

Article

How Economic Policy Uncertainty Is Associated with Spillover Networks: A TVP-VAR-DY Analysis of Energy and Carbon Markets

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and/or methodology.

- Develops a TVP-VAR-DY framework embedding economic policy uncertainty in a five-market energy-carbon risk network.
- Identifies real-economy, financial and expectation-sentiment channels associated with time-varying systemic connectedness.

What are the main findings and/or the implications of the main findings?

- Economic policy uncertainty is associated with variation in spillover intensity and transmission pathways across the energy-carbon network.
- Cross-market heterogeneity calls for mechanism-aware and network-oriented regulatory frameworks.

Abstract

This study uses a TVP-VAR-DY connectedness framework to examine dynamic connectedness among economic policy uncertainty, energy markets, and the Guangdong pilot carbon market. By integrating system-wide connectedness, market-level spillovers, and evolving network structures, the analysis captures the time-varying co-movement across the energy-carbon nexus. At the system level, EPU exhibits a time-varying, regime-dependent association with systemic connectedness. Rather than being uniformly associated with stronger connectedness, heightened uncertainty coincides with rapid synchronization during financial stress, whereas under real economy conditions it is associated with more persistent, expectation-related co-movement. At the market level, clear heterogeneity emerges. Coal displays relatively low sensitivity to uncertainty shocks, oil alternates between net directional roles across regimes, natural gas shows strong sensitivity to uncertainty variation, and the carbon market responds more directly to policy and regulatory changes. From a network perspective, net directional roles and pairwise connectedness pathways vary across uncertainty regimes. The findings suggest that EPU is associated not only with changes in the intensity of connectedness but also with time-varying differences in its distribution across markets, highlighting the relevance of network-oriented monitoring frameworks for energy-carbon market stability.

Keywords: economic policy uncertainty; energy markets; carbon market; dynamic connectedness; TVP-VAR-DY; forecast error variance decomposition



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1. Introduction

The global economic and political landscape has become increasingly volatile, driven by intensifying climate risks, geopolitical tensions, trade frictions, and recurring public health crises. These compounding shocks have heightened macroeconomic uncertainty, prompting more frequent and broad-based policy interventions across fiscal, monetary, and industrial domains. Consequently, firms and households face growing challenges in anticipating the timing, scope, and direction of policy shifts. Against this backdrop, Economic Policy Uncertainty (EPU) has been widely recognized as an important source of macroeconomic dynamics [1]. During crises, variations in the intensity and sequencing of policy interventions can prolong shock persistence and intensify cross-market co-movement, thereby increasing instability in energy markets.

Amid this growing uncertainty, the stability of energy markets has emerged as a pressing concern for policymakers and researchers alike. Unlike other asset classes, energy markets are characterized by long production lead times, capital-intensive structures, and pronounced institutional rigidities, rendering price formation highly sensitive to macroeconomic policy regimes and shifts in expectations [2], and making supply-side disruptions particularly consequential for overall market stability [3]. Under high-EPU environments, energy prices are more likely to deviate from their fundamental values [4], as fluctuations increasingly stem from multiple uncertainty sources rather than isolated supply–demand disturbances, thereby amplifying sensitivity to policy signals and expectation revisions [5]. Beyond price dynamics, EPU is also associated with changes in the risk structure of energy markets through production decisions, financial conditions, and market expectations. These changes are associated with stronger cross-market financial linkages and more intensive directional connectedness [6]. Carbon markets exhibit similar sensitivity to policy uncertainty, as their pricing mechanisms depend heavily on regulatory arrangements and policy expectations, and elevated EPU has been shown to amplify both carbon price volatility and compliance cost uncertainty [7]. In such environments, connectedness across energy and carbon markets provides an important channel through which uncertainty-related co-movement may spread throughout the energy system [8]. This connectedness is particularly pronounced during periods of heightened volatility [9]. However, existing studies predominantly rely on fixed-parameter VAR models [10], while rolling-window approaches impose arbitrarily chosen window lengths that may fail to capture smooth structural transitions. These limitations restrict the identification of continuous structural adjustments under evolving EPU regimes. Consequently, how policy uncertainty is associated with the time-varying architecture and intensity of cross-market connectedness remains insufficiently understood.

To address these gaps, the present study makes two contributions. First, we construct a TVP-VAR-DY connectedness framework that incorporates EPU into a dynamic risk network alongside coal, oil, natural gas, and carbon markets using daily data from 2013 to 2022. This configuration enables a comprehensive, system-wide examination of how policy uncertainty is associated with time-varying connectedness across heterogeneous energy assets. Second, the analysis reveals time-varying transmission patterns and changes in network structure across the energy-carbon nexus. The integration of EPU as a network node allows dynamic quantification of its directional connectedness and net directional role relative to energy markets, providing a more complete characterization of uncertainty-related variation in connectedness. By integrating system-wide, directional, and pairwise connectedness measures, the findings provide empirically grounded insights for energy policy coordination and connectedness-based market monitoring.

2. Literature Review

2.1. Economic Policy Uncertainty and Energy Market Dynamics

Economic policy uncertainty has been shown to exert substantial and multifaceted influence on energy markets, with transmission channels extending from carbon pricing mechanisms to fossil fuel trading and energy derivatives. Within China's nascent carbon emissions trading scheme, heightened policy uncertainty significantly amplifies market volatility and generates pronounced asymmetric effects on allowance prices, with distinct uncertainty types affecting prices differently across market regimes [11]. The adverse consequences further extend to environmental performance, as elevated uncertainty substantially undermines carbon emission efficiency across conditional quantiles [12]. Beyond carbon markets, the linkage between policy uncertainty and coal prices has been documented within China's pilot emissions trading systems, where uncertainty shocks propagate concurrently through fossil fuel and carbon pricing channels [13]. At the international level, multi-scale risk connectedness between China's economic policy uncertainty and global crude oil prices has been identified across time-frequency domains, revealing transmission dynamics that vary systematically with investment horizons [14]. Volatility spillovers between international crude oil benchmarks and Chinese energy future markets intensified markedly during periods of extreme uncertainty such as the COVID-19 pandemic, highlighting the vulnerability of energy derivatives to policy ambiguity shocks [15]. These findings collectively underscore that policy uncertainty operates as a significant destabilizing force across diverse energy market segments.

Research on energy market risk effects has expanded beyond a single uncertainty dimension to encompass three distinct analytical perspectives. The climate policy uncertainty perspective emphasizes that uncertainty about future climate regulations constitutes a critical driver of clean energy and energy metal price dynamics, with substantial market connectedness observed during periods of regulatory ambiguity [16], while the destabilizing effects intensify under extreme market conditions as climate policy uncertainty amplifies risk transmission channels [17], and extreme weather events compound these disruptions through physical risk channels that interact with policy ambiguity [18]. The geopolitical risk perspective treats political instability and international conflicts as distinct uncertainty sources that reshape energy market interdependencies, with geopolitical shocks inducing both homogeneous and heterogeneous responses across clean energy metal prices [19], and dynamic spillover patterns confirming that geopolitical risk and climate risk jointly influence energy market structures [20]. The economic policy uncertainty perspective, which constitutes the most extensively examined dimension, has documented that European electricity markets exhibit particular vulnerability to uncertainty shocks with asymmetric transmission patterns across different market states [21], while unconventional monetary interventions amplify uncertainty transmission to commodity returns [22], and the impact of U.S. monetary policy on real oil prices evolves substantially over time [23]. Despite these advances across multiple perspectives, existing investigations have predominantly focused on single markets or limited market combinations [24,25], with the dynamic relationships among energy markets captured primarily through bivariate or trivariate settings that omit the broader system architecture [26]. Consequently, no existing study has simultaneously incorporated coal, crude oil, natural gas, and carbon markets into a unified analytical framework alongside economic policy uncertainty as an integral component of the system-wide risk network.

2.2. Methodological Advances in Connectedness Analysis

Risk spillover measurement has evolved through a diverse set of methodological approaches. Vector autoregression-based variance decomposition was employed to capture

return and volatility spillovers across financial markets [27], and the network topology generalization of this framework further enhanced the flexibility of connectivity measures [28]. Frequency-domain connectivity methods extended the analysis to different time horizons [29], while GARCH-family models, particularly dynamic conditional correlation specifications, were widely adopted for volatility spillover modeling [30]. CoVaR and related tail-risk metrics grounded in quantile regression provided theoretically grounded measures of systemic exposure [31], and time-varying parameter VAR models provided a more flexible framework for dynamic spillover analysis [32]. These methods each serve distinct purposes, yet the TVP-VAR-DY framework has attracted increasing attention due to its simultaneous accommodation of time variation and independence from rolling-window specification.

The TVP-VAR-DY framework integrates time-varying parameter vector autoregression with the generalized forecast error variance decomposition-based spillover index and demonstrates substantial methodological advantages. Compared with fixed-parameter VAR models, this framework effectively captures the time-varying nature of cross-market connectedness; compared with rolling-window approaches, it eliminates the need for predetermined window lengths and thereby avoids estimation bias and information loss associated with window selection; compared with methods relying on prespecified structural breaks, it identifies continuous and gradual parameter evolution rather than discrete regime shifts, thus reflecting structural changes in financial markets more accurately. Originally proposed for macroeconomic analysis, the TVP-VAR model was subsequently combined with time-varying spillover indices to provide a more precise econometric tool for dynamic connectivity measurement. This framework has been applied to the time-varying decomposition of monetary policy transmission [33], the characterization of cross-asset connectivity during the COVID-19 pandemic [34], spillover analysis between green finance and renewable energy markets [35], and risk transmission research along energy futures industry chains [36]. More recently, the dynamic impact of carbon pricing spillovers on green asset prices has also been examined within this framework [37]. These applications demonstrate strong methodological adaptability of the TVP-VAR-DY framework in capturing structural changes and connectedness in financial markets.

Despite the widespread application of the TVP-VAR-DY framework in financial market connectivity research, the existing literature exhibits clear limitations in systematically incorporating economic policy uncertainty alongside multi-energy markets. Current studies can be broadly classified into three categories, each bearing specific shortcomings. The first category examines dynamic spillovers between economic policy uncertainty and individual energy markets [38], yet fails to characterize cross-linkages among coal, oil, natural gas, and carbon markets. The second category investigates risk connectivity across multiple energy markets but treats economic policy uncertainty as an external variable outside the core system rather than incorporating it into the spillover architecture [39]. The third category addresses multiple markets and uncertainty factors through alternative econometric frameworks rather than the TVP-VAR-DY connectedness approach [40], or employs fixed-parameter vector autoregressive models that cannot capture gradual structural evolution [41]. In other words, no existing study simultaneously satisfies all three conditions, namely incorporating economic policy uncertainty as an integral component of the system-wide risk network, constructing a multi-dimensional energy system encompassing coal, oil, natural gas, and carbon markets, and applying the TVP-VAR-DY framework for time-varying spillover analysis. This research gap motivates the present study, which constructs a five-dimensional energy system incorporating economic policy uncertainty to comprehensively examine time-varying connectedness relationships across all markets.

3. Methodology and Data

3.1. Conceptual Channels and Research Hypotheses

Energy markets are becoming increasingly interconnected and financialized. Uncertainty shocks no longer remain confined to individual assets. Instead, they propagate more easily across energy commodities and related financial instruments. This may increase system-wide co-movement across energy markets. EPU may alter firms' investment and production decisions, which can subsequently affect energy supply and demand dynamics. Heightened uncertainty typically prompts firms to delay or scale back investment in exploration, development, and infrastructure. This is especially true for firms operating in upstream and capital-intensive energy sectors. Such delays and reductions serve as a strategy to hedge against policy risk [42,43]. Such investment responses are rarely reflected immediately in market outcomes; instead, they materialize gradually through shifts in supply expectations and price formation processes. At the same time, policy-induced uncertainty tends to disrupt industrial chain coordination, which further aggravates supply–demand imbalances and amplifies the sensitivity of energy prices to external shocks [44,45]. From a financial market perspective, elevated EPU is associated with stronger cross-market linkages, consistent with adjustments in investors' risk appetite and asset pricing behavior. Rising uncertainty is commonly associated with higher risk premia and declining risk tolerance, which trigger portfolio rebalancing and intensify price co-movement and volatility spillovers across energy markets [7]. Uncertainty also operates through the expectation and sentiment channels, whereby collective beliefs are shaped by ambiguity surrounding future policy orientations and macroeconomic conditions. Frequent or opaque policy signals induce synchronized expectation revisions and sentiment-driven trading across markets. Elevated EPU has been widely linked to heightened exchange rate volatility [46] and shifts in inflation expectations [47], which may be reflected in energy prices through expectation-based channels, thereby reinforcing short-term co-movement and volatility clustering [48]. When individual energy markets are affected by EPU shocks through these channels, risks rarely remain localized. Owing to strong production interlinkages, overlapping financial characteristics, and shared macroeconomic exposures, localized disturbances may be associated with broader cross-commodity connectedness [49]. These channels do not operate in isolation. Their interaction may jointly strengthen both the intensity and persistence of cross-market connectedness.

In sum, the real economy channel, financial market channel, and expectation-sentiment channel are complementary pathways. Through these pathways, EPU may be associated with changes in energy market connectedness. Taken together, these mechanisms imply that risk transmission is inherently time-varying and subject to structural change, particularly under heightened uncertainty. Capturing such features requires an econometric framework. This framework must accommodate dynamic interdependence, evolving transmission mechanisms, and robustness to extreme market conditions. This requirement motivates the adoption of a time-varying parameter approach in the subsequent analysis. Figure 1 presents the conceptual framework of the transmission mechanisms, which shows how EPU influences energy market risk through three interrelated pathways: the real economy channel, the financial market transmission channel, and the expectation and sentiment channel.

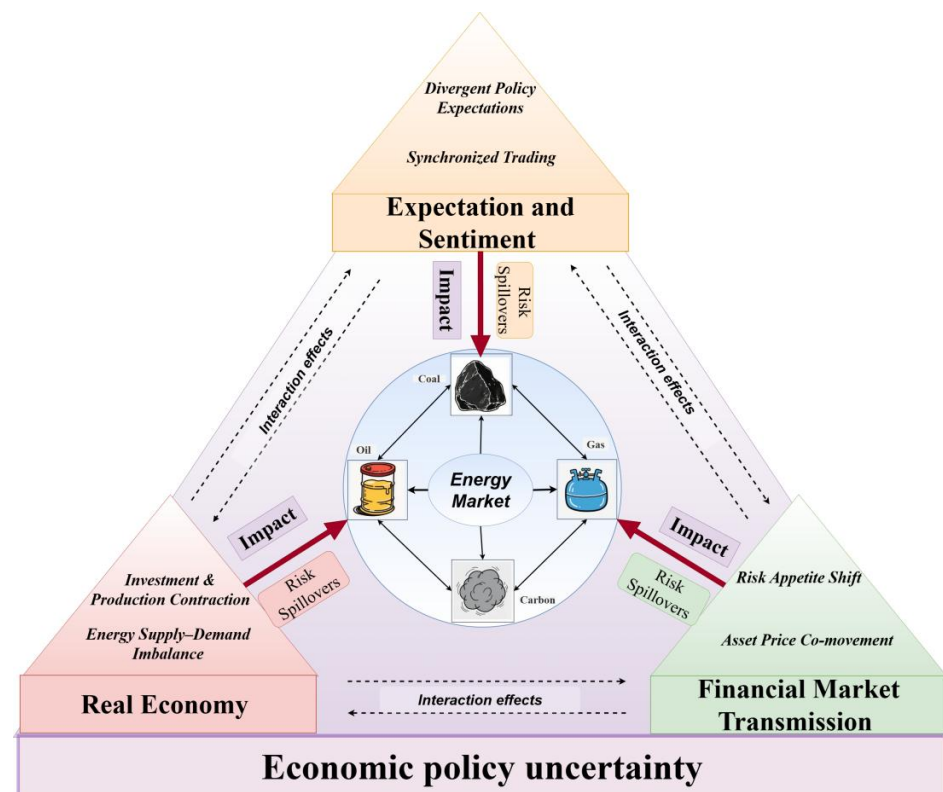


Figure 1. Conceptual channels linking EPU to energy-market connectedness. Note: The double-headed arrows among coal, oil, gas, and carbon markets denote bidirectional risk spillovers within the energy system, while the dashed arrows indicate interaction effects among the three transmission channels.

These channels provide an interpretive framework for the empirical estimates. They are not treated as formally identified causal mechanisms, because the TVP-VAR-DY framework measures predictive connectedness based on forecast error variance decompositions rather than structural causality. Based on the transmission mechanisms outlined above, three testable hypotheses are formulated.

H1: *System-wide connectedness between EPU and the energy–carbon system exhibits time-varying differences across uncertainty regimes.*

H2: *Directional connectedness between EPU and individual energy and carbon markets is heterogeneous, with each market exhibiting distinct net directional roles.*

H3: *The configuration of the connectedness network varies across uncertainty regimes, with event-dependent changes in net directional roles and pairwise connectedness pathways.*

3.2. TVP-VAR-DY Connectedness Framework

To examine dynamic connectedness between EPU, energy markets, and the carbon market, an empirical framework must meet three requirements. It must capture time-varying interdependence among markets. It must quantify the magnitude and direction of cross-market connectedness. It must also identify how these transmission relationships evolve with changing policy regimes and macroeconomic conditions.

Traditional fixed-parameter VAR models assume constant relationships. They cannot track gradual structural adjustments. Rolling-window approaches impose arbitrarily chosen window lengths. They may miss smooth transitions and can introduce estimation

noise. Neither approach systematically distinguishes how cross-market connectedness varies with EPU [50,51]. A more flexible framework is therefore needed. This study constructs a TVP-VAR-DY connectedness framework to address these limitations. The framework integrates a time-varying parameter vector autoregression (TVP-VAR) with the Diebold–Yilmaz (DY) spillover index based on generalized forecast error variance decomposition (GFEVD). The TVP-VAR component captures dynamic dependencies and evolving variance structures. The DY component quantifies the intensity, direction, and evolution of forecast-error variance connectedness. Together, they characterize how net directional roles and pairwise connectedness pathways vary over time.

The dynamic risk connectedness system can be conceptually expressed as Equation (1):

$$C_t = \Phi(EPU_t, Coal_t, Oil_t, Gas_t, Carbon_t) \quad (1)$$

where t denotes the time, C_t is the dynamic connectedness system; $\Phi(\cdot)$ denotes the mapping from the five endogenous variables to the connectedness measures; and EPU_t , $Coal_t$, Oil_t , Gas_t , $Carbon_t$ denote policy uncertainty, coal, oil, natural gas, and carbon market conditions, respectively. In the empirical implementation, $\Phi(\cdot)$ is captured by the TVP-VAR system in Equation (2), where these five variables enter as the endogenous vector $y_t = (EPU_t, Coal_t, Oil_t, Gas_t, Carbon_t)'$; the resulting connectedness measures C_t —including TCI, TO, FROM, NET, and NPDC—are derived from the generalized forecast error variance decomposition of this system, as detailed in Section 3.2.2.

The framework consists of two complementary components implemented sequentially. The first component estimates a TVP-VAR model to obtain time-varying coefficients and variance structures. The second component converts these estimates into a connectedness network via GFEVD and calculates directional, net, and pairwise spillover measures. The following two subsections describe each step in detail.

3.2.1. TVP-VAR Model

Following the connectedness system defined in Equation (1), the empirical specification is estimated using a TVP-VAR framework, which allows both the coefficient matrices and the innovation covariance matrix to evolve over time. The five stationary standardized variables constructed in Section 3.3 enter the system jointly, so that the dynamic dependence among EPU, coal, oil, natural gas, and the Guangdong carbon allowance market can be characterized within a unified framework.

The TVP-VAR model is specified as Equation (2).

$$y_t = A_t z_{t-1} + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma_t) \quad (2)$$

where $z_{t-1} = (y'_{t-1}, y'_{t-2}, \dots, y'_{t-p})'$, $A_t = [A_{1,t}, A_{2,t}, \dots, A_{p,t}]$, and Σ_t denotes the time-varying innovation covariance matrix. Since the standardized input matrix is centered before estimation, no separate intercept term is included.

The endogenous vector is defined as Equation (3).

$$y_t = (EPU_t, Coal_t, Oil_t, Gas_t, Carbon_t)' \quad (3)$$

where EPU and Carbon are standardized logarithmic levels, while Coal, Oil, and Gas are standardized first-order logarithmic differences. This mixed-transformation scheme follows the stationarity results reported in Section 3.3 and is used as the benchmark specification.

For estimation, the model is written in state-space form as Equation (4).

$$y_t = Z_t \beta_t + \varepsilon_t, \beta_t = \beta_{t-1} + v_t, v_t \sim N(0, \Xi_t) \quad (4)$$

where $\beta_t = \text{vec}(A_t)$, $Z_t = I_n \otimes z'_{t-1}$, and Ξ_t denotes the covariance matrix of the coefficient innovations.

The coefficient state is initialized using a zero-mean Minnesota-type diagonal prior, as shown in Equation (5).

$$\beta_0 \sim N(0, V_0), V_0 = \text{diag}(v_1, \dots, v_{pN^2}), v_q = \gamma / \downarrow_q^2 \quad (5)$$

where ℓq denotes the lag order associated with the q -th coefficient and $\gamma = 0.1$. This prior shrinks higher-order lag coefficients more strongly toward zero, while remaining agnostic about the sign of cross-market dependence. The initial innovation covariance matrix is set to the sample covariance matrix of the standardized input data.

The time-varying parameters are estimated recursively, using the Kalman filter with forgetting factors. The coefficient-state covariance and innovation covariance are updated as Equation (6).

$$P_{t|t-1} = \kappa_\beta^{-1} P_{t-1|t-1}, \Sigma_t = \kappa_\Sigma \Sigma_{t-1} + (1 - \kappa_\Sigma) e_t e_t' \quad (6)$$

where P_t is the covariance matrix of the coefficient state, $e_t = y_t - Z_t \beta_{(t|t-1)}$ is the one-step-ahead prediction error, and both forgetting factors are set to 0.99.

Given the Kalman gain, the coefficient state is updated as Equation (7).

$$K_t = P_{t|t-1} Z_t' [Z_t P_{t|t-1} Z_t' + \Sigma_t]^{-1}, \beta_{t|t} = \beta_{t|t-1} + K_t (y_t - Z_t \beta_{t|t-1}) \quad (7)$$

The benchmark model is estimated with two lags and a ten-step-ahead forecast horizon. At each recursive step, the companion matrix is checked for stability. When the maximum eigenvalue modulus exceeds one, the previous companion matrix is retained and the coefficient update is damped, thereby preventing unstable coefficient paths from affecting the connectedness estimates. Over the full sample of 2073 recursive estimation steps, this stability condition was violated in only 2 steps, corresponding to approximately 0.1% of all recursions, indicating that unstable coefficient paths are rare in the present application. All computations are conducted in R version 4.4.3 (R Foundation for Statistical Computing, Vienna, Austria), based on the TVP-VAR connectedness implementation of Antonakakis, Chatziantoniou, and Gabauer, including state-space estimation, generalized impulse-response calculation, forecast error variance decomposition, and connectedness aggregation. The ten-step-ahead horizon corresponds to ten trading days and is used to characterize short-horizon forecast-error variance connectedness. Although the estimated coefficients capture the evolving dependence structure, they do not directly quantify directional connectedness and are therefore transformed in the following subsection.

3.2.2. DY Connectedness Measures

Following the DY connectedness framework, the estimated time-varying coefficient and covariance matrices are transformed into the vector-moving average representation. The VMA coefficient matrices are obtained recursively as Equation (8).

$$B_{0,t} = I_N, B_{m,t} = \sum_{\downarrow=1}^{\min(m,p)} B_{m-\downarrow,t} A_{\downarrow,t} \quad (8)$$

where $B_{m,t}$ denotes the time-varying VMA coefficient matrix at horizon m .

Based on the generalized impulse response functions, the generalized forecast error variance decomposition is calculated as Equation (9).

$$S_{ij,t}(h) = \frac{\sum_{m=0}^{h-1} \left(e_i' B_{m,t} \Sigma_t e_j / \sqrt{\sigma_{jj,t}} \right)^2}{\sum_{j=1}^N \sum_{m=0}^{h-1} \left(e_i' B_{m,t} \Sigma_t e_j / \sqrt{\sigma_{jj,t}} \right)^2} \quad (9)$$

where $h = 10$, $\sigma_{jj,t}$ is the j -th diagonal element of Σ_t , and e_i is an $N \times 1$ selection vector. The element $S_{ij,t}(h)$ denotes the share of the h -step-ahead forecast error variance of variable i that is accounted for by shocks originating from variable j . Hence, rows represent receiving variables, whereas columns represent shock sources. Each row of the GFEVD matrix sums to one.

The total connectedness index is defined as Equation (10).

$$TCI_t(h) = \frac{100}{N} \sum_{i=1}^N \sum_{j=1, j \neq i}^N S_{ij,t}(h), \quad N = 5 \quad (10)$$

Higher TCI values indicate a larger average share of forecast error variance accounted for by cross-variable shocks.

Directional connectedness transmitted to and received from other variables is defined as Equation (11).

$$TO_{i,t}(h) = \frac{100}{N} \sum_{j=1, j \neq i}^N S_{ji,t}(h), \quad FROM_{i,t}(h) = \frac{100}{N} \sum_{j=1, j \neq i}^N S_{ij,t}(h) \quad (11)$$

Here, $TO_{i,t}$ measures the normalized directional connectedness from variable i to all other variables, while $FROM_{i,t}$ measures the normalized directional connectedness received by variable i . The $1/N$ normalization is applied to all directional measures, so that the static table, dynamic series, and pairwise network measures follow the same scaling convention. Under this convention, the sum of the five TO values and the sum of the five FROM values are both equal to the TCI.

Net total directional connectedness is defined as Equation (12).

$$NET_{i,t}(h) = TO_{i,t}(h) - FROM_{i,t}(h) \quad (12)$$

A positive value indicates that variable i accounts for a larger share of other variables' forecast error variance than other variables to account for its own forecast error variance. A negative value indicates the opposite directional position.

Net pairwise directional connectedness is defined as Equation (13).

$$NPDC_{i \rightarrow j,t}(h) = \frac{100}{N} [S_{ji,t}(h) - S_{ij,t}(h)] \quad (13)$$

A positive value indicates that variable i has stronger pairwise directional connectedness with variable j as a shock source than variable j has with variable i . The same $1/N$ normalization is used here to maintain consistency with the dynamic pairwise series and the network representation.

The same GFEVD matrix is used to construct the static connectedness table, the dynamic directional indices, and the pairwise network representation, thereby ensuring that all reported connectedness measures follow the same scaling convention. Overall, the TVP-VAR-DY framework converts the time-varying dependence structure estimated by the TVP-VAR model into multidimensional connectedness measures. It integrates system-wide,

directional, and pairwise connectedness, thereby allowing changes in the intensity and direction of predictive dependence to be examined across energy and carbon markets. These measures describe dynamic connectedness rather than structural causality. For each event window, a window-specific pairwise connectedness network is constructed from the averaged NPDC matrix. Let $M^{(w)} = [m_{ij}^{(w)}]$ denote the antisymmetric NPDC matrix in event window w , where rows represent receiving variables and columns represent shock-source variables. The element $m_{ij}^{(w)}$ is calculated as Equation (14):

$$m_{ij}^{(w)} = \frac{1}{T_w} \sum_{t \in w} NPDC_{j \rightarrow i, t} \quad (14)$$

where T_w is the number of daily observations in event window w . A positive $m_{ij}^{(w)}$ indicates that variable j has stronger net pairwise directional connectedness with variable i as a shock source than variable i has with variable j . By construction, $m_{ij}^{(w)} = -m_{ji}^{(w)}$.

A directed edge from variable j to variable i is drawn when $m_{ij}^{(w)} > 0$. The edge set and edge weights are defined as Equation (15):

$$E_w = \{(j, i) : m_{ij}^{(w)} > 0\}, w_{j \rightarrow i}^{(w)} = m_{ij}^{(w)} \quad (15)$$

Because the NPDC matrix is antisymmetric and the event-window matrices contain no zero off-diagonal entries, each pair of variables contributes one directed edge. Thus, each five-variable network contains ten directed edges.

The window-averaged NET value of variable j is calculated as the corresponding column sum of the NPDC matrix:

$$NET_j^{(w)} = \sum_{i=1, i \neq j}^N m_{ij}^{(w)} \quad (16)$$

Variables with positive and negative values are classified as net directional transmitters and net directional receivers, respectively. The numbers of net transmitters and net receivers reported in the table in Section 4.2.3 are the counts of variables satisfying these two conditions.

The average edge weight is defined as the mean of all positive directional edge weights:

$$\bar{w}^{(w)} = \frac{1}{|E_w|} \sum_{(j,i) \in E_w} w_{j \rightarrow i}^{(w)} \quad (17)$$

NET concentration is defined as Equation (18):

$$C_{NET}^{(w)} = \frac{\max_j |NET_j^{(w)}|}{\sum_{j=1}^N |NET_j^{(w)}|} \quad (18)$$

Higher values indicate that net directional connectedness is more concentrated in a single variable, whereas lower values indicate a more dispersed distribution across the network. All network measures are constructed from the same normalized NPDC and NET series used in the dynamic analysis, thereby ensuring consistency across the equations, dynamic figures, and event-window networks.

3.3. Data Sources and Processing

3.3.1. Data Sources

The empirical analysis uses daily data. The variables include EPU, coal, crude oil, natural gas, and carbon markets. The EPU index is obtained from the China Economic Policy Uncertainty Index for mainland China developed by Huang and Luk [52], which is publicly accessible at <https://cbade.hkbu.edu.hk/epu-mainland-china/> (accessed on 29 September 2025). This index provides a news-based measure of economic policy uncertainty. Daily price indices for coal, crude oil, and natural gas are collected from the WIND database (Wind Information Co., Ltd., Shanghai, China). Coal is represented by the Qinhuangdao coal spot price for power coal of grade Q5500 with Shanxi origin (Wind series ID: S5101377), reflecting the traditional fossil energy market. Oil is represented by the Brent crude oil futures settlement continuous contract (Wind series ID: S0031525), reflecting the internationally integrated energy market. Following established practice in the energy–econometrics literature, Brent crude oil futures are employed as the oil market proxy, as global supply–demand fundamentals and geopolitical risk factors directly affect China’s energy import costs and domestic price formation [14,38,53,54]. Natural gas is represented by the UK natural gas futures price (Wind series ID: S0212344), reflecting the transitional cleaner energy market. The use of UK natural gas futures is consistent with documented evidence of significant spillover effects from international gas benchmarks to China’s LNG market, which confirms the close interlinkage between global and Chinese natural gas prices [55]. The use of international energy prices to study China’s energy–carbon system is further justified by the well-documented integration between international and Chinese energy markets [56]. To ensure sample continuity and data comparability, the carbon emissions trading market uses Guangdong Provincial Government data from the WIND database. As the national carbon market was launched only in July 2021, leaving insufficient sample for dynamic connectedness estimation during the study period, a single pilot market is adopted. Guangdong was selected because it is the largest and most liquid pilot carbon market in China, with the longest continuous trading record and highest market capitalization among domestic pilots. The final sample covers the period from 19 June 2013 to 17 June 2022. It contains 2073 trading-day observations.

Table 1 summarizes the definitions and economic meanings of the variables used in the model.

Table 1. Definition of Variables.

Variable	Economic Meaning	Raw Data
EPU	Policy uncertainty shocks	Economic Policy Uncertainty Index
Coal	Coal market price fluctuations	Coal price
Oil	Crude oil market price fluctuations	Crude oil price
Gas	Natural gas market price fluctuations	Natural gas price
Carbon	Carbon market price fluctuations	Carbon emission allowance

Following the connectedness literature [10,32], risk spillovers in this study are operationalized through the price–return connectedness framework. Because underlying market risk is not directly observable, price fluctuations serve as the empirical proxy for risk exposure, reflecting the continuous repricing of supply–demand imbalances, policy shocks, and risk–premium adjustments. Within this framework, generalized forecast error variance decomposition quantifies the contribution of shocks in one market to the forecastable uncertainty of others. Since the GFEVD is based on forecast error variances, the resulting indices measure forecast–error variance connectedness rather than direct volatility, tail risk,

or structural causality. They should therefore be interpreted as measures of predictive dependence rather than direct measures of market risk.

3.3.2. Data Processing

Before transformation, the five series were first aligned according to their respective trading calendars. The dataset was then merged at the intersection of trading days, and all missing observations on common dates were excluded rather than interpolated. This ensures that every retained data point accurately reflects prices recorded on the same day. This procedure yields a balanced panel of 2073 daily observations, which is used throughout the estimation. Nevertheless, to ensure reliable connectedness estimates within the DY framework, it is necessary to address two potential sources of distortion prior to the model estimation.

First, the generalized forecast error variance decomposition presupposes covariance stationarity. If stochastic trends are left unaddressed, they can distort the variance decomposition and produce spurious spillover estimates. Second, pronounced cross-market heterogeneity in nominal price scales introduces a further complication. Connectedness measures are computed from variance shares. Variables with disproportionately large fluctuations can mechanically dominate the estimates. This can happen regardless of the true interdependence structure. Eliminating these distortions is therefore a prerequisite for obtaining spillover estimates that capture economically meaningful cross-market risk transmission.

To satisfy the stationarity assumption, all raw series are first transformed into logarithmic form. They are then tested for unit roots using the Augmented Dickey–Fuller test. As reported in Table 2, the log-transformed Coal, Oil, and Gas series each contain a unit root. EPU and Carbon are already stationary in logarithmic form. First-order logarithmic differencing is consequently applied to Coal, Oil, and Gas. After this transformation, all five variables meet the stationarity requirement.

Table 2. Results of Unit Root Tests.

Variable	Series	ADF Stat.	CV (1%)	<i>p</i> -Value	Stationarity at 1%
EPU	Log level	−7.470	−3.963	0.000	Yes
Coal	Log level	−0.670	−3.434	0.854	No
Coal	First difference	−9.314	−3.434	0.000	Yes
Oil	Log level	−2.607	−3.434	0.092	No
Oil	First difference	−7.175	−3.434	0.000	Yes
Gas	Log level	−1.027	−3.434	0.743	No
Gas	First difference	−9.569	−3.434	0.000	Yes
Carbon	Log level	−4.759	−3.963	0.001	Yes

Note: Deterministic terms are selected based on series transformation: EPU and Carbon (log levels) use intercept and trend; Coal, Oil, and Gas (first differences) use intercept only.

To ensure stationarity, all raw series are first transformed into logarithmic form and tested for unit roots using the Augmented Dickey–Fuller test. As reported in Table 2, the log-transformed Coal, Oil, and Gas series each contain a unit root, whereas EPU and Carbon are stationary in logarithmic levels. For the commodity series, first-order logarithmic differencing is applied to induce stationarity. Their returns capture marginal price adjustments driven by supply and demand shocks, portfolio rebalancing, and risk premium revisions, in line with standard practice in energy and financial market analysis [57]. EPU and Carbon enter the model as standardized logarithmic levels, preserving their level specific economic information. The EPU index directly measures uncertainty intensity, and carbon allowance prices reflect the contemporaneous stringency of emission regulation. The resulting specification combines level shocks for policy and regulatory variables with return shocks

for commodity markets, reflecting their structurally different roles in the energy–carbon system. Retaining EPU and Carbon in levels preserves low-frequency policy and regulatory information that would be lost under differencing, whereas the return-based measures for energy commodities provide a natural framework for analyzing transmission dynamics across asset prices. Under this specification, the estimated connectedness captures how shocks to policy uncertainty and regulatory stringency co-move with return shocks in commodity markets. With stationarity established for all five variables, the remaining concern is scale heterogeneity. Since DY measures are constructed from variance shares, even modest differences in nominal volatility can obscure the genuine cross market transmission structure. To mitigate this scale effect, all stationary series are standardized via z score normalization, yielding a common scale with zero mean and unit variance. Consequently, the five variables entering the TVP VAR DY model are the standardized logarithmic level of EPU and Carbon, and the standardized first-order logarithmic differences in Coal, Oil, and Gas.

3.3.3. Descriptive Statistics

Table 3 presents descriptive statistics for the resulting standardized series. Coal, crude oil, and natural gas returns exhibit pronounced skewness and excess kurtosis. These distributional features are commonly observed in energy markets. The carbon market, by contrast, displays comparatively moderate skewness and kurtosis. The Jarque–Bera test rejects normality for all variables. This confirms the presence of non-Gaussian behavior and nonlinear dynamics within the EPU–energy–carbon system.

Table 3. Descriptive statistics of standardized variables.

Variable	Mean	SD	Min	Max	Skewness	Excess Kurtosis	JB Statistic	JB <i>p</i> -Value
EPU	0	1	−5.6035	3.5467	−0.2693	1.0075	112.7360	0.000
Coal	0	1	−8.8121	13.7846	0.9756	44.9267	174,669.1120	0.000
Oil	0	1	−12.6978	8.7649	−1.1430	36.6717	116,609.6292	0.000
Gas	0	1	−11.8775	10.9101	0.4962	28.3679	69,594.0920	0.000
Carbon	0	1	−4.5246	2.2862	−0.5422	−0.0725	102.0392	0.000

Note: The zero mean and unit standard deviation reflect z-score normalization applied prior to model estimation.

Figure 2 plots the temporal evolution of all five standardized series over the sample period. The figure reveals evolving volatility dynamics and episodic clustering behavior under shifting policy and macroeconomic conditions.

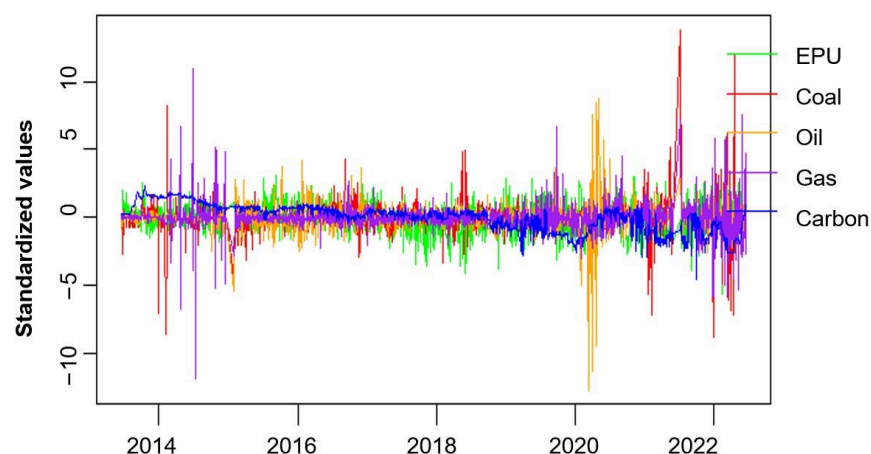


Figure 2. Stationary standardized time series of EPU and energy markets.

4. Results

4.1. Static Analysis

As a benchmark, the conventional VAR–DY framework is applied to characterize average risk connectedness among EPU, coal, oil, natural gas, and carbon markets. A fixed-parameter VAR with a lag length of two, chosen via the Schwarz Information Criterion, is estimated. A 10-step generalized forecast error variance decomposition is then applied. The resulting static connectedness matrix in Table 4 captures baseline cross-market risk transmission and highlights the interconnectedness between EPU and energy markets.

Table 4. Static Connectedness Matrix Based on the VAR–DY Framework.

	EPU	Coal	Oil	Gas	Carbon	FROM
EPU	93	1.7	1.5	1.7	2.2	1.4
Coal	1.1	94.2	1.4	2	1.2	1.2
Oil	1.1	1.5	93.1	3.3	1.1	1.4
Gas	1.3	2.2	2.7	92.8	1	1.4
Carbon	1.5	0.9	0.8	1.0	95.9	0.8
TO	1.0	1.2	1.3	1.6	1.1	
NET	−0.4	0.1	−0.1	0.2	0.3	TCI = 6.2

Note: All entries in the 5×5 matrix are row-normalized percentages of the ten-step-ahead generalized forecast error variance decomposition. Rows represent receiving variables, and columns represent shock sources. TO, FROM, NET, and NPDC are normalized by $N = 5$, consistent with the dynamic connectedness series. Under this convention, the sum of the five TO values and the sum of the five FROM values equal the TCI. Minor discrepancies in row totals are due to rounding.

The static spillover matrix in Table 4 reveals a modest average TCI of 6.2%, suggesting that cross-market risk transmission is generally weak over the full sample. Energy price fluctuations are therefore largely accounted for by idiosyncratic innovations rather than persistent system-wide connectedness, reflecting the absence of a tightly integrated risk structure at the aggregate level. Diagonal variance shares exceeding 92% across all markets confirm that own-market innovations dominate price dynamics, emphasizing the central role of market-specific fundamentals such as resource endowments, regulatory regimes, and institutional constraints. Notably, the EPU and Carbon markets exhibit particularly high own variance shares, 93% and 95.9%, respectively. For EPU, this reflects that uncertainty shocks originate primarily from policy information rather than external energy market feedback. For the carbon market, the highest own variance share suggests that carbon prices are more strongly shaped by policy architecture and compliance mechanisms than by short-term spillovers from fossil energy markets.

Directional connectedness measures further reveal substantial heterogeneity in transmission roles. Oil and natural gas display relatively stronger outward directional connectedness, indicating a greater capacity to propagate shocks across the energy system. By contrast, direct spillovers from EPU to energy markets remain limited, implying that policy uncertainty influences prices mainly through indirect channels such as expectations, financial conditions, and portfolio adjustments, rather than through immediate transmission. In net terms, carbon, natural gas, and coal act as net directional transmitters, whereas EPU and oil function primarily as net directional receivers.

This low average TCI does not, however, negate the presence of systemic risk dynamics. Rather, it underscores the necessity of examining time-varying spillovers, as static averages may mask episodic surges and structural reconfigurations that occur during high-uncertainty episodes. As demonstrated in the dynamic analysis below, EPU-related variation is associated with the energy–carbon network not primarily through a higher average level of connectedness, but through changes in net directional roles and pairwise connectedness pathways. The static and dynamic measures thus capture complementary

dimensions of connectedness, both of which are necessary for a complete understanding of how policy uncertainty affects the system. To capture the evolving risk structure, the analysis next turns to the TVP-VAR-DY framework.

4.2. Dynamic Analysis

4.2.1. Time-Varying Systemic Connectedness and Directional Connectedness Under EPU

The static spillover estimates in Table 4 capture only the average configuration of risk transmission over the full sample and therefore obscure the evolving nature of cross-market interactions under changing policy environments. During periods of heightened uncertainty, both the magnitude and direction of spillovers may adjust substantially as transmission mechanisms reconfigure. To evaluate H1 and capture these dynamics, this study employs the TVP-VAR-DY framework to examine the time-varying systemic dynamic connectedness between EPU and the energy market system, with results presented in Figures 3, 5 and 6.

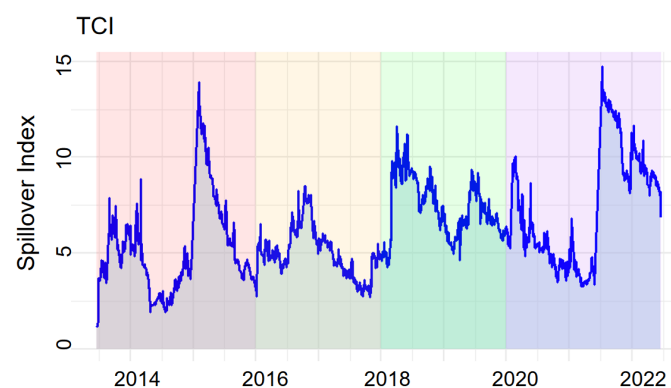


Figure 3. Dynamic System-wide Connectedness between EPU and Energy Markets. Note: The shaded background areas distinguish different sample periods, which are further annotated with major events in Figure 4.

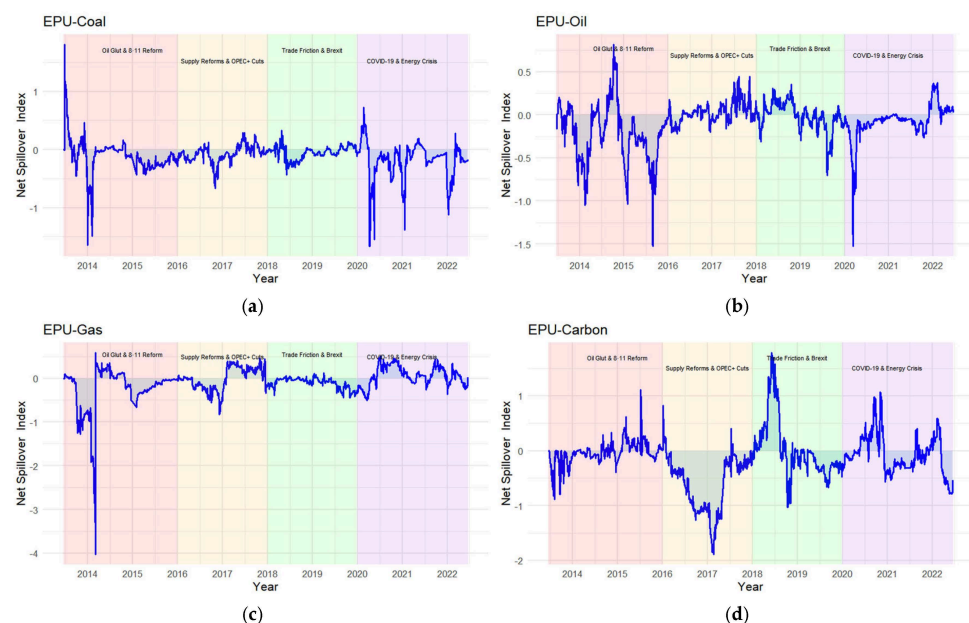


Figure 4. Dynamic net pairwise connectedness between EPU and individual energy and carbon markets. (a) EPU-Coal; (b) EPU-Oil; (c) EPU-Gas; (d) EPU-Carbon. Note: Positive values indicate stronger net pairwise connectedness from EPU to the corresponding market, whereas negative values indicate stronger connectedness in the opposite direction.

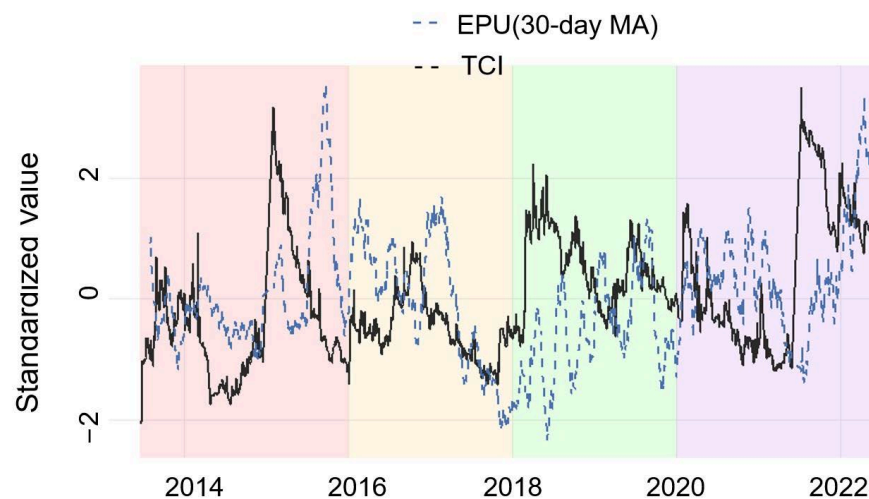


Figure 5. Dynamic Co-movement between System-wide Connectedness and EPU. Note: The shaded background areas distinguish different sample periods, which are further annotated with major events in Figure 4.

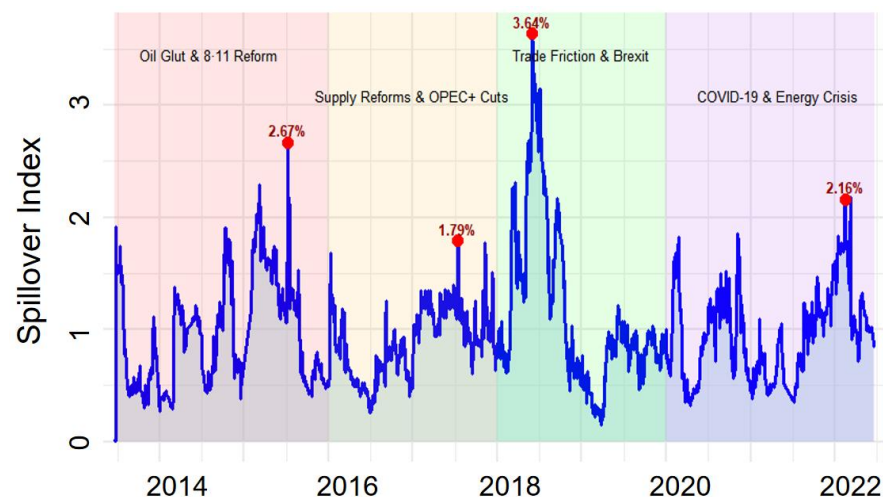


Figure 6. Directional Connectedness from EPU to Energy and Carbon Markets. Note: Shaded areas denote periods coinciding with major policy and macroeconomic events, including the Oil Glut and the 8-11 Reform which refers to the RMB exchange rate reform announced on 11 August 2015 (2013–2015), supply-side reforms and OPEC+ cuts (2016–2017), trade frictions and Brexit (2018–2019), and the COVID-19 pandemic and global energy crisis (2020–2022). The red dots mark the local peaks of the spillover index within each period, with the corresponding values annotated.

Figures 3 and 5 provide a systemic view of the evolving linkage between EPU and energy market risk. As shown in Figure 3, the TCI exhibits pronounced time variation, indicating that systemic interdependence is highly state-dependent rather than constant.

Figure 5 further illustrates the dynamic co-movement between EPU and systemic connectedness, using a 30-day moving average of the EPU index for visual smoothing. The two series display strong synchronization, with episodes of elevated EPU tending to coincide with elevated TCI. This co-movement pattern is consistent with heightened uncertainty being associated with stronger cross-market synchronization through financial and expectation-driven channels, whereby heightened uncertainty coincides with elevated risk perceptions, stronger asset co-movement, and intensified systemic spillovers. Consistent with the literature on information-driven trading and investor behavior [53], EPU is thus

associated with synchronized market responses and coincident intensification of systemic risk within the EPU–energy market framework.

Figure 6 depicts the time-varying directional spillovers from EPU to coal, oil, natural gas, and carbon markets, revealing clear phase-dependent transmission patterns.

During 2013–2015, the spillover index fluctuated at relatively elevated levels. It experienced its first major surge in 2015, reaching approximately 2.67%. Temporally, this surge overlaps with the global oil glut, intensified financial volatility, and China’s “8·11” exchange rate reform. These events can be interpreted through the three transmission channels. The oil glut is associated with the real economy channel. The exchange rate reform and associated portfolio reallocation reflect the financialization channel. The elevated volatility reflects the expectation channel. This temporal alignment is consistent with the interpretation that all three channels may have coincided with stronger cross-market connectedness. Heightened risk aversion and synchronized trading likely strengthened financial linkages, while rapid portfolio adjustments coincided with stronger co-movement across energy assets. Spillovers then declined and stabilized during 2016–2017, a period that also saw China’s supply-side reforms and OPEC+ production cuts. This temporal pattern is consistent with the interpretation that improved medium-term supply-demand expectations—anchored by these policy actions—may have weakened EPU-related connectedness. This moderation aligns with the finding that EPU-related connectedness weakens when expectations and supply conditions stabilize [38], suggesting a stronger real economy channel buffering effect in the energy–carbon nexus during this phase. The strongest amplification emerged in 2018–2019, with the spillover index climbing sharply to a sample peak of 3.64%. This peak coincides with a period of escalating trade frictions, Brexit uncertainty, and geopolitical tensions. Consistent with evidence that major macroeconomic shocks can substantially amplify systemic risk transmission [54], the joint reinforcement of expectation and financial channels provides a plausible contextual interpretation of this surge. Unlike earlier phases marked by transitory volatility shocks, EPU in this period exhibited a more persistently elevated spillover profile, consistent with a more enduring risk propagation role under this uncertainty regime. During 2020–2022, despite elevated EPU, the spillover index fluctuated within a markedly narrower range, indicating saturation or diminishing marginal returns. Directional connectedness increasingly coincided with real-economy conditions such as supply disruptions, production constraints, and demand reallocation, which contained further escalation in systemic connectedness. Taken together, Figures 3, 5 and 6 indicate that EPU is associated with the energy–carbon system through changes in both connectedness intensity and phase-dependent directional patterns. The observed lagged co-movement and phase-dependent directional spillovers suggest that policy uncertainty may serve as a time-varying measure of evolving connectedness within the broader energy–carbon market system.

4.2.2. Heterogeneous Directional Connectedness Roles Under EPU

While the systemic connectedness measures above capture the overall evolution of risk transmission under EPU, they reveal less about how individual markets differ in absorbing and transmitting shocks across macroeconomic phases: a gap that H2 addresses. Aggregate spillover measures may conceal substantial heterogeneity in how individual markets absorb, transmit, or amplify uncertainty. Therefore, market-level heterogeneity is further examined. Figure 4 reports time-varying net pairwise connectedness between EPU and coal, oil, natural gas, and carbon markets.

The coal market exhibits relatively low-amplitude pairwise connectedness. Net spillovers remain negative for most of the sample, with only brief upward deviations during the COVID-19 shock and the global energy crisis. This pattern reflects comparative

stability and low sensitivity to abrupt uncertainty shocks. This finding aligns with evidence that contagion effects in energy-intensive sectors intensify primarily during extreme market conditions [58]. Coal prices are closely tied to industrial production and long-term supply contracts, which are likely to strengthen the buffering role of the real economy channel and may limit the persistence of EPU-related connectedness.

In contrast, the oil market exhibits markedly higher volatility and more frequent sign reversals, particularly during the oil price collapse, heightened trade tensions, and the COVID-19 crisis. This reflects a pronounced regime-dependent transmission structure, wherein the oil market alternates between risk-transmitting and risk-absorbing roles across macroeconomic phases. This pattern is consistent with evidence that the oil price–uncertainty relationship evolves considerably over time [59]. It also indicates the dominance of the financialization and expectation channels. Through these channels, uncertainty coincides with rapid revisions in market expectations, risk pricing, and cross-market capital allocation.

Relative to coal and oil, the natural gas market exhibits even greater sensitivity to tail risks. This is reflected in deep negative spillovers during the early sample period and intermittent positive surges during supply-side reforms and the global energy crisis. The observed fluctuations suggest that natural gas markets are highly responsive to changing demand expectations and supply-side adjustments. This echoes prior research, which identifies substantial return and volatility interconnections between natural gas and broader energy markets under shifting market conditions [60]. From a transmission perspective, uncertainty shocks are associated with gas-price dynamics through both the expectation channel and the real-economy channel. Fuel substitution effects and production flexibility may amplify spillover volatility during periods of market stress.

Compared with energy markets, the carbon market exhibits the largest spillover amplitudes, the most frequent sign reversals, and the clearest policy-driven turning points. This pattern highlights its heightened sensitivity to institutional uncertainty and shifts in regulatory expectations. This finding aligns with studies showing that the impact of policy uncertainty on carbon market volatility varies across policy environments [61] and that climate-related uncertainty is associated with changes in the connectedness between carbon and energy markets [62]. The heightened sensitivity likely reflects the dominant role of the expectation channel, as carbon pricing mechanisms depend heavily on regulatory credibility, allowance allocation rules, and long-term decarbonization expectations.

Figure 7 provides the market-level evidence by tracing bilateral transmission pathways between market pairs. It clarifies not only which markets dominate risk transmission but also through which specific pairwise channels systemic risk is redistributed under EPU. Unlike a fixed transmission hierarchy, spillover directions vary substantially across market pairs and macroeconomic phases. This indicates that the internal allocation of systemic risk within the energy system is highly time-varying. During episodes of elevated financial stress, the oil market frequently emerges as a dominant bilateral risk exporter. It exports shocks to coal and natural gas markets through rapidly changing expectations and financial market interactions. By contrast, during episodes associated with supply-side adjustments and energy market disruptions, spillovers between coal, natural gas, and oil become more closely linked to real economy conditions. These include shifts in production costs, industrial demand, and energy substitution effects. The carbon market exhibits the most flexible bilateral transmission role within the system. In some periods, carbon markets primarily absorb shocks from fossil fuel markets. However, during phases of intensified regulatory adjustment and policy uncertainty, they increasingly transmit shocks back to traditional energy markets. This occurs through changing policy expectations and carbon–energy pricing interactions.

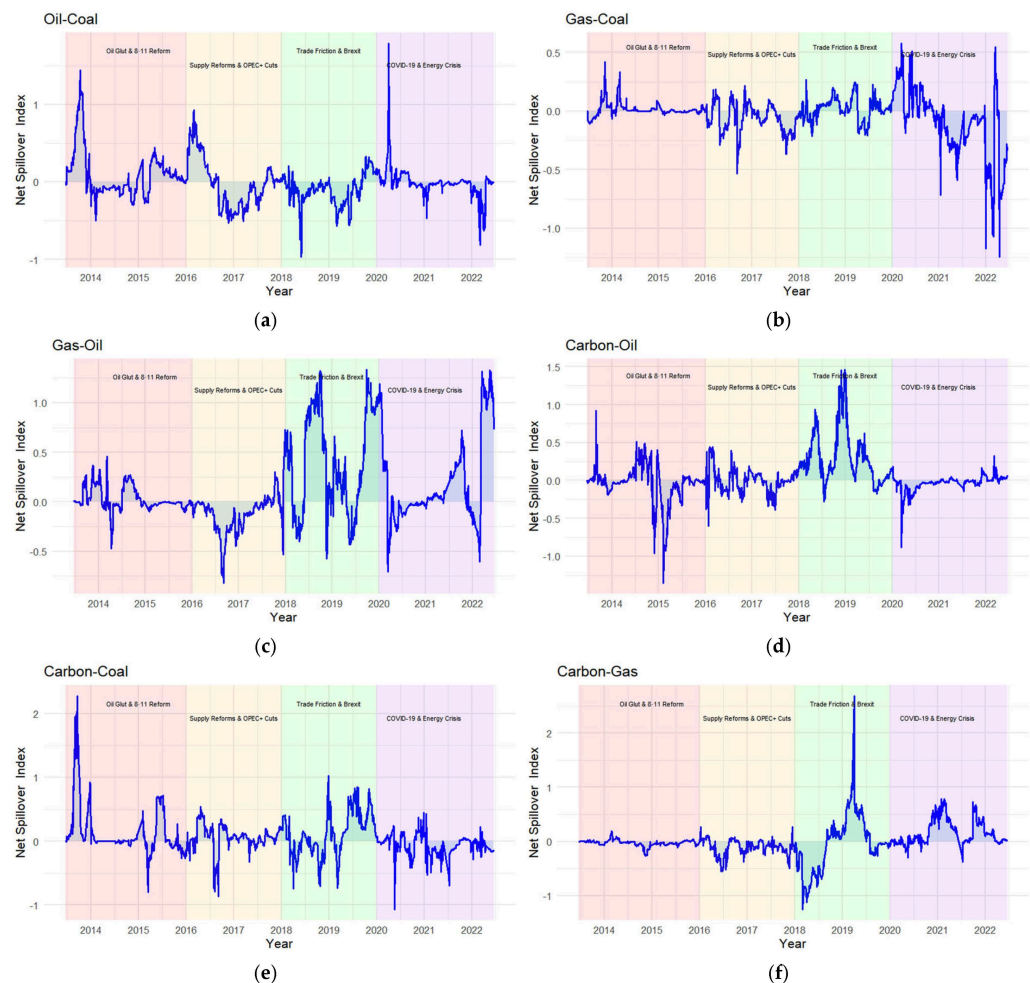


Figure 7. Dynamic net spillover effects among different energy markets. (a) Oil–Coal; (b) Gas–Coal; (c) Gas–Oil; (d) Carbon–Oil; (e) Carbon–Coal; (f) Carbon–Gas.

Taken together, Figures 4 and 7 present heterogeneous directional roles that are consistent with H2 and show that EPU-related variation is associated with changes in the internal distribution of connectedness within the energy system through real economy, financial market, and expectation–sentiment channels. Through expectation formation, pricing mechanisms, and crisis-related co-movement, policy uncertainty is associated with dynamic role switching, market-specific heterogeneity, and evolving spillover directions. These findings reinforce the dual role of EPU as an important correlate of system-wide stress and evolving market fragility in the energy–carbon network.

4.2.3. Evolution of Energy Connectedness Networks Under EPU

Figures 4 and 7 show dynamic role switching and pairwise heterogeneity across markets but do not fully summarize the system-wide configuration of these relationships. To evaluate H3, event-window connectedness networks are constructed from the window-averaged NPDC matrix defined in Equations (14)–(18). Table 5 first summarizes the resulting network structure metrics, while Figure 8 presents the corresponding network configurations for four representative event windows. These windows correspond to periods when the EPU index remained elevated and coincided with major macroeconomic and policy events, namely the oil price collapse, the supply-side structural reform, the trade-war escalation, and the COVID-19 energy crisis. The four windows are intended as illustrative cases rather than an exhaustive regime classification. They were selected according to a common rule. First, each window corresponds to an episode in which the

EPU index displayed a pronounced local peak relative to its surrounding observations. Second, the episode could be matched to a clearly identifiable and widely documented exogenous event. Third, the dominant shock types differ across windows, spanning a commodity supply shock, a domestic policy adjustment, a trade policy shock, and a public health crisis, so that the network configurations can be compared across heterogeneous uncertainty regimes. Window boundaries are delimited by the interval from the initial shock to the first clear stabilization of market prices.

Table 5. Network Structure Metrics Across Event Windows.

Event Window	Net Transmitters	Net Receivers	Avg. Edge Weight	NET Concentration
(a)	4	1	0.1124	0.500
(b)	2	3	0.0898	0.330
(c)	3	2	0.3641	0.257
(d)	3	2	0.1597	0.450

Note: All metrics are defined in Equations (14)–(18) and each five-variable network contains ten directed edges. (a) 18 September 2014–5 November 2014: the oil-collapse; (b) 6 July 2017–16 August 2017: the supply-side structural reform; (c) 9 May 2018–22 June 2018: the trade war escalation; (d) 19 October 2020–27 November 2020: the COVID-19 energy crisis.

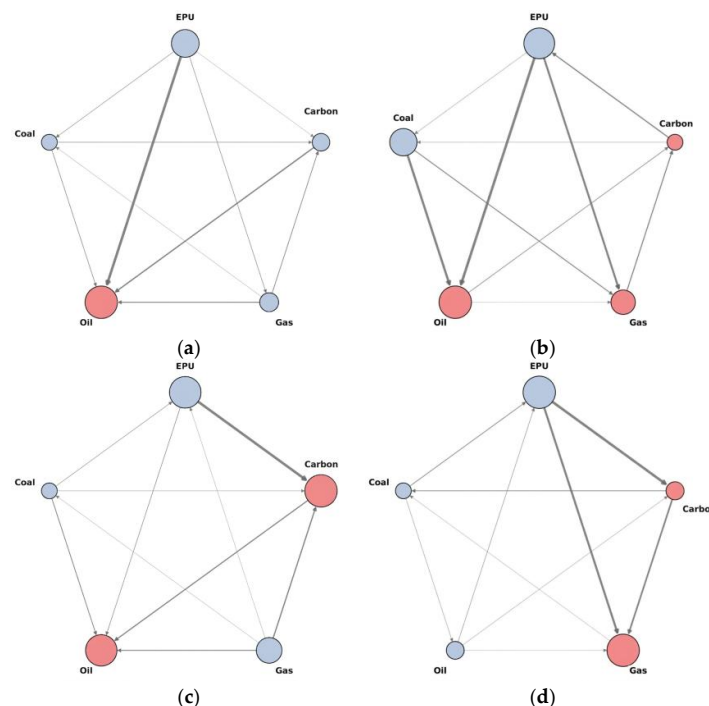


Figure 8. Dynamic connectedness networks within the system. (a) 18 September 2014–5 November 2014: the oil price collapse; (b) 6 July 2017–16 August 2017: the supply-side structural reform; (c) 9 May 2018–22 June 2018: the trade war escalation; (d) 19 October 2020–27 November 2020: the COVID-19 energy crisis. Note: Blue nodes indicate net directional transmitters, and red nodes indicate net directional receivers, with node size proportional to net directional connectedness. Directed edges show pairwise directional connectedness, and edge thickness reflects connectedness intensity.

Table 5 reveals clear differences in both the intensity and distribution of directional connectedness across the four event windows. The trade-war window exhibits the highest average edge weight of 0.3641, indicating the strongest average pairwise connectedness. In contrast, the supply-side reform window records the lowest average edge weight of 0.0898. The distribution of net directional roles also varies substantially. The oil-collapse window has the highest NET concentration at 0.500, followed by the COVID-19 window

at 0.450, whereas the trade-war window has the lowest concentration at 0.257. These results suggest that stronger average pairwise connectedness does not necessarily imply greater concentration in a single market. Figure 8 further illustrates how these quantitative differences are reflected in node roles and pairwise directional pathways.

In the oil-collapse window, EPU was a net directional transmitter, with its strongest pairwise linkage directed toward the oil market. The EPU-to-oil NPDC reached 0.4836, substantially exceeding its linkages with coal, natural gas, and carbon. Oil was the only net directional receiver in this window, with a window-averaged NET value of -0.8962 . Several additional linkages from coal, natural gas, and carbon were also directed toward oil, reinforcing its dominant receiving position. This configuration explains why NET concentration reached its highest value of 0.500 in Table 5. The pattern is consistent with the joint relevance of the real-economy and financial channels during the oil price collapse, as the commodity most directly exposed to the supply glut became the principal recipient of directional connectedness. During the supply-side reform window, the network became more distributed on the receiving side. EPU remained the largest net directional transmitter, with a window-averaged NET value of 0.3178, while coal was the strongest net transmitter among the energy and carbon markets. The outward linkages from EPU were mainly directed toward oil and natural gas, while a reverse linkage from carbon to EPU also emerged. Coal displayed outward directional connectedness toward oil and natural gas, whereas oil, natural gas, and carbon were all classified as net receivers. This broader distribution of receiving roles is consistent with the presence of three net receivers in Table 5. At the same time, the average edge weight declined to 0.0898, the lowest value among the four windows, indicating weaker average pairwise connectedness during this policy adjustment period. This pattern is consistent with evidence that policy changes can coincide with shifts in net directional roles and pairwise connectedness structures [63]. The trade-war escalation window exhibited the strongest average pairwise connectedness. EPU was the largest net directional transmitter, with a window-averaged NET value of 1.4379, and its outward connectedness was heavily concentrated in the carbon market. The EPU-to-carbon NPDC reached 1.4153, making it the strongest single linkage across the four event windows. Carbon was the largest net receiver, followed by oil, while natural gas and coal joined EPU as net transmitters. Although the strongest linkage was directed toward carbon, the presence of two large net receivers and three net transmitters produced the lowest NET concentration of 0.257. Thus, the trade-war window combined the highest average edge weight with the most dispersed distribution of net directional roles. The prominent receiving position of carbon is consistent with the expectation channel, because carbon pricing depends heavily on long-term policy credibility and regulatory expectations [64]. A different configuration emerged during the COVID-19 energy crisis. EPU remained the largest net directional transmitter, but coal and oil also became modest net transmitters. Coal-to-EPU and oil-to-EPU linkages indicated that fossil-fuel market disruptions coincided with stronger pairwise connectedness directed back toward EPU. At the same time, EPU displayed substantial outward linkages toward natural gas and carbon. Natural gas became the dominant net receiver, reflecting incoming linkages from EPU, oil, and carbon, while carbon also remained a net receiver. This configuration produced a relatively high NET concentration of 0.450, second only to the oil-collapse window. The dominant receiving position of natural gas is consistent with the real-economy channel, as pandemic-related supply disruptions and demand uncertainty affected gas-market balances more directly during this period. This pattern is also consistent with evidence that energy-market connectedness varies substantially under extreme conditions [65].

Overall, Table 5 and Figure 8 jointly indicate that the configuration of the connectedness network varies across uncertainty regimes. The oil-collapse and COVID-19 windows

were characterized by relatively high NET concentration, with oil and natural gas serving as the dominant net receivers, respectively. The supply-side reform window displayed the weakest average pairwise connectedness, whereas the trade-war window combined the strongest average pairwise connectedness with the most dispersed distribution of net directional roles. These findings are consistent with H3 and indicate that changes in EPU are associated with regime-dependent variation in both the intensity and distribution of directional connectedness across the energy–carbon system.

4.2.4. Robustness Tests

The credibility of the preceding results rests on the extent to which they survive alternative empirical choices, and this section evaluates their robustness along several dimensions that proceed from static to dynamic evidence. We begin by examining whether the full-sample connectedness structure is sensitive to the transformation applied to the raw series. The baseline specification combines standardized log levels for EPU and Carbon with standardized first log differences for the three energy markets, a choice motivated by the distinct statistical properties of these variables. As a check, the model is re-estimated after all five series have been subjected to a uniform transformation of standardized first log differences, and the resulting connectedness matrix is compared with its baseline counterpart in Figure 9. The two matrices are virtually indistinguishable. Deviations across the twenty off-diagonal entries never exceed 0.4 percentage points, and the total connectedness index shifts only marginally from 6.2% under the baseline to 6.0% under the uniform transformation. Equally important, the directional character of every market is preserved, with EPU continuing to absorb shocks on net, Coal, Gas and Carbon continuing to transmit them, and Oil remaining positioned close to the boundary between transmission and reception.

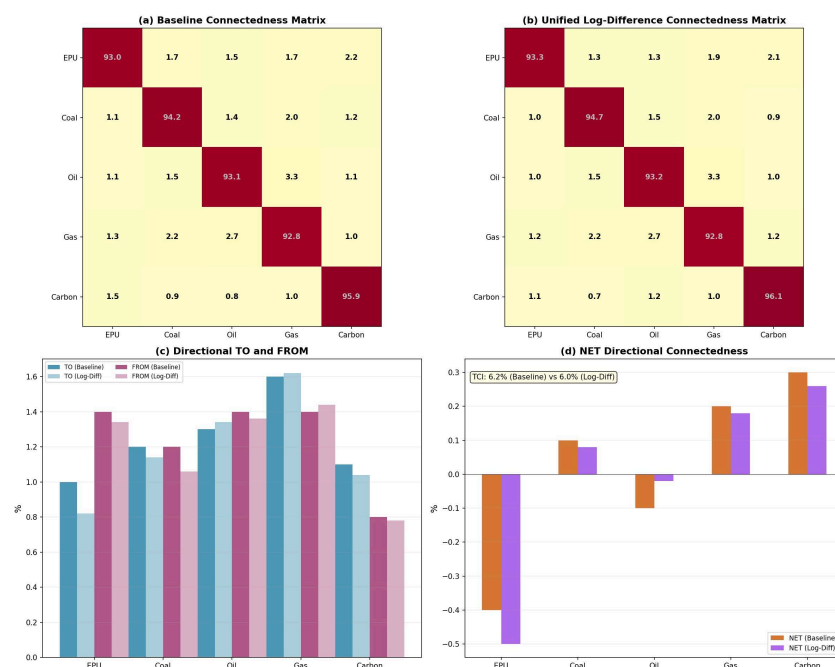


Figure 9. Static connectedness matrices under the baseline mixed transformation and the unified log-difference transformation. Note: In panels (a,b), the color scale ranges from yellow to dark red, with darker red cells indicating larger connectedness values; diagonal entries represent own-variance shares and off-diagonal entries represent pairwise connectedness. In panels (c,d), the two colors distinguish the baseline results from those under the unified log-difference transformation, as indicated by the legends.

Temporal stability is assessed next through the subperiod analysis summarized in Table 6, which reports static connectedness measures over four subperiods aligned with the major event windows identified in Figure 6. The outward connectedness of EPU attains its maximum during 2016–2017, a pattern consistent with the role-switching behavior documented in the dynamic analysis. Coal evolves from a net receiver in 2013–2015 into the dominant net transmitter by 2020–2021, while Oil remains a persistent net receiver throughout. Natural gas displays the most frequent directional reversals among the five variables, and the carbon market alternates between transmission and reception, reaching its strongest net-transmitting position in 2018–2019. These structural regularities are preserved when the estimation window is restricted, which suggests that the full-sample results are not disproportionately shaped by any single episode.

Table 6. Subperiod Connectedness Summary.

Subperiod	TCI	EPU to Energy Market	Coal NET	Oil NET	Gas NET	Carbon NET
2013–2015	6.0	1.4	−0.1	−0.3	0.2	0.5
2016–2017	8.8	2.9	0.2	−0.3	−0.1	−0.3
2018–2019	8.5	1.2	−0.2	−0.9	0.5	1.3
2020–2022	8.9	1.5	1.1	−0.3	−0.9	0.3

Dynamic evidence is provided in Figure 10, which portrays the time-varying total connectedness index obtained under alternative model specifications. The baseline model employs a lag length of two and a ten-period forecast horizon, selected on the basis of the AIC, SC, HQ, LR and FPE criteria, with residual diagnostics confirming the absence of significant autocorrelation. Models estimated with one and three lags, forecast horizons of five and fifteen periods, and the unified log-difference transformation described above yield trajectories that co-move closely with the baseline, exhibiting comparable magnitudes and nearly identical peak timings around the major crisis episodes. The event-time interpretation developed in the preceding sections is therefore confirmed across the entire specification space considered here.

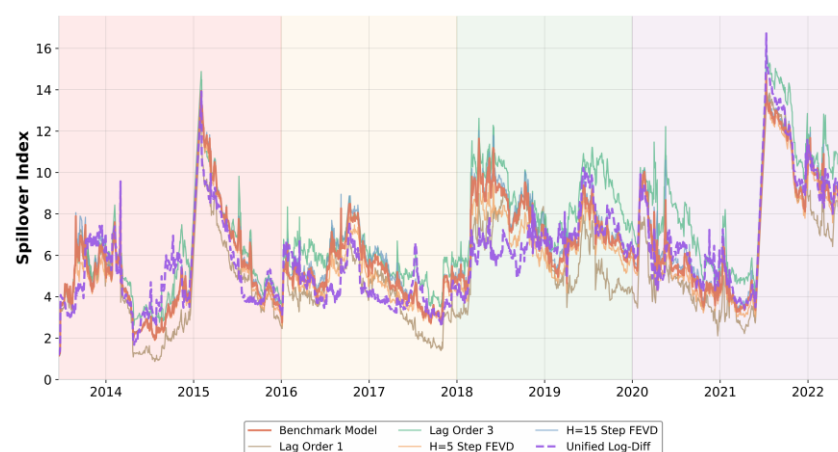


Figure 10. Time-varying total connectedness under alternative lag lengths, forecast horizons and variable transformations. Note: Shaded areas denote the same event periods as in Figures 5 and 6.

A final check concerns the influence of extreme observations, which is evaluated by Winsorizing every series at its first and ninety-ninth percentiles and re-estimating the model. The resulting index is displayed alongside the baseline in Figure 11. The two series

move together closely throughout most of the sample, and the major crisis episodes are reproduced at identical points in time, indicating that the dynamics documented above are not an artifact of outlying observations. A visible divergence nonetheless emerges during the energy crisis of 2021–2022, where the Winsorized series lies markedly below the baseline. This divergence admits a natural interpretation once the origin of the extreme observations is inspected in Figure 12, which reveals that values falling outside the Winsorization bounds are clustered almost exclusively within genuine crisis periods, most notably the outbreak of COVID-19 and the energy crisis itself. Observations of this kind cannot be dismissed as measurement noise, since they embody precisely the comovement through which crises propagate across markets, and their removal mechanically compresses the estimated connectedness of those very episodes. The non-Winsorized specification is therefore retained as the baseline, while the Winsorized estimates are regarded as a conservative lower bound on the intensity of crisis-period connectedness.

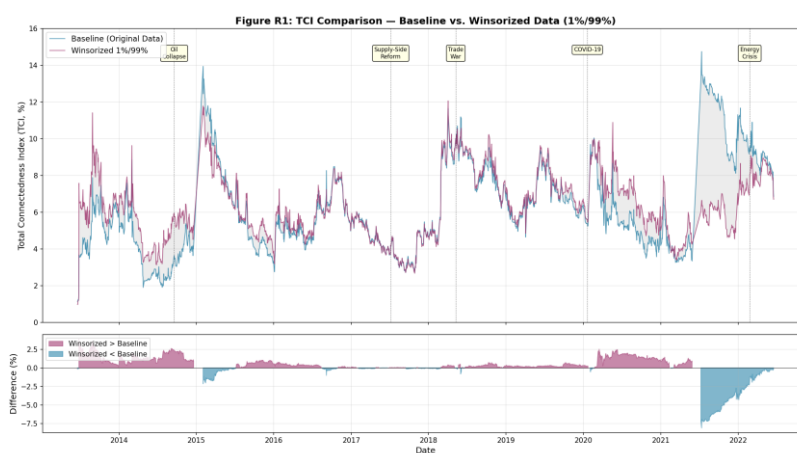


Figure 11. Time-varying total connectedness under the baseline data and data Winsorized at the first and ninety-ninth percentiles.

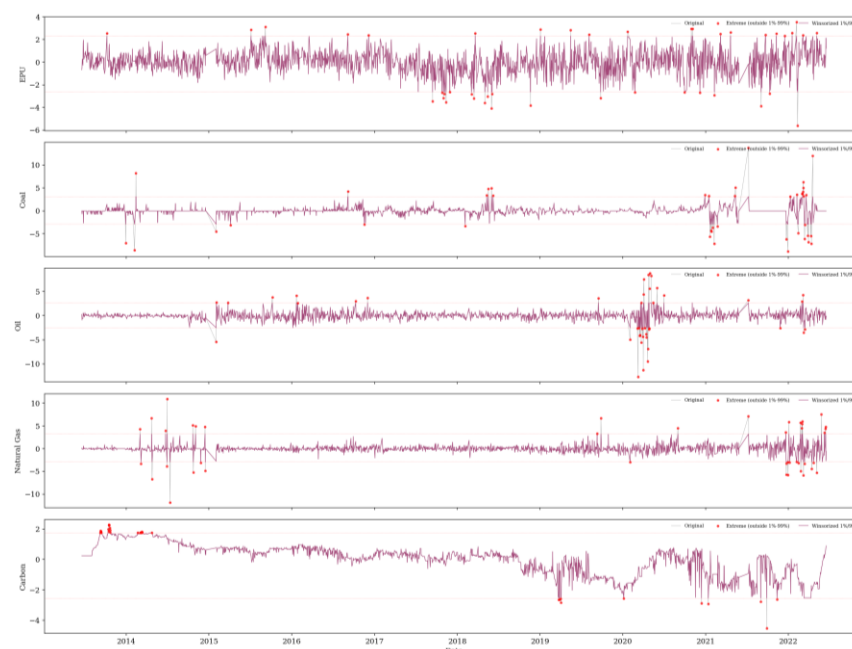


Figure 12. Time series of the five standardized variables, with observations falling outside the first and ninety-ninth percentile bounds highlighted.

Taken together, the evidence assembled in this section indicates that the static structure, the directional ranking and the event-time dynamics of connectedness are robust to alternative transformations, parameter settings, restricted samples and the treatment of extreme values, whereas only the magnitude of crisis-period connectedness is moderated once genuine crisis observations are trimmed. The core conclusions of this study thus reliably characterize the dynamic interdependence among economic policy uncertainty, energy markets and the Guangdong pilot carbon market.

5. Conclusions and Policy Implications

5.1. Conclusions

Employing a TVP-VAR-DY framework, this study investigates the dynamic association between EPU and connectedness across energy and carbon markets, integrating system-wide, market-level, and network perspectives. The findings indicate that EPU-related variation is associated with changes in directional connectedness, net market roles, and network configurations across the energy–carbon system.

At the system level, although the full-sample average connectedness is modest, EPU and system-wide connectedness exhibit pronounced time-varying co-movement. Rather than increasing mechanically with higher uncertainty, systemic spillovers display distinct dynamic trajectories across different market regimes. In some periods, shocks are characterized by rapid synchronization across assets and abrupt expansions in system-wide connectedness, whereas in others, connectedness adjusts more gradually, exhibiting persistence and path-dependent co-movement. These contrasting patterns indicate that EPU is associated not only with the magnitude of system-wide connectedness but also with its persistence over time. In this sense, EPU serves as an important signal of evolving interconnectedness.

Market-level analysis reveals marked heterogeneity and time variation. Coal predominantly displays a net directional recipient or buffering role within the connectedness network. Oil alternates between stronger outward and inward directional connectedness through portfolio rebalancing, speculative flows, and price discovery during periods of heightened uncertainty. Natural gas demonstrates elevated sensitivity, reflecting the combined influence of financial and expectation-driven forces amid macroeconomic stress and energy transition pressures. In contrast, carbon markets exhibit strong responsiveness to policy signals, frequently alternating between net transmitter and net receiver roles. Collectively, these patterns indicate that EPU-related variation is associated with differentiated connectedness patterns across heterogeneous assets.

From a network perspective, the configuration of the connectedness network varies over time, with changes in net directional roles and pairwise connectedness pathways across uncertainty regimes. The resulting network configurations vary with the dominant transmission channels. When financial and expectation-driven channels prevail, spillovers tend to become highly concentrated. Systemic importance clusters in policy-sensitive or financialized markets, as observed when EPU shocks were channeled predominantly to oil or carbon. Real economy disruptions, by contrast, generate more reciprocal and asymmetric patterns. They induce feedback effects and shift hub positions across commodities. Across all regimes, the energy–carbon system repeatedly moves from relatively decentralized configurations toward more asymmetric and concentrated configurations during periods of elevated EPU. Importantly, EPU is associated not only with the intensity of connectedness but also with differences in how connectedness is organized across the energy–carbon network.

Collectively, these results are consistent with H1–H3 and indicate that EPU-related variation is associated with time-varying and regime-dependent connectedness across energy and carbon markets. Through changes in directional connectedness, net market roles, and network configuration, policy uncertainty is associated with continuous adjustments in

the internal connectedness structure of the energy system. These insights highlight the necessity of mechanism-aware, network-oriented regulatory frameworks. Such frameworks facilitate early identification of systemic vulnerabilities and enable targeted interventions that stabilize the broader energy–carbon system.

5.2. Policy Implications

The state-dependent nature of systemic risk connectedness documented above implies that regulatory frameworks should move beyond static, volatility-based indicators when connectedness tends to strengthen and its directional distribution may change rapidly across markets. Conventional monitoring tools may fail to detect emerging vulnerabilities during episodes of heightened policy uncertainty, when spillover risks tend to intensify and reallocate rapidly across markets. Energy regulators and financial supervisors may therefore benefit from incorporating time-varying connectedness measures into routine risk surveillance systems.

Policy interventions should explicitly account for cross-market heterogeneity in connectedness patterns. The buffering role of coal, anchored in physical supply–demand conditions, implies that maintaining stable supply arrangements and inventory management constrains the diffusion of uncertainty shocks to broader energy markets. For oil, where financialization is associated with regime-dependent outward and inward directional roles, regulatory scrutiny of speculative capital flows and leveraged positions during uncertainty episodes may be warranted. Carbon markets, whose frequent directional reversals reflect dependence on regulatory credibility, benefit from enhanced transparency in allowance allocation rules and advance guidance on compliance timelines to reduce uncertainty associated with abrupt expectation revisions. Uniform stabilization strategies are therefore unlikely to be effective across heterogeneous energy assets.

The finding that EPU-related variation is associated with changes in network configuration, rather than uniform amplification, further suggests that regulatory assessments should account for the evolving architecture of directional connectedness. When financial and expectation-driven channels dominate and systemic risk concentrates in policy-sensitive markets, priority may be given to stabilizing price expectations in carbon markets and monitoring cross-market capital reallocation. When real economy disruptions generate more reciprocal patterns with hub rotation, attention should broaden to encompass supply-chain coordination across energy assets. Integrating network-oriented risk assessment into the policy design process can help reduce increases in cross-market connectedness following policy changes and enhance coordination across regulatory domains.

5.3. Limitations and Future Research

Several limitations of this study suggest avenues for future research. First, the TVP-VAR-DY framework captures time-varying connectedness but does not formally identify causal mechanisms behind the observed connectedness. The event interpretations offered are based on temporal coincidence rather than formal identification and remain illustrative. Future research could employ structural identification or regime-switching specifications to test the causal pathways through which EPU may affect cross-market connectedness. Second, this study relies on a single carbon market and international energy price benchmarks. While Guangdong is the largest and most liquid pilot in China, it may not capture the full heterogeneity across regional pilots. Similarly, Brent crude and UK natural gas futures reflect global dynamics that transmit to China through trade and pricing channels, though domestic energy futures could enhance the country-specific dimension. Future work could expand coverage to include multiple carbon pilots, renewable energy assets, and domestic energy futures. Third, this study treats EPU as a composite index. Disaggregating EPU into

fiscal, monetary, and trade policy components would help identify which policy domains drive risk transmission most intensely.

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