_i^{m-1})}{\partial \hat{y}_i^{m-1}} \tag{25 - 1}$$

$$h_i = \frac{\partial^2 l(y_i, \hat{y}_i^{m-1})}{\partial \hat{y}_i^{2(m-1)}} \tag{25 - 2}$$

In this formulation, I_j denotes the j-th leaf node, and G_j and H_j are defined as the sum of the first- and second-order gradients over the instance set assigned to leaf j. Consequently, the objective can be simplified as follows:

$$L^m = \sum_{j=1}^{T} \left[G_j w_j + \frac{1}{2}\left(H_j + \lambda\right)\left(w_j^m\right)^2 \right] + \gamma T \tag{26}$$

It can be seen that the objective function is quadratic with respect to w_j. The optimal leaf weight w_j^* and the corresponding optimal objective value are given by:

$$w_j^m = -\frac{G_j}{H_j + \lambda} \tag{27}$$

$$L^m = -\frac{1}{2}\sum_{j=1}^{T}\frac{G_j^2}{H_j + \lambda} + \gamma \mathrm{T} \tag{28}$$

During training, a greedy algorithm is employed, where all feasible splitting points are enumerated to evaluate potential splits. The model calculates the reduction in loss for each candidate split and selects the leaf node that maximizes the gain. The gain G is computed as follows:

$$G = \frac{1}{2}\left[\frac{(G_L)^2}{H_L + \lambda} + \frac{(G_R)^2}{H_R + \lambda} - \frac{(G)^2}{H + \lambda}\right] - \gamma \tag{29}$$

where I_L and I_R represent the sets of instances assigned to the left and right branches after splitting, respectively, and G_L, H_L (G_R, H_R) are the corresponding gradient sums.

This study uses XGBoost-SHAP as a post-estimation predictive framework for nonlinear feature contributions to spillover intensity. Because the dependent variables are time-series connectedness measures constructed from the TVP-BK model rather than directly observed economic variables, random five-fold cross-validation is used only as a preliminary tuning reference, while blocked five-fold validation is used as the main time-respecting validation strategy. The SHAP values are interpreted as predictive feature contributions, not causal effects.

This positioning clarifies the relationship between the econometric and machine-learning components. The TVP-BK model is responsible for estimating dynamic and frequency-specific spillover indices, while XGBoost-SHAP is applied afterward to examine which macro-financial and policy-related variables help predict changes in those constructed indices. Thus, the machine-learning analysis complements the econometric spillover analysis by revealing nonlinear predictive patterns; it does not replace structural identification or establish causal mechanisms.

Therefore, the SHAP results should be interpreted as nonlinear feature-association evidence regarding spillover intensity rather than causal estimates of the determinants of connectedness.

3.4.2 SHapley additive exPlanations (SHAP) model interpretation

SHAP, rooted in game theory (Lundberg and Lee, 2017), is a widely used method for interpreting machine learning model predictions. By quantifying the contribution of each input feature to the model's output, SHAP enhances the interpretability and transparency of complex models. In this study, XGBoost models were constructed to explain the short- and long-term total spillover indices. SHAP was then applied to identify the global importance of macroeconomic, financial, liquidity, policy-uncertainty, and geopolitical variables in shaping spillover intensity. The SHAP results are interpreted as nonlinear association-based feature contributions rather than causal marginal effects.

$$\varphi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!}\left(\nu(S \cup \{i\}) - \nu(S)\right) \tag{30}$$

Here, F denotes the complete set of features, $S \subseteq F\backslash\{j\}$ represents any subset of features excluding feature j, and $|S|$ is the number of features in subset S. The term $f_S(x_S)$ is the model prediction using only the features in S, while $f_{S\cup\{j\}}(x_{S\cup\{j\}})$ is the prediction when feature j is also included. The difference between these two predictions measures the marginal contribution of feature j, and the SHAP value ϕ_j is the weighted average of this marginal contribution over all subsets S.

4 Empirical results analysis

4.1 Static spillover index

It should be noted that although China's national ETS was launched in 2021, its initial sectoral coverage and market activity were relatively limited. Meanwhile, the Guangdong ETS has continued to operate independently with active trading. In addition, the TVP-VAR framework adopted in this study allows for gradual time variation in model parameters, thereby capturing potential changes in market dynamics associated with institutional developments over the sample period. This study incorporates oil price shocks, carbon prices, and climate risk indices into the TVP-VAR model for estimation. Based on this framework, the short-term and long-term volatility spillover relationships among the variables are derived at each time point. Table 1 presents the static time-domain total spillover effects, while Table 2 reports the frequency-domain total spillover effects. The results indicate significant heterogeneity in volatility spillover intensity across short-term and long-term horizons. Notably, the short-term TCI reaches 24.91, whereas the long-term TCI is only 5.30, nearly five times lower. This suggests that the connectedness among the three variables is predominantly driven by short-term spillovers, consistent with the findings of Chen et al. (2022) and Zhang Z. et al., 2025. More importantly, the Hubei robustness test confirms that the key static conclusions are not specific to Guangdong: short-term connectedness remains substantially stronger than long-term connectedness, and carbon prices retain a net risk-receiving role in the alternative pilot market.

Previous studies have also observed that the volatility spillover intensity of financial assets is generally higher in the short term than in the long term. This heterogeneity arises from differences in underlying drivers. Short-term connectedness mainly reflects rapid portfolio adjustments and abnormal shifts in investor sentiment (Chen et al., 2022; Yu and Wang, 2026; Zhang and Chen, 2024). Fluctuations in oil price shocks and climate risks can quickly propagate to the carbon market via changes in investor sentiment, producing pronounced spillover effects. Such "irrational sentiment transmission" and "resonance of trading behaviors" substantially amplify the connectedness among variables. In contrast, at longer-term frequencies, the macroeconomic system exhibits greater self-regulatory capacity. Firms can reduce reliance on carbon prices through low-carbon technological innovations, mitigate oil shock impacts via supply chain restructuring, and smooth risk exposures using hedging instruments such as climate insurance and carbon futures. Consequently, the market gradually returns toward fundamental equilibrium, with carbon price fluctuations increasingly reflecting intrinsic factors. This dampens risk transmission channels and leads to a marked decline in overall connectedness (Zhang T et al., 2025).

TABLE 1 Total Spillover effects in the Frequency Domain.

Short term	RS	DS	SS	Carbon	TRI	PRI	From
RS	59.00	5.09	5.52	3.04	4.98	5.54	24.17
DS	5.36	57.96	5.73	3.24	5.05	5.83	25.20
SS	4.04	6.24	61.73	3.26	4.21	5.61	23.37
Carbon	3.78	3.46	2.99	59.37	4.90	4.87	20.00
TRI	4.08	3.92	4.04	3.65	54.51	11.75	27.43
PRI	4.33	5.21	4.14	4.11	11.49	54.07	29.28
TO	21.59	23.92	22.42	17.30	30.64	33.60	149.46
NET	−2.58	−1.28	−0.96	−2.71	3.21	4.31	TCI = 24.91
Long-term							
RS	12.60	1.17	0.81	0.56	0.90	0.80	4.23
DS	1.17	11.70	0.84	0.65	1.34	1.14	5.14
SS	0.64	1.09	10.63	0.54	1.29	0.71	4.27
Carbon	0.78	1.09	1.11	15.13	1.40	1.12	5.50
TRI	0.98	0.83	0.96	0.52	11.91	2.86	6.15
PRI	0.75	0.86	1.01	0.58	3.34	10.12	6.53
TO	4.32	5.03	4.73	2.85	8.27	6.62	31.82
NET	0.09	−0.10	0.45	−2.65	2.12	0.09	TCI = 5.30

Furthermore, examining the net spillover index (NET) reveals that the carbon market primarily functions as a net receiver of risks, whereas climate risks serve as the main net transmitters. Specifically, the NET values for carbon prices are −2.71 in the short term and −2.65 in the long term, indicating a consistently net receiving status. Carbon prices are influenced not only by the energy substitution effects of oil supply and DS but also by fluctuations in climate policies (transition risk, TRI) and extreme weather events (physical risk, PRI). In contrast, transition risk (TRI) consistently acts as a net transmitter, with NET values of 3.21 in the short term and 2.12 in the long term. This reflects the persistent impact of long-term trends, such as stricter carbon neutrality policies and energy structure transformation, on carbon prices and oil demand. For physical risk (PRI), the short-term NET value reaches 4.31, indicating strong net spillover, but declines sharply to 0.09 in the long term, approaching neutrality. This discrepancy arises because short-term extreme weather events exert sudden shocks on energy infrastructure and emission reduction costs, whereas in the long term, the market can adapt through measures such as infrastructure upgrades (e.g., flood control and high-temperature–resistant facilities) and industrial restructuring, thereby mitigating transmission effects. Additionally, the NET values of oil DS and SS exhibit short-term net inflows with weak long-term volatility. This suggests that feedback from the oil market to carbon prices and climate risks is predominantly reflected in short-term adaptive adjustments rather than long-term structural drivers.

Examining the spillover effects of different variables on carbon prices reveals that, in the short term, physical climate risk (PRI) and transition climate risk (TRI) shocks exhibit the strongest bilateral volatility spillover to carbon prices, with values of 4.90 and 4.87, respectively. By comparison, the three types of oil price shocks exert relatively smaller impacts, with spillover intensities of 3.78, 3.46, and 2.99. This pattern persists in the long term: the bilateral spillover intensities of TRI and PRI on carbon prices are 1.29 and 0.71, respectively, whereas oil price shocks show values of 0.78, 1.09, and 1.11.

The heterogeneous effects are economically intuitive. TRI is directly connected to expectations about allowance allocation, compliance costs, and regulatory tightening, so transition-risk news can be priced into carbon allowances quickly. PRI mainly

TABLE 2 Total spillover effects across all frequency domains.

Variables	RS	DS	SS	Carbon	TRI	PRI	From
RS	71.60	6.26	6.33	3.60	5.88	6.33	28.40
DS	6.53	69.66	6.57	3.89	6.40	6.96	30.34
SS	4.69	7.33	72.35	3.80	5.50	6.33	27.65
Carbon	4.56	4.55	4.10	74.50	6.30	5.99	25.50
TRI	5.06	4.75	4.99	4.17	66.42	14.61	33.58
PRI	5.08	6.06	5.15	4.69	14.83	64.18	35.82
TO	25.91	28.95	27.14	20.14	38.91	40.22	
NET	−2.50	−1.38	−0.50	−5.36	5.34	4.40	TCI = 30.21

TCI, stands for total spillover effect.

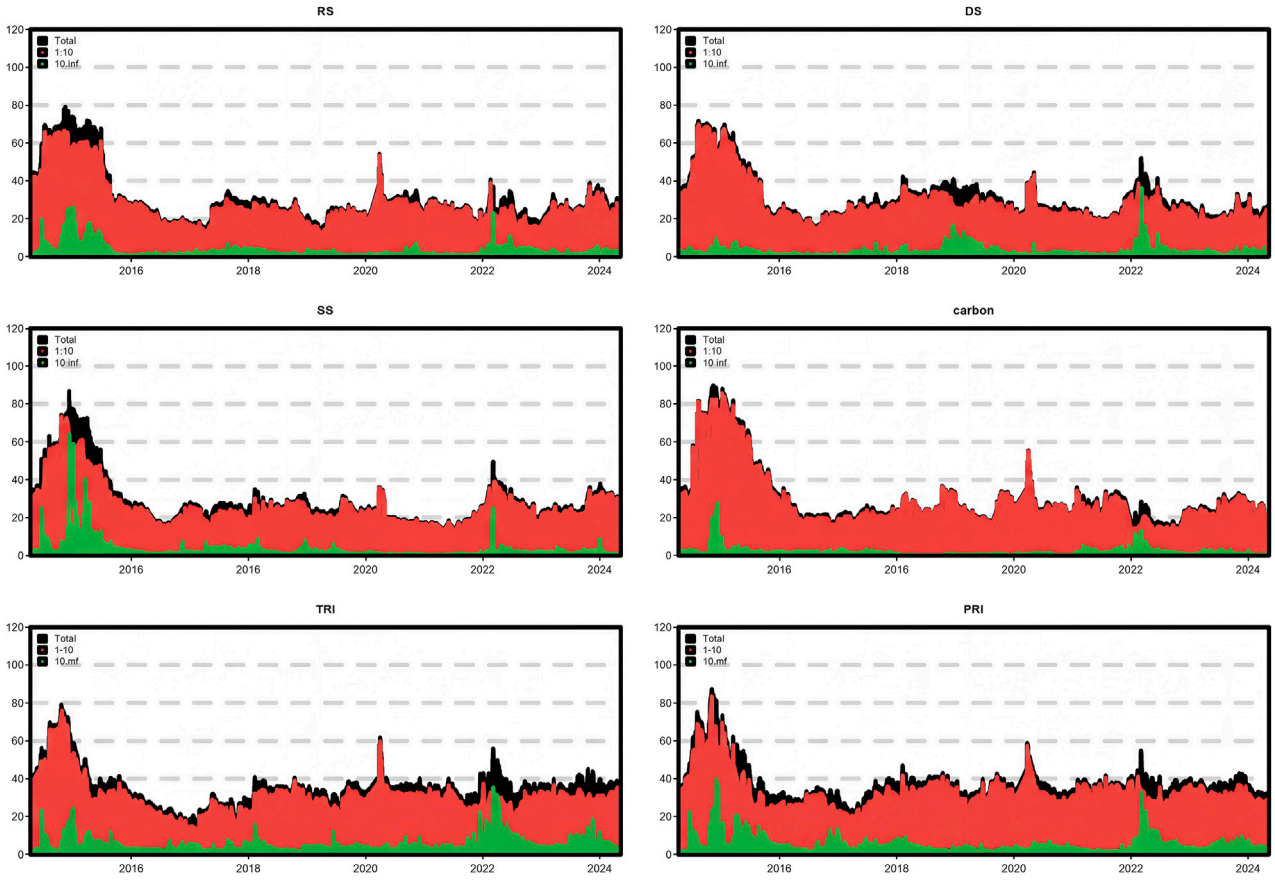


FIGURE 2
Total directional connectedness from others (FROM).

affects carbon prices through physical disruptions to production, electricity demand, and energy infrastructure, which explains its stronger short-term role. Oil risk shocks primarily capture precautionary demand and geopolitical or financial-market sentiment, making their effects more short-lived. By contrast, oil demand and supply shocks are more closely linked to real-economy fundamentals and energy-cost pass-through; their influence is therefore more persistent and becomes relatively more visible at lower frequencies.

4.2 Dynamic total spillover

Static spillover effects provide insights into the direction and intensity of interactions among carbon prices, oil price shocks, and climate risks; however, they do not capture the time-varying nature of inter-market spillovers. To examine the dynamic spillover effects over time, this study presents the results of the dynamic total spillover (TCI) among carbon prices, oil price shocks, and climate risks in both the time and frequency domains, as shown in Figure 1. The time series plot illustrates that spillover effects exhibit pronounced time-varying characteristics and frequency-domain heterogeneity. Notably, peaks in spillover intensity are closely associated with major policy events and RS.

In the short term, total spillover intensity generally exceeds the long-term counterpart and displays considerably higher volatility. During extreme climate and financial market events, the connectedness between variables tends to intensify. For example, following the signing of the Paris Agreement at the end of 2015, global financial markets received stronger signals regarding accelerated transitions away from fossil energy, and the estimated connectedness among oil prices, carbon prices, and climate risks rose accordingly. A plausible explanation is that investors adjusted portfolios in response to transition-policy expectations, reducing exposure to oil-related assets while increasing attention to carbon-related assets; this interpretation is consistent with evidence that portfolio rebalancing strategies can respond rapidly to market information in Chinese asset markets (Yu and Wang, 2026). Similarly, during the COVID-19 pandemic in 2020, disruptions to global supply chains coincided with sharp oil-price movements and expectations of green recovery policies, which may have strengthened the connectedness between carbon prices and climate risks. These interpretations should be understood as event-consistent associations rather than formal causal estimates.

In contrast to short-term spillovers, which are primarily driven by investor behavior and policy expectations, long-term volatility spillovers among variables are shaped by the structural evolution of economic fundamentals and policy frameworks. Around 2022, long-term spillover intensity increased notably, likely reflecting the accelerated global energy transition and heightened physical risks stemming from frequent extreme events amid the Russia-Ukraine

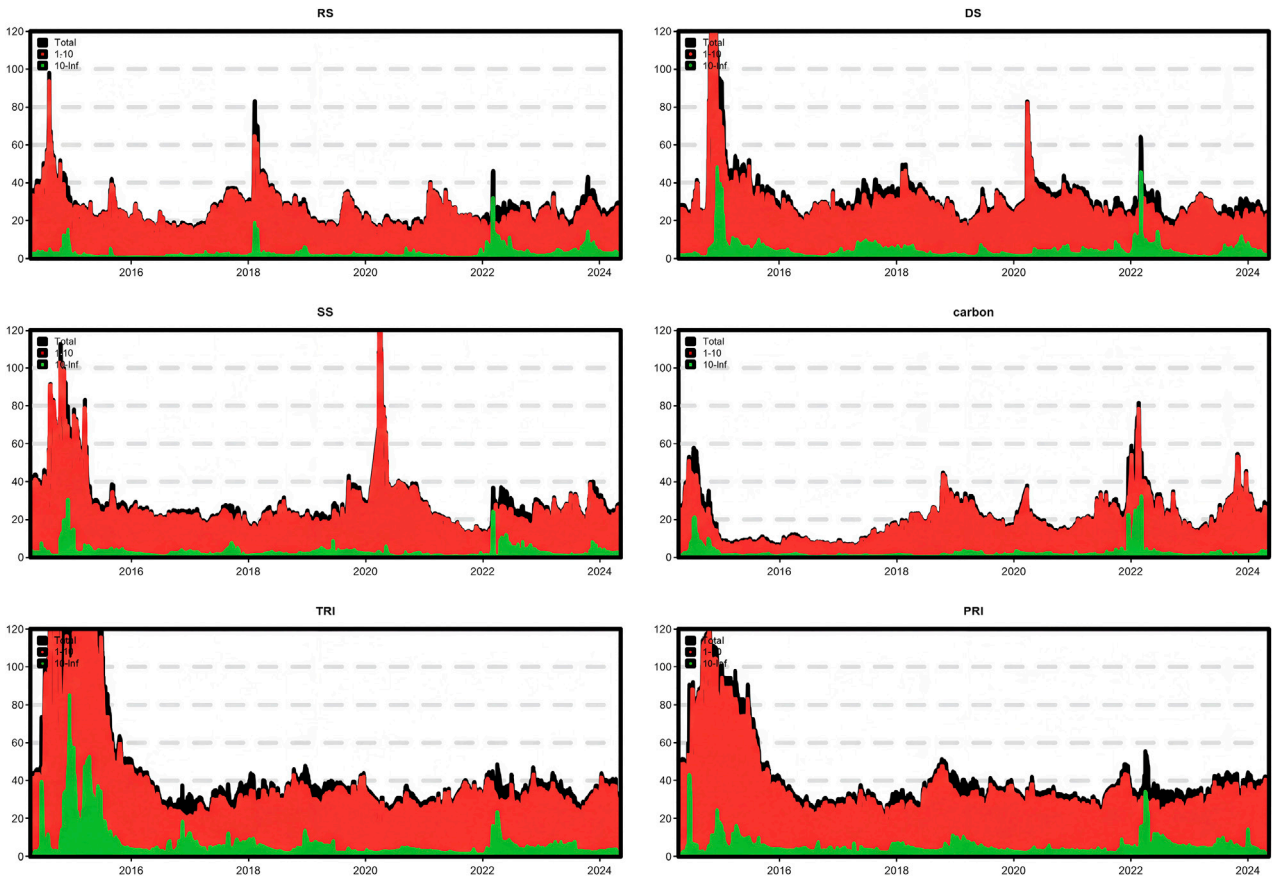


FIGURE 3
Total directional connectedness (TO).

conflict. These developments strengthened the long-term connectedness among oil prices, carbon prices, and climate risks. As the transformation of the energy structure progresses and climate risks cumulatively reshape market fundamentals, oil prices and climate risks are expected to influence carbon prices through mechanisms such as the energy substitution effect over the long term.

To examine the temporal evolution of directional spillovers among various asset price shocks, this study presents directional spillover outflow, inflow, and net spillover indices in Figures 2–4. Between 2015 and 2016, the directional spillover inflow indices of all variables increased substantially, coinciding with the Paris Agreement and stronger global transition-policy signals. From the net-spillover perspective, both PRI and TRI rose markedly during this period, suggesting that climate-risk information became an important transmitter of market connectedness. In early 2018, Guangdong's carbon market experienced adjustments related to paid allowance allocation and stricter industry benchmarking, and the estimated carbon-price spillover indices increased at the same time. During 2020, the COVID-19 pandemic coincided with large oil-price fluctuations and changing climate-policy expectations, while oil demand and supply shocks showed positive net spillovers. In the early stage of the Russia-Ukraine conflict in 2022, disruptions to the global energy landscape were also accompanied by stronger oil-shock spillovers to the carbon market. These event references are used to contextualize visible changes in connectedness and should not be interpreted as isolated causal tests.

The event-related interpretation in this section should be understood as event-consistent association rather than formal causal identification. The Paris Agreement, COVID-19, and the Russia-Ukraine conflict are used as historically meaningful reference points that coincide with visible changes in connectedness, but the TVP-BK framework does not isolate event-specific causal effects.

Similarly, the reported differences between short- and long-term spillovers are interpreted through the magnitude, direction, and robustness of the connectedness indices rather than through conventional coefficient-level significance tests. Because DY/BK spillover indices are constructed from forecast-error variance decompositions, this study avoids overstating statistical significance and emphasizes whether the qualitative patterns remain stable across alternative specifications, including the Hubei proxy and the 1–10 trading-day frequency partition.

4.3 Volatility network structure analysis

To examine the impacts of climate risks and oil price shocks on carbon prices, this study constructs network structure diagrams.

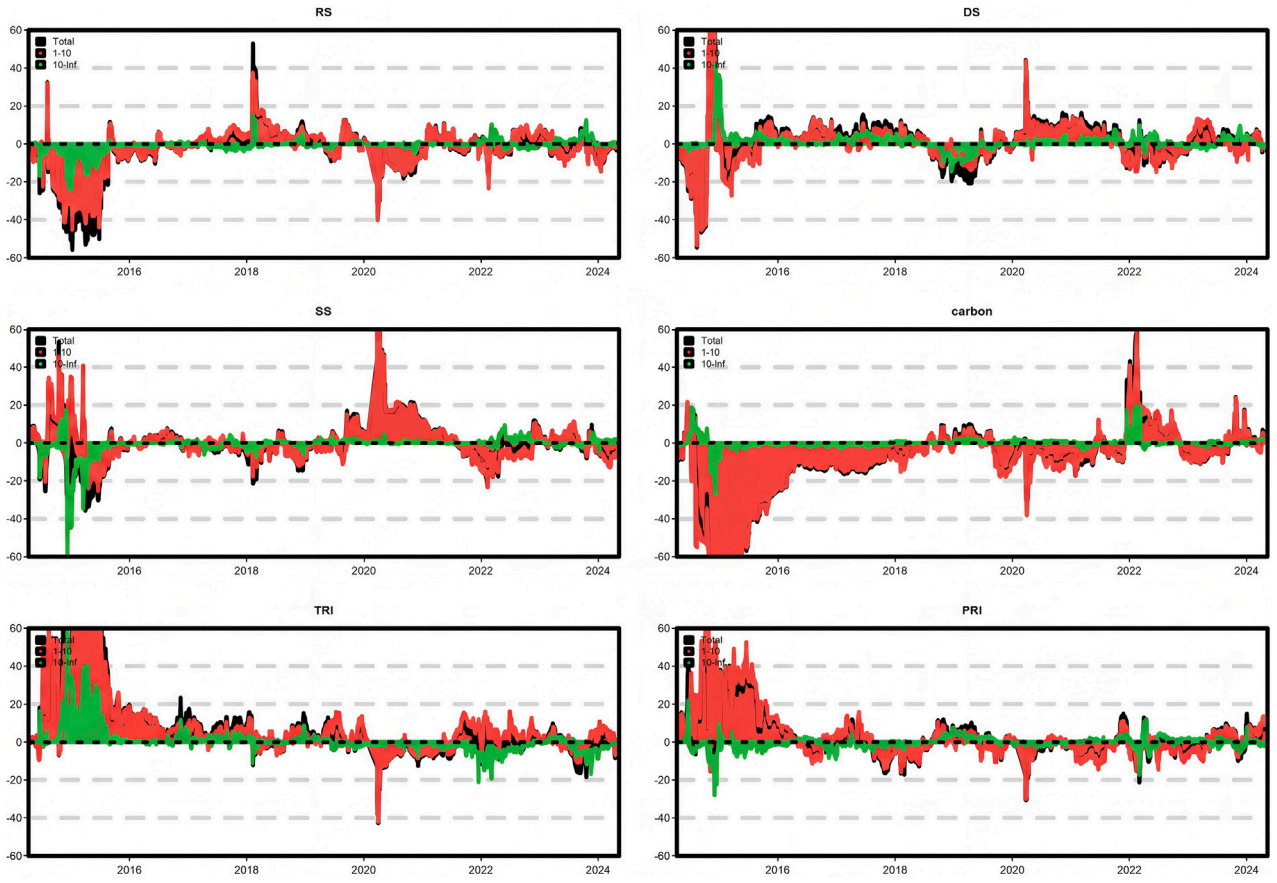


FIGURE 4
Total directional connectedness (NET).

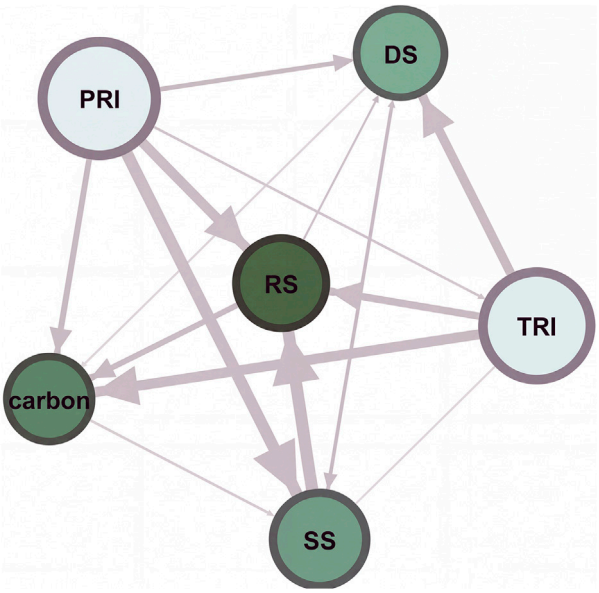


FIGURE 5
Short-term spillover network diagram.

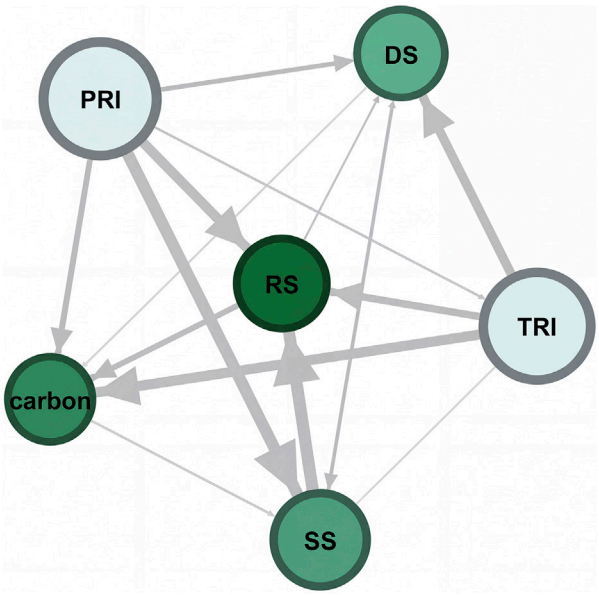


FIGURE 6
Pairwise net directional connectedness.

Following the methodology of Qin et al. (2024), nodes represent oil price shocks, carbon prices, and climate risk indices, while the network is based on bilateral net spillover intensity between variables. The Fruchterman-Reingold algorithm is employed to visualize the weighted directed network. In this representation, the depth of node color reflects the magnitude of the weighted in-degree, and the node radius corresponds to the weighted out-degree. The direction of arrows on the edges indicates the path of volatility spillover, while edge thickness reflects the spillover weight. The resulting short-term and long-term volatility spillover network structures are presented in Figures 5, 6, respectively.

As shown in Figures 5, 6, the volatility spillover relationships among variables differ markedly between short-term and long-term horizons. In the short-term network, nodes representing physical climate risks (PRI) and transition climate risks (TRI) display larger radii and lighter colors, indicating that they act as primary net transmitters of risks. In the long-term network, the TRI node remains relatively prominent, highlighting the persistent role of transition-risk information in shaping long-horizon spillover transmission.

Across both horizons, the carbon price node consistently exhibits a relatively small radius and dark color, suggesting that carbon prices are highly susceptible to spillover effects from other variables. In the short term, directed edges from oil RS and TRI to carbon prices are wider, emphasizing the need to closely monitor their short-term volatility spillover effects. In the long term, TRI, PRI, and oil supply and DS all exert significant spillover effects on carbon prices, whereas the bilateral net effect of oil RS on carbon prices is comparatively smaller. This indicates that, over the long run, greater attention should be directed toward the combined impacts of oil supply, oil demand, and climate risks on carbon prices. In the long-term horizon, asset volatility is more strongly influenced by macroeconomic conditions and fundamental factors, which explains why the effects of oil supply and DS remain prominent while the influence of oil RS diminishes This pattern is economically intuitive: carbon allowances are policy-created assets whose short-run price discovery is sensitive to external energy shocks and climate-policy news, while their long-run adjustment is constrained by allowance allocation rules, compliance cycles, and regulatory expectations.

4.4 Post-estimation determinants of total spillover intensity

Previous studies have primarily focused on the risk spillover relationships and transmission mechanisms among different variables, but have paid limited attention to the underlying determinants of total spillover intensity. Changes in total spillover intensity reflect the overall level of inter-market risk transmission, making the identification of its drivers highly valuable for investors in asset allocation and policymakers in financial supervision. In this study, the time-varying total spillover intensity is set as the dependent variable. A comprehensive time-series feature set encompassing multiple categories of indicators, including macroeconomic variables, financial market factors, and policy uncertainty, is constructed, and machine learning methods are applied to examine the relative contributions of each variable to total spillover intensity. Unlike previous studies that primarily use linear models and focus on the marginal effects of individual variables, this study utilizes the XGBoost model in combination with SHAP value analysis. This approach allows for the simultaneous characterization of nonlinear relationships and synergistic effects among variables within a unified framework, providing a more comprehensive identification of the core factors influencing volatility spillover intensity.

To select the drivers affecting the time-varying spillover intensity among oil price shocks, carbon prices, and climate risks, this study constructs a feature variable system spanning four dimensions: policy and sentiment, macroeconomic fundamentals, market liquidity, and geopolitics. First, from the perspective of policy uncertainty and investor sentiment, prior research indicates that uncertainties in climate and economic policies can amplify connectedness and volatility transmission among energy asset prices. Accordingly, the study incorporates the EPU Indices of the United States and China (EPU_US, EPU_CN), the Chinese CPU index (CPU_CN), and the investor sentiment index (ISI) as proxies. Second, for macroeconomic fundamentals, economic growth and inflation influence the dynamic connectedness of energy and carbon markets through demand expectations and price levels. Thus, China's purchasing managers' index (PMI_CN) and the year-on-year growth rate of the consumer price index (CPI_CN) are included to represent economic activity and inflation, respectively. Third, with respect to market liquidity, liquidity conditions affect investors' risk preferences and asset allocation behaviors, thereby shaping the connectedness between oil and carbon prices. The 10-year government bond yield (y10) and the year-on-year growth rate of broad money supply (M2) are selected as proxies for liquidity and financial conditions. Financial innovation and policy-driven changes in consumption can also affect macro-financial expectations and liquidity transmission, as shown by evidence from China's e-CNY pilot (Jiang and Yuan, 2026). Finally, considering the impact of major international events such as the Russia-Ukraine conflict on the global energy landscape and asset correlations, China's geopolitical risk index (GPR_CN) is included as a potential external shock variable. The selection rationale and detailed descriptions of each indicator are summarized in Table 3.

Figures 7, 8 present the SHAP summary results for the feature variables corresponding to short-term and long-term total spillover intensity, respectively. Overall, the most important predictive variables for both horizons show notable similarities: exchange rate levels, EPU indices, and liquidity indicators emerge as the main contributors to the model's predicted spillover intensity. These results are interpreted as nonlinear predictive associations rather than causal estimates, which is consistent with the post-estimation role of the XGBoost-SHAP framework.

From both short-term and long-term perspectives, the RMB exchange rate is the primary determinant of total spillover intensity. As a crucial channel for external financial shocks, exchange rate fluctuations not only modify the domestic currency-denominated costs of energy prices priced in US dollars but also influence domestic asset price connectedness through international capital flows. The role of exchange-rate adjustment is consistent with recent evidence on oil-price effects on real exchange-rate dynamics (Charles, 2025). Changes in the RMB exchange rate prompt international investors to adjust their holdings of RMB-denominated assets, thereby affecting the sensitivity of carbon

TABLE 3 Selection of potential predictors of TCI.

Variable names	Meanings	Measurement methods	Data sources
Exr	RMB exchange rate	RMB/USD exchange rate	Invest.com
y10	Long-term interest rates	10-year treasury yield	
M2	Broad money supply	Year-on-year growth rate of M2	
ISI	Investor sentiment index	ISI index	CSMAR
PMI_CN	Economic growth rate	Manufacturing sentiment indicators	
inf_CN	Inflation rate	Year-on-year CPI growth rate	
GPR_CN	Geopolitical risk index	GPR geopolitical risk	policyuncertainty.com
EPU_US	U.S. economic policy uncertainty	The United States EPU index	
EPU_CN	China's economic policy uncertainty	China EPU index	
cpu_CN	Climate policy uncertainty index	China CPU index	cnefe.com

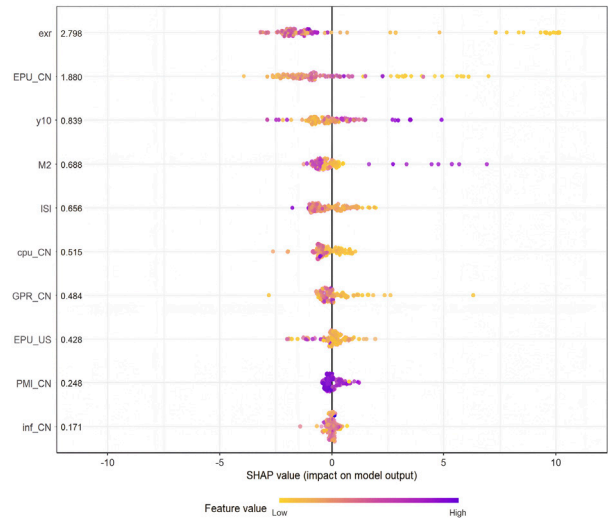


FIGURE 7
Variable importance analysis for short-term total spillover index.

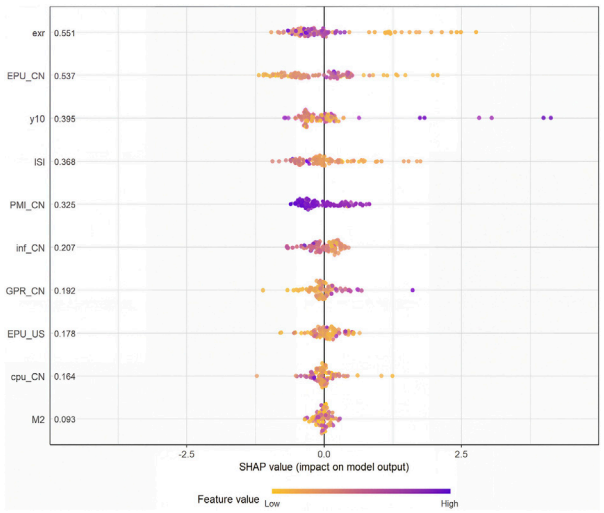


FIGURE 8
Variable importance analysis for long-term total spillover index.

prices to oil prices and climate risks. EPU_CN also demonstrates high importance, reflecting the dominant role of macroeconomic policy orientation in shaping market expectations. Rising policy uncertainty increases market participants' risk aversion, simultaneously amplifying volatility in energy and carbon markets. Compared with other countries, the development of China's carbon market is more influenced by macroeconomic policy than by individual climate policies. Its price formation mechanism depends not only on supply and demand but also on a combination of macroeconomic regulation, industrial policies, and other regulatory measures (Broadstock and Cheng, 2019; Zhang et al., 2020). In addition, the long-term interest rate (y10) plays a systematic role: increases in interest rates raise capital costs and tighten financial conditions, further amplifying inter-market risk spillover effects (Broadstock and Cheng, 2019).

The impacts of the manufacturing prosperity index (PMI_CN) and the inflation rate (INF_CN) differ across short-term and long-term horizons. In the long-term total spillover intensity model, PMI_CN and INF_CN rank as the fifth and sixth most important variables, respectively. In contrast, their importance declines markedly in the short-term model, where they rank ninth and 10th. This finding suggests that macroeconomic fundamentals primarily influence market connectedness through long-term channels, with fluctuations in the real economy serving as a fundamental driver of risk resonance in energy and carbon markets. Conversely, in the short term, total spillover intensity is more sensitive to external financial shocks and changes in policy expectations, while the influence of macroeconomic fundamentals is comparatively weaker (Vo and Nguyen, 2024) This horizon-specific result supports the economic mechanism that high-frequency spillovers are more strongly driven by financial and expectation variables, whereas lower-frequency connectedness is more closely linked to real-economy fundamentals.

4.5 Robustness checks

To strengthen the empirical support for the main conclusions, this study conducts three robustness checks. First, replacing Guangdong with Hubei carbon prices yields the same qualitative pattern: short-term connectedness is much stronger than long-term connectedness, and carbon prices remain mainly net risk receivers. The Hubei-based short-term cTCI/TCI is 30.30%/25.25%, compared with 5.98%/4.99% in the long term.

These robustness checks are designed to address three empirical uncertainties: the representativeness of the Guangdong carbon-price proxy, the subjectivity of the baseline frequency cutoff, and the reliability of the machine-learning prediction stage. The checks do not transform the connectedness framework into a causal identification design, but they help assess whether the main empirical patterns are sensitive to reasonable alternative specifications.

Second, as a sensitivity check we re-estimate the frequency-domain system with an alternative short-term band of 1–5 trading days. Short-term connectedness remains substantially larger than long-term connectedness, and climate-risk variables remain important transmitters. Thus, the dominance of short-term spillovers is not an artifact of the baseline 1–10 days cutoff.

Third, XGBoost-SHAP is validated under both random and time-respecting partitions. The blocked five-fold results show lower RMSE and MAE than a regularized linear benchmark for both short- and long-term spillover intensity, supporting the reliability of the nonlinear driver-identification framework and reducing the possibility that the SHAP results are driven by overfitting.

5 Conclusion and policy implications

Against the backdrop of global efforts to combat climate change and China's pursuit of its "dual carbon" goals, carbon prices have emerged as a critical indicator for assessing emission reduction progress and market expectations. As a key traditional energy source, oil influences the carbon market through price fluctuations, which affect energy structures and production costs. Simultaneously, intensifying climate risks, both physical and transition, alter market expectations and contribute to carbon price volatility.

Systematically examining the mechanisms through which oil prices and climate risks affect carbon prices is therefore essential for improving the carbon trading market, optimizing the energy structure, and promoting low-carbon economic development. This study employs the TVP-BK spillover index method to analyze the volatility spillover relationships among three types of oil price shocks, climate risks, and carbon market prices across different frequency domains. Building on this, the XGBoost-SHAP model is used to identify the core driving factors behind the time-varying volatility spillover intensity. The main findings are as follows:

First, substantial volatility spillover effects exist among oil price shocks, carbon prices, and climate risks. Carbon prices predominantly act as net receivers of risks, while climate risks function as net transmitters. Frequency-domain analysis indicates that spillover effects are much stronger in the short term and relatively weaker in the long term. These findings are robust to replacing the Guangdong carbon market with the Hubei carbon market and to redefining the short-term frequency band as 1–5 trading days.

Second, both oil price shocks and climate risks exert notable spillover effects on carbon prices. Physical and transition climate risks display the strongest bilateral spillover intensity, whereas oil price shocks have comparatively smaller effects. Specifically, oil RS play a more prominent role in the short term, whereas oil DS emerge as the most influential factor over the long term.

Third, volatility spillovers demonstrate clear time-varying characteristics and are associated with multiple macro-financial and policy-related predictors. The XGBoost-SHAP analysis identifies the RMB exchange rate, market liquidity, and EPU_CN as the most important feature contributors to time-varying spillover intensity. The validation results further indicate that the nonlinear model provides useful predictive information beyond a regularized linear benchmark, although the SHAP results should be interpreted as feature-contribution evidence rather than causal estimates.

Based on the research findings, this study proposes the following policy recommendations:

First, establish an operational cross-market monitoring dashboard for carbon-market risk. Because short-term spillovers dominate the system, regulators should track high-frequency indicators including oil-risk shocks, transition and physical climate-risk news, RMB exchange-rate movements, long-term interest rates, liquidity conditions, and economic policy uncertainty. These variables can be incorporated into a tiered early-warning framework: when several indicators simultaneously exceed historical thresholds, exchanges and regulators could strengthen margin monitoring, disclose risk alerts, and conduct stress tests on allowance-price volatility.

Second, improve the climate-risk information channel in carbon pricing. Since PRI and TRI exhibit strong spillovers to carbon prices, policymakers should develop standardized disclosure of climate-event exposure, energy-transition plans, and allowance-compliance expectations for covered firms. Regional carbon exchanges could publish periodic climate-risk bulletins that combine physical-risk news, transition-policy signals, and allowance-market liquidity indicators, enabling market participants to distinguish between short-lived sentiment shocks and persistent changes in fundamentals.

Third, integrate macro-financial variables into carbon-market supervision. The XGBoost-SHAP results show that exchange rates, liquidity indicators, and EPU_CN are key determinants of spillover intensity. Therefore, carbon-market regulators should coordinate with macroprudential authorities to include RMB exchange-rate volatility, M2 growth, long-term interest rates, and policy-uncertainty indicators in regular carbon-market risk reports. In operational terms, regulators could set monitoring thresholds for exchange-rate volatility and liquidity deterioration, combine them with carbon-market indicators such as turnover and bid-ask spreads, and trigger pre-announced measures such as risk alerts, additional margin monitoring, liquidity-support arrangements, or temporary stress tests when multiple indicators breach warning bands. AI-supported carbon-emission monitoring and dynamic trading mechanisms may further improve the timeliness of such early-warning systems (Li et al., 2026), while digital financial innovation can influence liquidity conditions and consumption

expectations that enter macro-financial monitoring (Jiang and Yuan, 2026). This would make carbon-market supervision more actionable than a framework based only on allowance prices and trading volume.

Finally, the policy relevance of this study is strongest for emerging carbon markets that operate alongside fossil-energy dependence and increasing climate-risk exposure. The Chinese case suggests that carbon-market governance should not be isolated from energy, financial, and climate-policy systems. However, because the empirical design identifies dynamic connectedness rather than structural causality, these policy recommendations should be viewed as risk-management implications supported by observed spillover patterns and robustness tests.

This study also has limitations. First, the empirical analysis relies on regional pilot carbon markets (Guangdong as baseline, Hubei as robustness check). Regional pilots differ from the national ETS launched in July 2021 in liquidity, sector coverage, and allowance fungibility; therefore the results cannot be automatically extrapolated to the national system. Second, the physical and transition climate-risk indices are constructed from global English-language media and may miss high-frequency domestic regulatory policy swings; China-specific daily climate-risk indices covering the full sample remain scarce. Third, while the Ready (2018) decomposition orthogonalizes oil shocks, the TVP-VAR–BK spillover indices remain reduced-form measures of forecast-error variance shares and do not identify micro-level corporate or trading-desk transmission mechanisms. Fourth, the XGBoost–SHAP stage is a post-estimation predictive association analysis, not a causal identification design. Future research could exploit national-ETS transaction data, China-specific climate-risk measures, external-instrument identification, and formal event-study designs to strengthen causal inference and external validity. Future work should also account for regional and sectoral heterogeneity in carbon-mitigation performance, since mitigation outcomes and policy responses may vary across regions and industries (Liu and Zhou, 2026). Future research could further incorporate transaction-level data from the national ETS and China-specific high-frequency climate-policy indicators to examine institutional transmission mechanisms more precisely.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://policyuncertainty.com/https://data.csmar.com/.

Author contributions

SZ: Writing – original draft, Formal Analysis, Methodology, Conceptualization. JY: Visualization, Data curation, Writing – review and editing, Software.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2026.1888062/full#supplementary-material

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