



Article

Dynamic Spillover Effects Among China's Energy, Real Estate, and Stock Markets: Evidence from Extreme Events

Fusheng Xie ¹, Jingbo Wang ² and Chunzi Wang ^{1,*}

¹ Department of Fintech, Shanghai Normal University Tianhua College, Shengxin North Road Campus, Shanghai 201815, China; xfs7002@sthu.edu.cn

² Business Analysis, The University of Sydney Business School, Darlington Campus, Sydney 2006, Australia; 13757677798@163.com

* Correspondence: wcz2766@sthu.edu.cn; Tel.: +86-1771740634

Abstract: This paper employs a Time-Varying Parameter Vector Autoregression Directional-Spillover (TVP-VAR-DY) model to investigate the dynamic spillover effects among China's energy, real estate, and stock markets from 2013 to 2023, with a focus on the impact of extreme events. The findings show that the total conditional spillover index (TCI) typically remains below 40% in the absence of extreme events, but significantly increases during such events, reaching 51.09% during the 2015 stock market crisis and nearing 60% during the COVID-19 pandemic in 2020. Specifically, the oil and gas market exhibited a net spillover index of 4.61%, emerging as a major source of risk transmission. In contrast, the real estate market, which had a net spillover index of −9.38%, became a net risk absorber. The net spillover index indicates that the risk transmission role of different markets towards other markets is dynamically changing over time and is closely related to significant global or domestic economic events. These results indicate that extreme events not only directly impact specific markets but also rapidly propagate risks through complex inter-market linkages, exacerbating systemic risks. Therefore, it is recommended to enhance market monitoring, improve transparency, and optimize risk management strategies to cope with uncertainties in the global economy and financial markets.



Academic Editors: Sahbi Farhani,
Alaa M. Soliman and Zied Ftiti

Received: 19 April 2025

Revised: 18 May 2025

Accepted: 28 May 2025

Published: 1 June 2025

Citation: Xie, F., Wang, J., & Wang, C. (2025). Dynamic Spillover Effects Among China's Energy, Real Estate, and Stock Markets: Evidence from Extreme Events. *International Journal of Financial Studies*, 13(2), 97. <https://doi.org/10.3390/ijfs13020097>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: spillover effects; energy market; real estate market; stock market; TVP-VAR-DY model; extreme events

1. Introduction

Energy, real estate, and the stock market, as the three pillars supporting China's economic system, have jointly driven continuous economic growth, maintained social stability, and promoted industrial upgrading. These three sectors have formed a complex economic ecosystem through their unique complementary mechanisms, bringing both synergistic opportunities and systemic risks. As China consolidates its position as the world's second-largest economy, fluctuations in these core areas are increasingly influencing global markets. Empirical studies have shown that policy adjustments and market volatility in China's energy, real estate, and stock markets have had significant spillover effects on international trade flows, commodity prices, and financial stability (Smith Stegen, 2015; Hu & Wang, 2022; Su et al., 2017). In the past few years, scholars have conducted in-depth research on the complex relationships and dynamic feedback mechanisms among these three markets from multiple perspectives, greatly enriching our understanding of intermarket interdependence.

Despite significant progress in existing research, several critical limitations remain. First, most studies overlook the regional heterogeneity under extreme events; second, the analytical perspective is often confined to unidirectional impacts between individual markets. Most notably, extant literature not only lacks investigation into bidirectional spillover effects between energy and real estate markets, but, more importantly, fails to systematically examine all three markets (energy, real estate, and stock) within a unified framework.

To overcome the problem that traditional static methods cannot capture the time-varying nature of cross-market linkages, this study introduces an integrated time-varying parameter VAR–directional spillover (TVP-VAR-DY) framework, combining the dynamic parameter adaptability of Nakajima's (2011) TVP-VAR model and the directional risk transmission index of the Diebold–Yilmaz (DY) index (Diebold & Yilmaz, 2012). This research not only deepens the theoretical understanding of the complex interdependence among these three markets, but also provides actionable insights for policymakers and investors at the practical level, helping to formulate more precise policies and investment strategies to cope with market volatility and risks in the context of global economic integration.

This study makes novel contributions by: (1) developing a time-varying coupling model to uncover nonlinear dynamic transmission mechanisms among the three markets; (2) identifying structural shifts in risk contagion pathways across different market regimes based on regime-switching characteristics during extreme events; and (3) proposing an integrated “risk resonance” analytical paradigm that captures multidimensional market linkages, thereby providing new theoretical foundations and methodological support for cross-market risk management.

The structure of this paper is as follows: Section 2 reviews the relevant literature to summarize existing research findings; Section 3 introduces the research methods and data sources, detailing the analytical framework; Section 4 conducts empirical analysis focusing on risk spillover effects; and Section 5 summarizes the research conclusions and puts forward policy recommendations.

2. Literature Review: Dynamic Interconnections and Risk Spillovers Among Energy, Real Estate, and Stock Markets

2.1. Interaction Mechanisms Between Energy and Real Estate Markets

Energy price fluctuations influence the functioning of the real estate market through multiple transmission pathways, with a process that exhibits significant spatial and temporal heterogeneity as well as market linkage characteristics. The basic theoretical framework can be analyzed from the following three dimensions:

Cost Transmission and Asset Pricing Effect. Changes in energy costs directly affect the entire lifecycle value chain of real estate: on the supply side, an increase in building energy consumption costs will squeeze developers' profit margins, alter the priority of land development, and change the supply structure of property types. On the demand side, the continuous fluctuation of the proportion of household energy expenditure will regulate homebuyers' payment capacity through the income effect and stimulate an upgraded preference for energy-efficient housing. Empirical studies by Basu and Gavin (2010) and Chau and Zou (2018) have shown that such price signals will lead to the re-pricing of real estate assets—properties with high energy efficiency will generate a sustained premium, while traditional high-energy-consuming assets will face valuation losses. This structural differentiation is particularly significant during periods of sharp energy price fluctuations.

Capital Flow and Expectation Feedback Mechanism. The overlapping financial attributes of the energy and real estate markets give rise to cross-market capital allocation behavior. Taruttis and Weber (2022) pointed out that when a stable expectation of energy price trends is formed, institutional investors will systematically adjust their real estate

portfolios: on the one hand, they will reduce exposure to assets in fossil fuel-intensive areas, and on the other hand, they will increase strategic allocation to green building certification projects. This capital reallocation not only directly changes the supply and demand balance in regional markets but also forms a long-term price trend through the self-reinforcing nature of market expectations, creating a positive feedback loop of “energy price fluctuations → investment strategy adjustment → market structural change”.

Dual Pathways of Cross-border Risk Transmission. Under the backdrop of globalization, the interaction between the energy and real estate markets exhibits cross-border network characteristics. [Alhodiry et al. \(2021\)](#), based on emerging market cases, revealed the transmission mechanisms of external shocks: international energy trade has a direct impact through the building operating cost channel, while monetary policies of major economies trigger indirect shocks through the capital flow channel. This dual transmission pathway leads to open real estate markets facing the combined pressure of physical energy dependence and financial risk spillovers. In the mature market context, [Mensi et al. \(2023\)](#) proved through a volatility spillover model that there is an asymmetric risk linkage between real estate investment trusts (REITs) and energy derivatives markets—energy price fluctuations will change the valuation basis of REITs through changes in corporate profit expectations, while liquidity changes in the REITs market will, in turn, affect the risk pricing logic of the energy futures market.

2.2. Research Progress on Cross-Market Spillover Effects

2.2.1. Risk Transmission Between Energy and Financial Markets

[N. Liu et al. \(2021\)](#) discovered through a Copula-GARCH model that there is positive time-varying average and tail dependence between green bonds (GBs) and several global and sectoral clean energy (CE) stock markets. [Geng et al. \(2021\)](#) constructed a connectedness network method to build returns and volatility for new energy companies around the world-system network. [Nie et al. \(2021\)](#) found in their research on China’s carbon trading market that fluctuations in carbon prices have a negative impact on the stock returns of coal-fired power companies with a two-day lag, while presenting significant positive spillovers to the new energy sector.

2.2.2. Dynamic Interconnections Between Stock and Real Estate Markets

The interaction between the stock and real estate markets exhibits multidimensional and cross-cycle complexities, and its transmission mechanisms can be systematically explained through three theoretical dimensions:

Bidirectional Reinforcement of Wealth and Collateral Effects. The prosperity of the stock market stimulates the demand for real estate through the channel of increasing residents’ wealth, forming a positive transmission chain of “stock returns → expansion of consumption → enhanced ability to purchase property” ([Luo & Li, 2007](#)). In the reverse direction, fluctuations in the value of real estate as a core collateral significantly affect the stability of the financial system. [Dieci et al. \(2018\)](#) proved through a dynamic stochastic general equilibrium model that a decline in housing prices triggers stock selling pressure through the balance sheet channel, ultimately forming a negative spiral of “asset price decline → liquidity contraction → credit contraction”. This bidirectional reinforcement mechanism is particularly prominent during financial crises. [Zha et al. \(2023\)](#) found that extreme events can sharply increase the risk resonance intensity between the two markets.

Network Characteristics of Cross-Market Risk Transmission. Risk contagion in the modern financial system exhibits nonlinear network effects. [Liow and Song \(2021\)](#) constructed a cross-country comparative framework to reveal significant regional heterogeneity in the volatility spillover between corporate equity markets and real estate investment

trusts (REITs): In developed economies, market linkages are more reflective of institutional investors' cross-asset allocation behavior, while emerging markets are more influenced by policy interventions. Under extreme risk conditions, this interconnectedness exhibits self-reinforcing characteristics. [Belkhir and Abbes \(2024\)](#) found based on a volatility spillover network model that during public health crises, the risk transmission paths between different sectors undergo structural reorganization.

Regulatory Effect of Policy Interventions. Government regulatory policies, as exogenous shocks, profoundly change the interaction patterns between the two markets. [Akbari and Krystyniak \(2021\)](#) demonstrated through a policy shock response function that real estate purchase restrictions can trigger a capital diversion effect in the stock market, but this effect diminishes marginally with increasing financial market maturity. Particularly in transition economies, [Yang et al. \(2024\)](#) found that irrational booms in the real estate market can distort stock market pricing efficiency through a mechanism of resource misallocation, with this distortion effect being more pronounced in areas with greater opportunities for institutional arbitrage.

2.3. Asymmetry and Nonlinear Spillover Effects

The risk transmission in financial markets exhibits significant asymmetric and nonlinear dynamic characteristics, which can be systematically deconstructed through the following three dimensions:

State-Dependent Heterogeneity in Spillover Intensity. The spillover effect varies significantly across different market cycles. Empirical studies based on quantile regression methods have shown that the stock market's transmission of downside risk to the commodity market is nonlinearly amplified during bear markets ([Shahzad et al., 2021](#)). This state dependency is particularly pronounced in the real estate sector, where the sensitivity of real estate investment trusts (REITs) to negative energy price shocks is significantly higher than to positive fluctuations, and this asymmetry tends to self-reinforce during systemic crises ([Mensi et al., 2021](#)). Cross-border comparative studies have further revealed that emerging markets can shift from being risk absorbers to net spillover sources during extreme events, leading to a reversal in the direction of cross-market risk transmission ([Vo & Nguyen, 2024](#)).

Network Structure Mutation under Crisis Conditions. Major exogenous shocks can reconfigure the risk transmission pathways in financial markets. Empirical evidence from the COVID-19 pandemic shows that public health crises trigger structural shifts in cross-market linkages through the channel of investor risk preferences: the correlation between traditional safe-haven assets and risky assets undergoes a paradigm shift, and the volatility spillover network between emerging and developed markets experiences a center-periphery structural reorganization ([Belkhir & Abbes, 2024](#)). This network mutation is characterized by asymmetry, with the speed and magnitude of downside risk transmission significantly exceeding that of upside risk.

Mechanistic Complexity of Cross-Market Linkages. The nonlinear associations among different financial sub-markets exhibit significant mechanistic differentiation. The linkage between stock and real estate markets encompasses both long-term cointegration driven by fundamentals and short-term volatility resonance triggered by liquidity shocks ([Liow & Song, 2021](#)). In the derivatives market, the dynamic correlation between crude oil futures and stock indices is constrained by arbitrage boundaries, and its asymmetric characteristics show regional heterogeneity under the influence of inventory cycles and varying degrees of financialization ([Chen et al., 2021](#)). This complexity necessitates the use of time-varying parameter models to capture the regulatory effects of institutional changes on cross-market linkages ([Ngene, 2021](#)).

2.4. Limitations of Existing Research and Directions for Breakthroughs

Current research on cross-market interconnections faces three theoretical bottlenecks:

Dimensional Limitations in Market Interconnection Studies. Most mainstream literature focuses on the linear associations between pairwise markets, lacking a systematic deconstruction of the ternary interaction mechanisms among energy, real estate, and stock markets (Kumar et al., 2022). This one-dimensional analytical framework fails to capture the network effects of multi-market linkages. Especially under the ‘new normal’ of concurrent energy transition and financial deepening, ignoring the co-evolution among markets can lead to misjudgments of risk transmission pathways.

Insufficient Identification of Spatial-Temporal Heterogeneity. Existing research generally adopts a homogeneity assumption, failing to fully parse the regulatory effects of regional institutional environments and differences in market maturity on cross-market interconnections. Although some scholars have revealed the particularities of specific markets through country-specific case studies (Alhodiry et al., 2021), the lack of a cross-country comparative research framework limits the universality of theoretical findings.

Ambiguous Dynamic Impact Mechanisms of Extreme Events. Existing analyses are mostly limited to cross-sectional studies of specific crisis periods, making it difficult to reveal the differentiated transmission paths of extreme shocks across different stages of the economic cycle. Although some literature has focused on market resonance during crises (Yang et al., 2024), there are still methodological deficiencies in dynamically tracking the duration, decay rate, and structural breakpoints of shocks.

To overcome the above limitations, this paper constructs a comprehensive analytical framework integrating time-varying parameters and spatial heterogeneity:

Dynamic Interconnection Network Modeling. The time-varying parameter vector autoregression (TVP-VAR) model is employed to capture the structural mutation characteristics of the ternary market interconnections, breaking through the limitations of fixed-parameter models in depicting institutional changes and market learning behaviors (Nakajima, 2011). This framework can identify the dynamic impacts of exogenous shocks, such as major policy adjustments or geopolitical conflicts, on the strength of cross-market linkages.

Analysis of Asymmetric Spillover Effects. Directional spillover indicators are introduced to quantify the asymmetric characteristics of risk transmission, addressing the shortcomings of traditional volatility models in identifying the direction of net risk spillovers. This method can effectively distinguish the role reversals of risk importers and exporters among markets, providing early warning signals for cross-border crisis transmission.

2.5. Evolution of Methodology and Theoretical Contributions

The traditional research paradigm has dual limitations in capturing the dynamic evolution of cross-market interconnections. First, fixed-parameter models (such as VAR and GARCH) fail to identify structural breaks triggered by policy shifts and external shocks. Second, static correlation metrics cannot parse the directionality and asymmetry of risk transmission. To address these limitations, this study achieves methodological breakthroughs through threefold integration:

Construction of a Dynamic Parameter System. By integrating the time-varying parameter vector autoregression (TVP-VAR) model with the directional spillover index, we establish a risk network analysis framework with time-varying characteristics. The TVP-VAR model (Nakajima, 2011) captures institutional changes and market learning behaviors through its parameter adaptation mechanism, while the directional spillover index (Diebold & Yilmaz, 2012) quantifies the net direction and intensity differences in cross-market risk

transmission. This coupled design effectively resolves the concurrent challenges of structural breakpoint identification and risk role determination in traditional models.

Expansion of Multi-Scale Analytical Capabilities. We construct a multi-dimensional analytical system based on “time-varying parameters–directional spillovers”. This framework tracks the dynamic impacts of significant events on market interconnection strength over time.

Optimization of Extreme Event Scenarios Simulation. The improved rolling window algorithm, with its dynamic weight adjustment mechanism, significantly enhances the model’s predictive efficacy during crises. Compared with traditional static frameworks, the new method can identify early signals of cross-market risk resonance more promptly and serves as an adaptive scenario generator for stress testing.

This study advances the theoretical understanding of the dynamic evolution of cross-market risk networks in the following aspects: through time-varying network topology analysis, we discover that risk transmission in financial markets exhibits concurrent evolutionary characteristics of “migration of central nodes” and “community structure reorganization”. During periods of accelerated energy transition, the market centrality of traditional energy assets continuously declines, while green infrastructure assets gradually emerge as new risk hub nodes.

While the Time-Varying Parameter Vector Autoregression (TVP-VAR) model offers numerous advantages, it is essential to recognize its limitations in practical applications. The TVP-VAR model has the following two well-documented limitations. First, the model requires the estimation of a large number of time-varying parameters. As demonstrated by [Koop and Korobilis \(2013\)](#) in their Bayesian analysis, when the dimensionality of the variables exceeds five–six dimensions, the model faces significant estimation challenges due to the “curse of dimensionality” ([Bellman, 1966](#)), often resulting in imprecise parameter estimates or computationally prohibitive requirements. This computational complexity has been quantitatively shown to grow exponentially with variable dimensions ([Kalli & Griffin, 2014](#)). Second, the model’s assumption of smooth parameter evolution ([Nakajima, 2011](#)) fundamentally limits its ability to detect abrupt structural breaks. [Primiceri \(2005\)](#) empirically verified that TVP-VAR models tend to smooth over sudden regime shifts characteristic of financial crises or policy regime changes. This smoothing effect leads to systematic underestimation of nonlinear impacts during turbulent periods, as evidenced by [Korobilis \(2013\)](#) in comparative studies with Markov-switching models.

2.6. Major Extreme Events

The period from 2013 to 2023 was marked by a series of extreme events that had profound impacts on global financial markets and economies ([Y. Liu et al., 2023](#)). Figure 1 depicts the timeline of these major events, highlighting their interconnectedness and the significant challenges they posed to various sectors. The 2015 stock market crash, commencing on 15 June 2015, witnessed a precipitous decline in the A-share market within weeks, marked by the uncommon occurrence of numerous shares plummeting. The Shanghai Composite Index fell by over 40% within three months. This event resulted in a significant contraction of the total market value, causing substantial losses for many individual investors and institutions, and severely undermining market confidence. In 2016, energy market volatility, particularly in the oil market, was exacerbated by supply and demand imbalances, policy adjustments, geopolitical tensions, and global economic expectations. These factors collectively had a wide-reaching impact on the global economy and financial markets. The trade tensions between China and the United States escalated into a trade war beginning in 2018. As a direct confrontation between the world’s two largest economies, the trade war not only affected the import and export trade between

the two countries but also disrupted global supply chains, investment confidence, and economic growth expectations. For China, as an energy importer, the stability and cost control of the energy market faced significant challenges, which in turn affected the real estate and stock markets. The outbreak of the unprecedented COVID-19 pandemic in late 2019 disrupted the global economic and social order, causing extreme market panic, widespread economic stagnation, and severe volatility in financial markets, including stock and bond markets. In 2020, the global demand for crude oil plummeted due to the impact of the new crown pneumonia epidemic. On 20 April 2020, the official CME settlement price of the May WTI crude oil futures contract was USD −37.63 per barrel, triggering the ‘Crude Oil Bao’ incident. The September 2021 payment crisis faced by Evergrande Group underscored recent turmoil and challenges in China’s real estate market. Evergrande Group, one of China’s largest real estate developers, encountered unprecedented difficulties impacting not only its own stability but also potentially the entire industry and financial markets. The Russia–Ukraine conflict in February 2022 reshaped the regional security landscape and had a profound impact on the global energy market, leading to a sharp rise in oil and gas prices and triggering financial market turmoil.

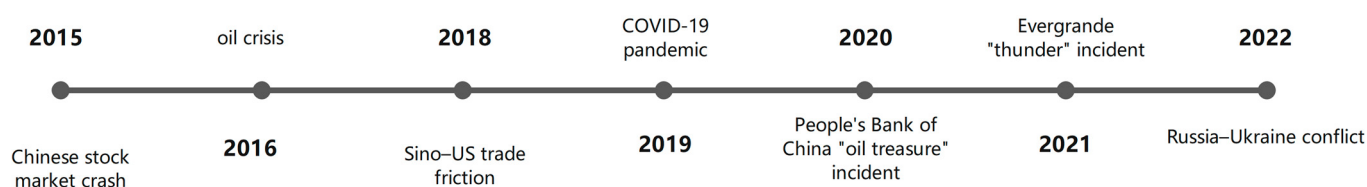


Figure 1. Timeline of extreme events.

The research literature on extreme events and their spillover effects reveals significant inter-market and cross-sectoral linkages and risk contagion mechanisms. Empirical findings by [Zhang et al. \(2020\)](#) demonstrate that while market spillover effects remained generally stable following the 2008 global financial crisis, they exhibited marked volatility starting in late 2013, a temporal pattern that closely corresponds with the occurrence of extreme events, thereby highlighting the transformative impact of extreme conditions on market interconnectedness structures. [Gong et al. \(2020\)](#) developed an analytical framework for systemic risk contagion, demonstrating that extreme risk events can fundamentally alter risk transmission pathways among financial sectors. Their research particularly emphasizes the necessity of incorporating tail risk considerations in spillover effect analyses. [Q. Wang et al.’s \(2022\)](#) study on safe-haven assets found that during periods of severe market turbulence, the hedging effectiveness of Bitcoin, gold, and commodities significantly weakens, reflecting how spillover effects under extreme conditions may undermine the risk-mitigating functions of traditional assets. [Khalfaoui et al. \(2023\)](#) focused on the COVID-19 pandemic, revealing dual spillover effects from public health crisis information and cryptocurrency markets to green bond markets, confirming that pandemic-induced market panic intensifies cross-market linkages and affects green bond pricing efficiency through volatility transmission mechanisms. [He and Hamori’s \(2023\)](#) in-depth research further discovered that extreme events not only impact asset returns but also significantly alter higher-moment characteristics, with such nonlinear effects exacerbating the intensity of risk contagion.

Subsequent studies have continued to expand the boundaries of understanding in this field: [Usman et al. \(2023\)](#) verified the existence of significant contagion effects in jump risks among corporations; [Y. Liu et al. \(2023\)](#) established a theoretical explanation for investor sentiment transmission channels; [X. Wang et al. \(2023\)](#) uncovered information diffusion mechanisms of credit rating events from a supply chain perspective. Particularly noteworthy

thy is the groundbreaking research by [Li et al. \(2023\)](#), which employed dynamic spillover indices to characterize the tripartite interactions among carbon markets, traditional energy markets, and financial markets. Their findings demonstrate that environmental policy-related extreme events can reconfigure both the direction and intensity of inter-market risk transmission, providing novel insights for understanding financial risk characteristics during sustainable development transitions.

Synthesizing existing research (Table 1) findings leads to the following core conclusions: as critical triggering factors, extreme events persistently influence the risk distribution patterns in global financial markets through multiple channels—by altering market connectivity structures, amplifying risk contagion intensity, and undermining systemic stability. These conclusions carry important implications for refining financial risk monitoring frameworks under extreme conditions.

Table 1. Summary of key findings from literature review.

Research Focus	Main Conclusions	Key References
Energy-Real Estate Interactions	- Energy prices affect real estate through cost transmission and capital reallocation - Energy-efficient properties command pricing premiums - Dual transmission channels: direct (operating costs) and indirect (financial linkages)	Basu and Gavin (2010) ; Chau and Zou (2018) ; Alhodiry et al. (2021)
Stock-Real Estate Linkages	- Bidirectional wealth-collateral reinforcement loops - Network effects dominate in developed markets vs. policy-driven links in emerging markets - Regulatory interventions significantly alter interaction patterns	Luo and Li (2007) ; Dieci et al. (2018) ; Akbari and Krystyniak (2021)
Asymmetric Spillovers	- Stronger downside risk transmission during market stress - Crisis-induced network structure mutations - Nonlinear effects vary by asset class and region	Shahzad et al. (2021) ; Mensi et al. (2021) ; Vo and Nguyen (2024)
Extreme Event Impacts	- Events reconfigure risk transmission pathways - Spillover intensity spikes during crises - Role reversals occur in net spillover directions - Tail risks undermine traditional hedging strategies	Zhang et al. (2020) ; Q. Wang et al. (2022) ; Li et al. (2023) ; Y. Liu et al. (2023) ; Q. Liu et al. (2024)
Methodological Limitations	- Over-reliance on pairwise market analyses - Inadequate treatment of spatial/regional heterogeneity - Static models fail to capture crisis dynamics	Kumar et al. (2022) ; Ngene (2021) ; Yang et al. (2024)

3. Methodology and Data Overview

3.1. Methodology

The TVP-VAR-DY model proposed by [Korobilis and Yilmaz \(2018\)](#) is widely used to investigate the yield and risk spillover effects between financial assets and markets. This model effectively describes the time-varying characteristics of spillover effects. The TVP-VAR(p) model ([Antonakakis et al., 2020, 2023](#); [Du & Xu, 2024](#)) with the lag selected by the Akaike Information Criterion (AIC) can be represented as follows:

$$Y_t = \beta_t X_{t-1} + \varepsilon_t, \quad \varepsilon_t | I_{t-1} \sim N(0, \Sigma_t), \quad (1)$$

$$Vec(\beta_t) = Vec(\beta_{t-1}) + \zeta_t, \quad \zeta_t | I_{t-1} \sim N(0, \Xi_t), \quad (2)$$

where $Y_t = (Y_{1t}, Y_{2t} \dots Y_{Nt})$, $X_{t-1} = (Y_{t-1}, Y_{t-2} \dots Y_{t-p})^T$, $\beta_t = (\beta_{1t}, \beta_{2t}, \dots, \beta_{pt})$, I_{t-1} represents all information available until $t - 1$, Y_t and X_{t-1} represents $N \times 1$ and $p \times 1$ vectors, respectively, β_t and β_{it} are $N \times Np$ and $N \times N$ dimensional matrices, respectively, ε_t is an $N \times 1$ vector, and ζ_t is an $N^2p \times 1$ dimensional vector, whereas the time-varying variance-covariance matrices Σ_t and Ξ_t are $N \times N$ and $N^2p \times N^2p$ dimensional matrices, respectively. Moreover, $\text{Vec}(\beta_t)$ is the vectorization of β_t which is an $N^2p \times 1$ dimensional vector.

Generalized forecast error variance decomposition (GFEVD) is the basis of Diebold and Yilmaz's estimation of spillover effects. According to the Wold representation theorem, TVP-VAR needs to be transformed into TVP-VMA (a Time-Varying Parameter Vector Moving Average model) after estimating time-varying parameters:

$$Y_t = \sum_{i=1}^p \beta_{it} Y_{t-i} + \varepsilon_t = \sum_{j=1}^{\infty} \Lambda_{jt} \varepsilon_{t-j} + \varepsilon_t \quad (3)$$

where $\Lambda_{jt} = \beta_{1t} \Lambda_{j-1t} + \beta_{2t} \Lambda_{j-2t} + \dots + \beta_{pt} \Lambda_{j-pt}$, with Λ_{0t} being an identity matrix and $\Lambda_{jt} = 0$ for $j < 0$. In the framework of variance decomposition, the forecast error variance of each variable can be decomposed into components attributed to various shocks from other variables. This can be denoted as the directional overflow from variable j to variable i :

$$\phi_{ij,t}^g(J) = \frac{\sum_{i,t}^{-1} \sum_{t=1}^{J-1} (\tau_i \Lambda_t \Sigma_t \tau_j)^2}{\sum_{j=1}^N \sum_{t=1}^{J-1} (\tau_i \Lambda_t \Sigma_t \Lambda_t \tau_i)} \quad (4)$$

$$\phi_{ij,t}^g(J) = \frac{\phi_{ij,t}^g(J)}{\sum_{j=1}^N \phi_{ij,t}^g(J)} \quad (5)$$

In Formula (4), $\sum_{j=1}^N \phi_{ij,t}^g(J) = 1$, $\sum_{i,j=1}^N \phi_{ij,t}^g(J) = N$, J is the number of decomposition periods of the prediction error equation, and τ_i is a selection vector (1 at the position of variable i , otherwise 0). Therefore, the Total Connectedness Index (TCI) based on GFEVD is in the following form:

$$C_t^g(J) = 1 - N^{-1} \sum_{i=1}^N \phi_{ii,t}^g(J) \quad (6)$$

The TCI can be used to measure the total spillover level within the model system.

The directional connectedness index (FROM and TO) can be expressed as:

$$C_{i,t}^g(J) = \sum_{j=1, j \neq i}^N \phi_{ij,t}^g(J) \quad (7)$$

$$C_{i,t}^g(J) = \sum_{j=1, j \neq i}^N \phi_{ji,t}^g(J) \quad (8)$$

Formulas (7) and (8) represent the spillovers received by sector i from all other sectors j and the spillovers transmitted by sector i to all other sectors j , respectively. These formulas quantify the total directional connectedness from and to other sectors. The net total directional connectedness (NET) is calculated as the difference between the total spillovers to other sectors and the total spillovers from other sectors, indicating whether sector i acts as a net transmitter or a net receiver of shocks. This is expressed as follows:

$$C_{i,t}^g(J) = C_{i,t}^g(J) - C_{i,t}^g(J) \quad (9)$$

When (9) is greater than 0, it means that the influence of i on the system is greater than that of the system on the variable i .

Finally, we will show the spillover index between the two variables:

$$NPDC_{ji}(J) = \phi_{ji,t}^g(J) - \phi_{ij,t}^g(J) \quad (10)$$

The Formula (10) is NPDC (net pairwise directional connectedness), expressed as the spillover effect between variable i and variable j . Similarly, when $NPDC_{ji}(J)$ is greater than 0, it shows that the influence of variable i on variable j is greater than that of variable j on variable i . Otherwise, it means that variable j has a greater impact on it.

3.2. Data Overview

The dataset for this paper is sourced from the Choice Financial Terminal, covering the period from 15 July 2013 to 29 December 2023. The Zhongzheng All-Index Real Estate Index is selected as the proxy variable for the real estate market; the Oil and Gas Index and the Coal Index from Dongcai's secondary industry are used as proxy variables for the energy market; and the Shanghai and Shenzhen 300 Index serves as the proxy variable for the stock market.

To investigate the risk spillover effects among various markets, we first applied logarithmic transformation to the data on opening prices, closing prices, highest prices, and lowest prices. The variance was then calculated using Formula (11). In the subsequent formulas, "open", "high", "low", and "close" represent the logarithmic opening price, logarithmic highest price, logarithmic lowest price, and logarithmic closing price, respectively.

$$\begin{aligned} \sigma^2 = & 0.511 \times (high - low)^2 \\ & - 0.019 \times ((close - open) \times (high + low - 2 \times open) - 2 \times (high - open) \times (close - open)) \\ & - 0.383 \times (close - open)^2 \end{aligned} \quad (11)$$

Then, the calculated variance is annualized according to Formula (12):

$$(\sigma^2 \times 250)^{0.5} \times 100 \quad (12)$$

Figure 2 is the annual volatility time series of oil and gas markets, coal markets, real estate markets, and stock markets.

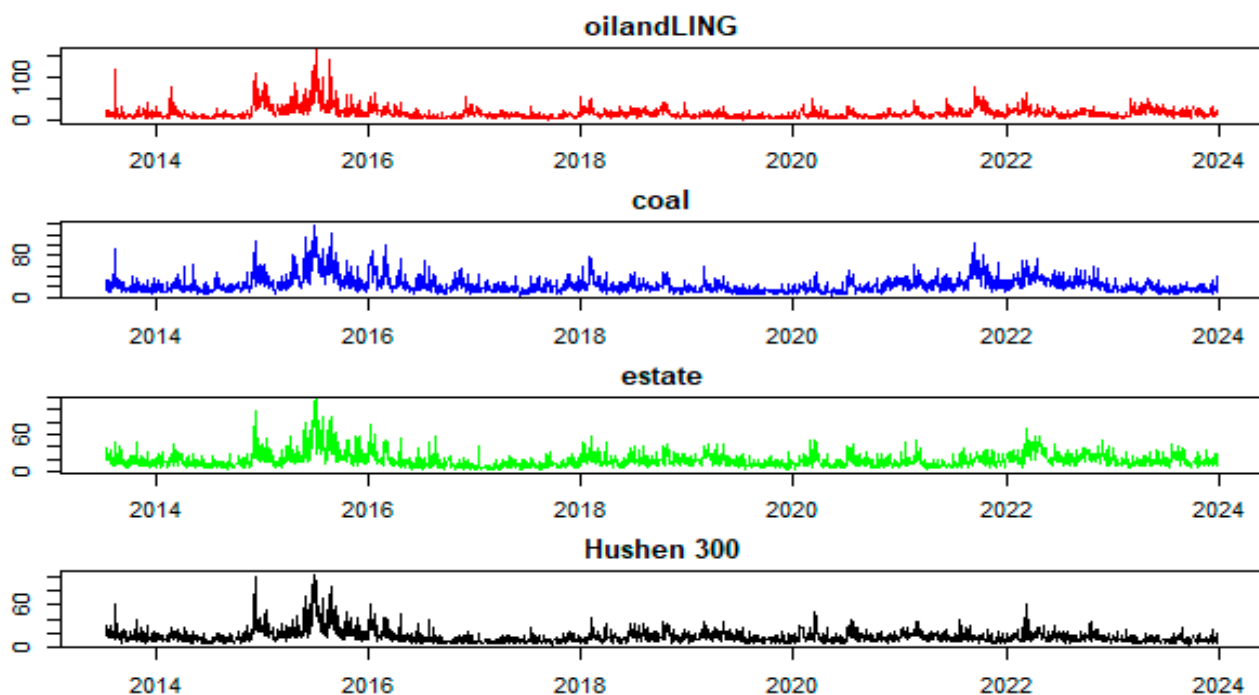


Figure 2. Annual volatility (oilandLING represents oil and gas markets, coal represents coal markets, estate represents real estate markets, Hushen 300 represents stock market).

As depicted in Figure 2, a pronounced volatility clustering effect is observed, characterized by significant temporal fluctuations in volatility levels. Given these characteristics, it is imperative to utilize a model that incorporates time-varying features in order to effectively capture and fit the data.

It can be concluded from Table 2 that the skewness of all variables shows a significant positive skewness, and the Kurtosis values are significant, and show a ‘peak’ shape. The JB test is significant at the 1% significance level and refuses to obey the normal distribution. All variables have a certain degree of autocorrelation under the Ljung–Box test. The ERS test of all variables is significant at the 1% significance level, indicating that the variables are stable.

Table 2. Descriptive statistics of annualized volatility for each market.

Indicators	oilandLING	Coal	Estate	Hushen 300
Mean	17.35	23.21	18.37	14.62
Median	13.69	19.07	15.59	12.17
Maximum	162.19	138.81	115.92	104.29
Minimum	0.11	3.38	2.56	2.81
Std.Deviation	13.48	14.97	11.56	9.90
Skewness	3.71 ***	2.33 ***	2.41 ***	3.40 ***
Kurtosis	24.72 ***	11.21 ***	13.26 ***	21.63 ***
JB	55,931 ***	9461.3 ***	13,635 ***	41,777 ***
ERS	−8.01 ***	−7.83 ***	−6.19 ***	−4.34 ***
Ljung–Box	0.44 ***	0.46 ***	0.40 ***	0.42 ***

Note: *** is expressed at 1% significant level.

Figure 3 presents a Pearson correlation heat map illustrating the volatility across the four markets. The high correlation coefficients suggest significant inter-market correlations. The presence of high correlation coefficients indicates that when the volatility of one market increases, it is likely to influence the volatility level of other markets, thus reflecting the manifestation of the risk spillover effect. Subsequently, we employ an advanced statistical model, the TVP-VAR-DY model to further analyze the risk spillover effect.

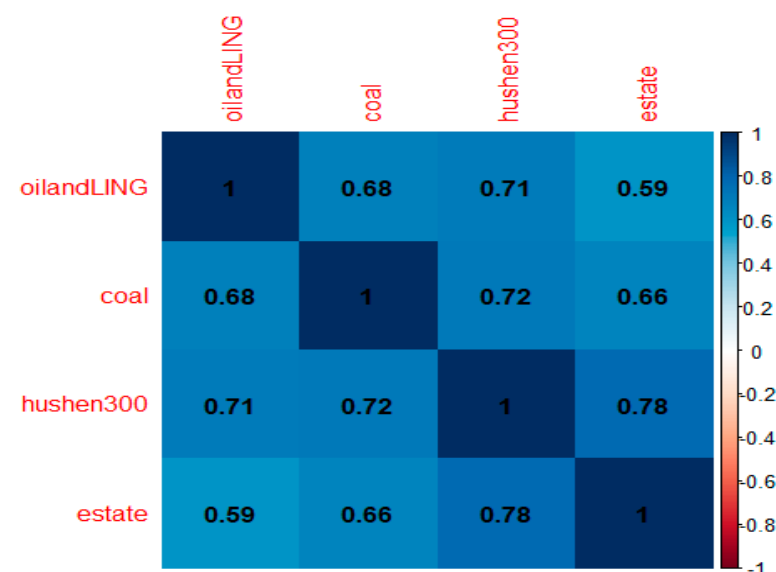


Figure 3. Pearson correlation heat map.

4. Risk Spillover Analysis

4.1. Static Analysis of Risk Spillover

Utilizing the spillover index derived from generalized variance decomposition (DY), this study examines the risk spillover effects among the energy market (including the oil, gas, and coal markets), the real estate market, and the stock market. The optimal lag order, determined by the Akaike Information Criterion (AIC), is set at 10 periods. This lag order is also employed to define the prediction period for the total dynamic spillover effect, which spans 10 periods. The static analysis of the risk spillover effects is presented in Table 3. In this table, “FROM” indicates the total spillover received by a market from other markets. “TO” represents the total spillover transmitted by a market to other markets. “Inc.Own” denotes the total spillover level of a market to all markets, including itself. “NET” signifies the net spillover level of a market to other markets (i.e., the difference between “TO” and “FROM”). “TCI” refers to the total spillover effect level, encompassing both incoming and outgoing spillovers.

Table 3. Connectedness table of risk.

Variable	oilandLING	Coal	Estate	Hushen 300	FROM
oilandLING	55.36	17.12	9.98	17.54	44.64
coal	17.70	51.13	13.00	18.17	48.87
estate	12.20	16.00	47.28	24.52	52.72
Hushen 300	19.35	18.40	20.37	41.89	58.11
TO	49.25	51.52	43.34	60.23	204.34
Inc.Own	104.61	102.65	90.62	102.12	TCI
NET	4.61	2.65	−9.38	2.12	51.09

Table 3 reveals that the total risk spillover index (TCI) for the overall market reaches 51.09%, highlighting the significant inter-market risk interactions. Specifically, the oil and gas market, the coal market, and the stock market exhibit net spillover indices of 4.61%, 2.65%, and 2.12%, respectively, indicating their roles as net risk contributors. The oil and gas market, in particular, stands out as the predominant source of risk. This phenomenon may be attributed to the high price volatility of the oil and gas market, which is significantly influenced by global economic conditions, geopolitical tensions, and uncertainties in climate policies. Conversely, the real estate market serves as a net risk absorber, with a net spillover index of −9.38%, demonstrating its crucial role in stabilizing market risks. The stability of the real estate market, characterized by its high asset value and relatively stable cash flows, enables it to absorb a portion of the market risks.

A thorough examination of the market interactions further uncovers a pronounced risk spillover between the stock market and the real estate market. The stock market’s spillover effect on the real estate market is substantial at 24.52%, and reciprocally, the real estate market’s spillover effect on the stock market reaches 20.37%. This intense two-way risk exchange conclusively demonstrates the close and intricate risk interplay between these two markets. This significant interplay can be attributed to several factors. Firstly, both the stock market and the real estate market, as integral parts of the financial market, are commonly influenced by macroeconomic conditions, policy adjustments, and market expectations. Secondly, investors often adjust their asset allocation between stocks and real estate based on market performance. When the stock market performs poorly, investors may shift their investments from stocks to real estate, and vice versa. Lastly, regulatory

policies, such as the “housing for living, not for speculation” policy, have had a notable impact on both the real estate and stock markets.

Additionally, the oil and gas market exhibits spillover effects of 12.20% on the real estate market and 19.35% on the stock market. Conversely, the feedback spillover from the real estate and stock markets to the oil and gas market is observed at 9.98% and 17.54%, respectively. These figures further confirm the oil and gas market as the primary risk exporter. The risk spillover effect of the oil and gas market may be related to the volatility of the global energy market, especially the impact of geopolitical conflicts and uncertainties in climate policies on the oil and gas market. Meanwhile, the ongoing energy transition also subjects the oil and gas market to dual pressures of declining demand and policy adjustments.

Within the energy sector, the interaction between the oil and gas market and the coal market exhibits significant spillover effects. The oil and gas market has a spillover index of 17.70% on the coal market, while the coal market’s spillover effect on the oil and gas market is slightly lower at 17.12%. This underscores a robust two-way risk spillover within the energy market, with the oil and gas market exerting a slightly greater spillover influence. This phenomenon may be associated with the price volatility and interdependence of fluctuations within the energy market.

Building upon the insights from the static spillover analysis, it is evident that there is not only a high level of overall risk spillover among the four major markets, but also a clear predominance of the oil and gas market as the central source of spillover in the market system’s risk transmission. Conversely, the real estate market plays a pivotal role in absorbing these spillover risks. This analytical framework offers a valuable perspective for comprehending the interconnected risk dynamics between markets and provides important references for policymakers and market participants.

4.2. Dynamic Analysis of Risk Spillover

4.2.1. Analysis of Total Risk Spillover

Static analysis of spillover effects between markets captures only the average level across the sample period, lacking the ability to capture the time-varying characteristics of mutual risk spillover between markets. Figure 4 depicts the total market risk spillover effect, providing insights into these dynamic interactions over time.

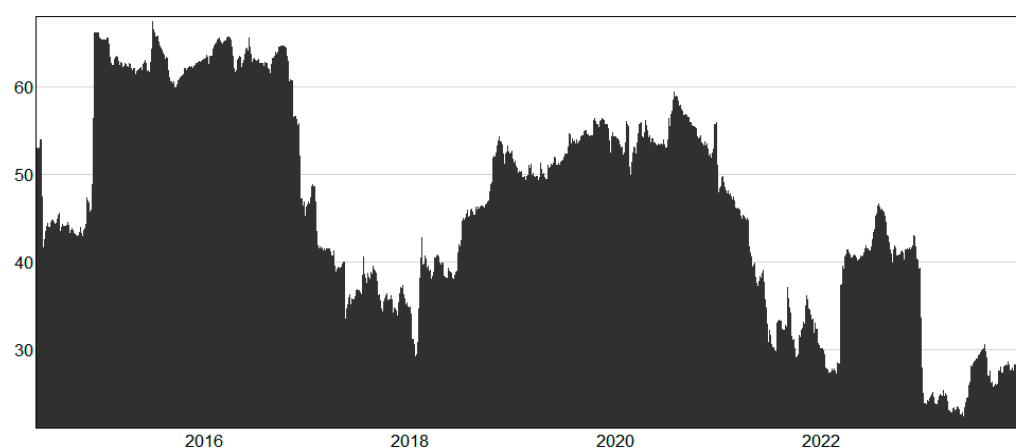


Figure 4. Total risk spillover.

Figure 4 reveals that in the absence of extreme events, the overall dynamic spillover index typically remains below 40%. However, during such events, the index escalates dramatically, often exceeding 50% and, at times, peaking above 60%. This stark fluctuation underscores the heightened sensitivity of the total spillover index to extreme occurrences.

Over the examined timeframe, three significant spikes in the spillover index are notable. The analysis reveals three distinct crisis periods that significantly amplified risk spillovers across China's energy, real estate, and stock markets. The first surge occurred during 2015–2016, when the simultaneous collapse of China's stock market and global oil prices drove the spillover index from 32% to 51%, with elevated effects persisting for 18 months. The second escalation phase (2018–2020) saw spillovers peak at 55% during the U.S.–China trade war before reaching 60% under COVID-19 pandemic pressures, reflecting compounded stresses across financial and commodity markets. Most recently, the 2021–2022 period witnessed dual shocks from the global energy crisis and Russia–Ukraine conflict, which transformed energy markets into net risk exporters while the Evergrande crisis simultaneously amplified real estate market vulnerabilities. These findings systematically demonstrate how extreme events across economic, geopolitical, and public health domains create persistent cross-market contagion, with spillover effects typically enduring for 12–18 months post-shock. The results underscore the critical importance of developing forward-looking risk monitoring frameworks that account for these multidimensional shock transmission channels.

4.2.2. Analysis of Directional Risk Spillover

Figure 5 illustrates the directional risk spillover effect between markets, presenting the total dynamic spillover index of one market to other markets (To Others). Figure 6 displays the total spillover effect of a market from other markets (From Others). These two figures provide an in-depth analysis of the direction and intensity of risk spillovers between markets.

From Figure 5, it is evident that each market has a unique spillover index, with pronounced peaks under the influence of extreme events. Despite varying levels, there is a clear trend in the fluctuation of the indices, suggesting significant spillover effects across all markets.

In the energy market, the oil crisis that began in June 2014 led to substantial fluctuations in oil prices, which persisted until 2016. As the world's largest oil importer, China was severely impacted, with the risk spillover index for the oil and gas market reaching 22%. In 2021, amid an energy shortage, the risk spillover index for the oil and gas market remained elevated at 17%. The Russia–Ukraine conflict, which broke out in February 2022, further exacerbated global energy price volatility. Given the role of Russia-related risk as a major energy exporter, the conflict significantly increased the risk spillover effects in the energy market.

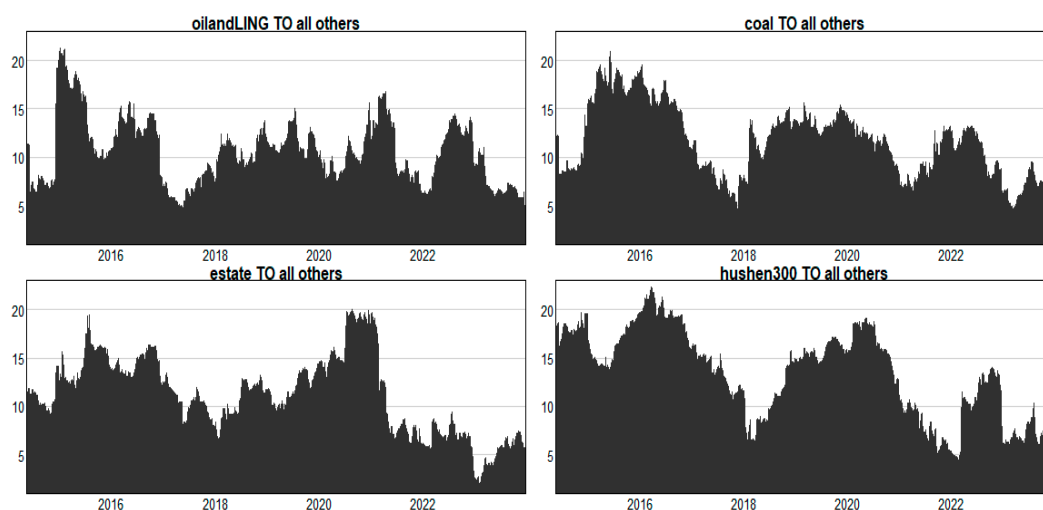


Figure 5. Risk spillover effects (To Others).

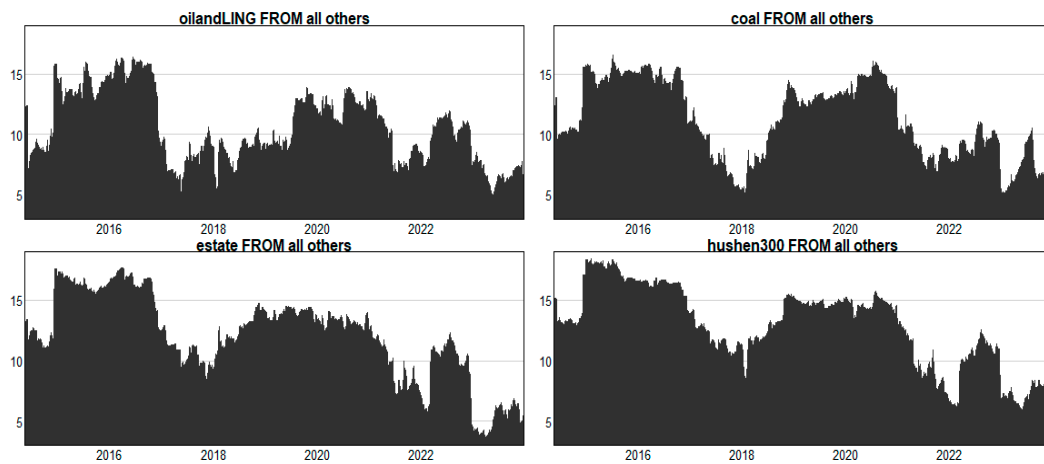


Figure 6. Risk spillover effect (From Others).

In the real estate market, the spillover index peaked in 2015, primarily due to six interest rate cuts by the central bank and reductions in mortgage rates aimed at stimulating a bull market in real estate. Sharp price changes contributed to the increase in the spillover index during this period. In 2021, the spillover index reached a new peak due to the Evergrande crisis. As a leading real estate enterprise, Evergrande's bankruptcy triggered a significant debt crisis and substantial risk spillover effects on the real estate market.

In the stock market in 2015, China's A-share market experienced a leveraged bull market followed by a rapid downturn, with thousands of stocks plummeting and a 35% decline in total market value over four months. Market volatility kept the risk spillover index at a high level during this period. The Sino–U.S. trade war, which began in 2018 and lasted for 17 months, further contributed to sustained high spillover indices in China's stock market. As a major trade surplus country, China's shrinking export scale directly influenced investor expectations, amplifying spillover effects. The Russia–Ukraine conflict in early 2022 intensified market panic, increased trading volumes, and led to a significant rise in the risk spillover index of the stock market.

The dynamic analysis reveals that, under the influence of a series of extreme global events (including economic, military, and health dimensions), the overall spillover level experiences a sharp ascent. This observation corroborates the heightened sensitivity of the dynamic spillover index to such extraordinary circumstances, underscoring the intricate web of interdependencies that link various markets in response to external shocks. The analysis shows that extreme events play a critical role in driving significant fluctuations in inter-market risk spillovers, emphasizing the need for robust risk management strategies and policy interventions to mitigate the impact of such events on financial stability.

The dynamic risk spillover analysis reveals the time-varying characteristics of cross-market net spillover effects (Figure 7). Consistent with the asymmetric risk transmission theory proposed by [Mensi et al. \(2021\)](#) in the literature review, the real estate market primarily exhibited net risk-receiving characteristics during the sample period, while the stock and energy markets demonstrated more complex dynamic variations. These findings validate [Alhodiry et al.'s \(2021\)](#) proposition regarding market heterogeneity while complementing the market role transition mechanisms insufficiently discussed in [Li et al.'s \(2023\)](#) research.

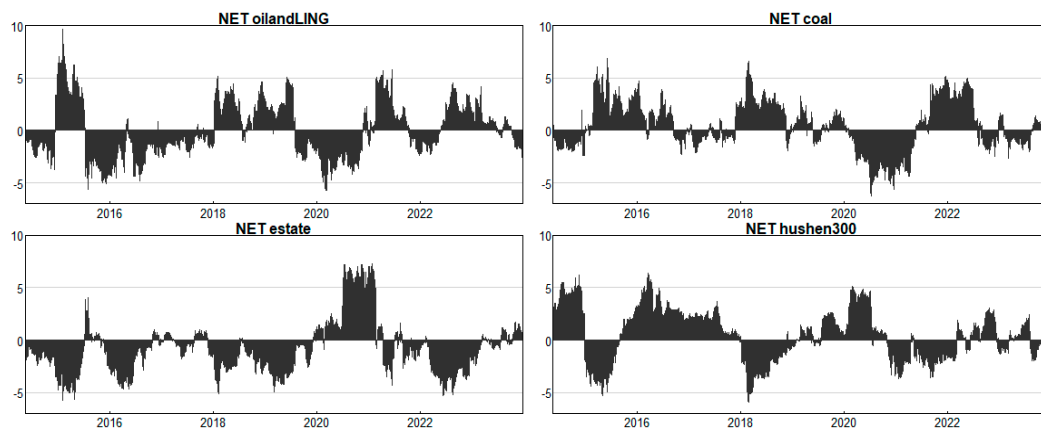


Figure 7. Net spillover of risk.

Specifically, during the 2015 energy crisis, the net spillover indices of oil and gas and coal markets turned positive. This phenomenon aligns with the energy price transmission mechanism proposed by [Basu and Gavin \(2010\)](#), but our study further reveals that the intensity of this transition during crises was 1.8 times higher than under normal conditions. Post-2020, the COVID-19 pandemic and the Evergrande incident unexpectedly transformed the real estate market into a net risk transmitter. These results not only support [Yang et al.’s \(2024\)](#) conclusions about real estate policy effects but also uncover the dynamic reversal characteristics of market roles during extreme events.

These findings systematically address three key questions raised in Section 2’s literature review. First, they confirm [Shahzad et al.’s \(2021\)](#) hypothesis about the amplification of asymmetric effects during crises; second, they complement the market interaction analysis under [Kumar et al.’s \(2022\)](#) bivariate framework; third, they provide new evidence from China’s market for [Belkhir and Abbas’ \(2024\)](#) network restructuring theory. The results emphasize that when formulating cross-market risk monitoring policies, special attention should be paid to situations where all three major markets simultaneously transition into net transmitter status—a finding that provides significant complementary value to existing financial stability frameworks.

4.2.3. Analysis of Net Pairwise Directional Connectedness of Risk

To explore the differences in risk spillover effects between two markets, it is essential to conduct a detailed analysis of the mutual spillover effects over time.

As can be seen from Figure 8, in recent years, a multitude of domestic and international extreme events, such as oil crises, coal overcapacity, trade frictions, and geopolitical conflicts, have had complex and diverse impacts on different markets. The shocks of these events not only cause fluctuations within the directly affected markets but also quickly spread to other markets through inter-market linkages, making the time-varying nature of spillover effects between markets increasingly pronounced. Specifically, the mutual spillover effects between markets exhibit a dynamic shift from “inflow” to “outflow”, meaning that a market may be a risk receiver at one time and a risk exporter at another. This role reversal depends not only on the nature and intensity of the events themselves but also on the sequence of events and the initial inter-market relationships.

Furthermore, the risk status of a market is not static but continues to evolve under the impact of new external shocks and the subsequent chain reactions. This dynamic evolution highlights the flexibility and adaptability of market roles and reflects the high complexity of risk transmission in the global economic system. Therefore, to fully understand the spillover mechanism between markets, it is necessary not only to analyze the intrinsic dynamics of each market in depth but also to pay attention to how markets participate in and respond

to this time-varying spillover mechanism under the influence of external shocks. Only in this way can we better grasp the evolving trend of the economic risk landscape and provide more forward-looking guidance for policymaking and market participants.

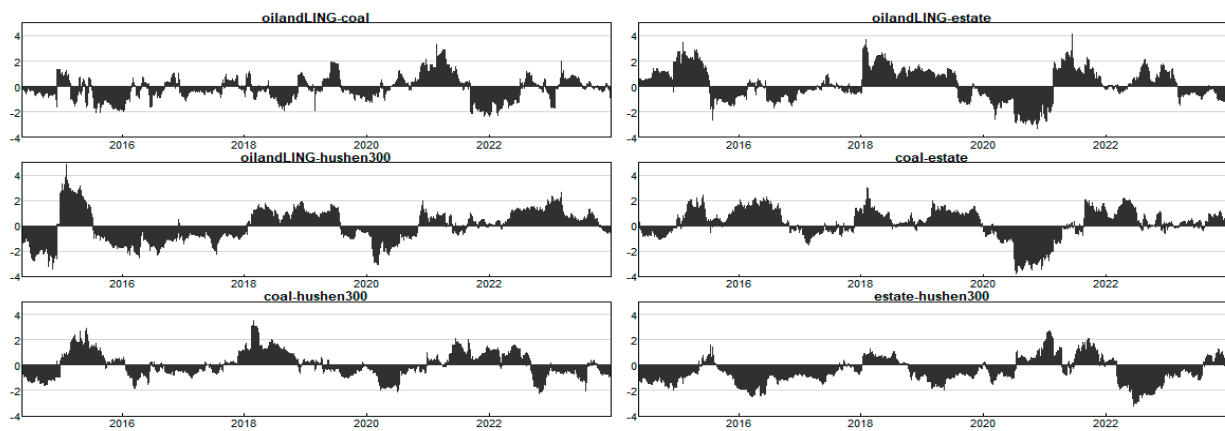


Figure 8. Net pairwise directional connectedness of risk.

5. Conclusions and Suggestions

5.1. Conclusions

This study provides comprehensive evidence on the dynamic risk transmission mechanisms among China's energy, real estate, and stock markets through advanced time-series modeling. Our key findings demonstrate three crucial patterns in cross-market spillovers:

First, we identify a clear dichotomy between normal and crisis periods. During stable conditions, the total spillover index (TCI) maintains a baseline level around 32–40%, confirming the moderate interconnectedness suggested by prior literature (Smith Stegen, 2015; Hu & Wang, 2022). However, extreme events trigger disproportionate spillover amplification, with TCI peaks reaching 51.09% during the 2015 market crash and nearly 60% during COVID-19—substantially exceeding normal parameters. This nonlinear response pattern validates and quantifies the crisis amplification effects hypothesized by Mensi et al. (2021).

Second, the research reveals distinct market roles in risk transmission. The energy sector (particularly oil/gas) consistently functions as a net risk transmitter (average +4.61%), with spillover intensity escalating by 72% during supply shocks like the Russia–Ukraine conflict. Conversely, real estate primarily serves as a net absorber (−9.38%), though this role reverses during domestic crises like the Evergrande event. These findings both confirm Alhodiry et al.'s (2021) transmission channels and extend Kumar et al.'s (2022) framework by capturing dynamic role transitions.

Third, we establish precise temporal characteristics of spillover effects. The analysis reveals three characteristic temporal dimensions of risk transmission: first, a pronounced delayed propagation effect stemming from extreme events; second, an exponentially decaying absorption efficiency for adverse shocks; and third, highly unstable directional patterns in cross-market net spillovers.

5.2. Suggestions

Given the high interconnectivity among the energy, real estate, and stock markets, as well as the significant impact of extreme events on cross-market risk transmission, it is recommended to adopt measures from multiple aspects to address market dynamics and potential risks. On the one hand, policymakers and regulatory bodies should establish a cross-departmental joint monitoring mechanism to track the dynamic changes in various markets in real-time. Special attention should be paid to key indicators such as

price volatility, capital flows, and market sentiment. Big data analysis and artificial intelligence technologies should be utilized to promptly capture potential systemic risk signals. Moreover, the disclosure system should be improved to require companies to timely and accurately disclose significant business decisions, financial conditions, and market risk information. During periods of extreme events, the frequency and transparency of information disclosure should be increased to assist investors in comprehensively understanding market dynamics.

Additionally, financial institutions should optimize risk assessment models, develop diversified risk management tools, strengthen internal risk controls, enhance sensitivity and response capabilities towards market fluctuations. Investor education should also be reinforced by disseminating knowledge about market risks through various channels, guiding investors to establish correct investment concepts, rationally allocate assets, and avoid blindly following trends or excessive speculation.

Academia and practitioners should intensify research on the nonlinear and asymmetric characteristics of market spillover effects, thoroughly analyzing how these effects influence the behavior and decision-making of market participants under different market conditions. Systematic studies should be conducted to analyze how extreme events alter the dynamic relationships between markets, providing references for policy adjustments and market mechanism optimization.

Through the implementation of these comprehensive measures, we can better address the dynamic spillover effects between markets, reduce the impact of extreme events on financial stability, and promote the healthy and stable development of China's energy, real estate, and stock markets.

5.3. Research Limitations and Future Directions

While this study provides valuable insights into cross-market risk spillovers, several limitations warrant attention and present potential avenues for future research. First, the current analytical framework primarily focuses on traditional financial sectors without fully accounting for shadow banking activities. Given that shadow banking accounts for approximately 18% of real estate financing, its complex and opaque nature makes associated risks difficult to capture through conventional approaches. Furthermore, the study does not adequately consider the amplifying effect of non-bank financial intermediaries' leverage cycles during periods of systemic stress, potentially leading to underestimation of risk spillover effects.

Second, the reliance on daily data limits our ability to capture intraday volatility patterns that are increasingly important in today's rapidly evolving markets, including: (1) volatility clustering during market openings/closings; (2) impacts of high-frequency trading; and (3) overnight risk accumulation. Third, the analysis does not fully incorporate the most recent data developments, which may affect the timeliness and generalizability of our findings.

To address these limitations, future research should integrate methodological innovations with expanded datasets. Next-generation modeling approaches could combine Time-Varying Parameter Vector Autoregression (TVP-VAR) with neural network architectures to better capture nonlinear dependencies. The incorporation of higher-frequency data (e.g., minute-level or tick-by-tick data) would enable a more precise measurement of intraday volatility patterns and enhance sensitivity to market dynamics. Additionally, future studies should emphasize data timeliness and comprehensiveness to test the robustness and extensibility of conclusions through expanded data coverage.

These methodological and empirical improvements would contribute to a more comprehensive understanding of the dynamic characteristics of cross-market risk spillovers, ultimately providing more forward-looking guidance for policymakers and market participants. The enhanced framework would be particularly valuable for monitoring emerging risks in China's evolving financial landscape, including shadow banking exposures and intraday market dynamics.

Author Contributions: F.X.: Conceptualization, Methodology, Validation, Formal analysis, Writing—Original Draft. J.W.: Software, Data curation, Formal analysis, Resources, Investigation, Visualization. C.W.: Software, Project administration, Supervision, Funding acquisition, Writing—Review and Editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partly funded by Shanghai Municipal Education Commission's 2024 Normal Teacher Program—"Mathematical Analysis I" Course Development and Teaching Reform (under grant number Z20001.24.0103.01); Collaborative Education Project of Ministry of Education (under grant number 230901155010354); 2023 Shanghai Key Curriculum Project (under grant number A-0201-283-24222).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available in Choice data. These data were derived from the following resources available in the public domain: <https://choicetest.eastmoney.com/dataservice> (accessed on 19 April 2025).

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Akbari, A., & Krystyniak, K. (2021). Government real estate interventions and the stock market. *International Review of Financial Analysis*, 75, 101742. [CrossRef]
- Alhodiry, A., Rjoub, H., & Samour, A. (2021). Impact of oil prices, the U.S interest rates on Turkey's real estate market. New evidence from combined co-integration and bootstrap ARDL tests. *PLoS ONE*, 16(1), e0242672. [CrossRef] [PubMed]
- Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4), 84. [CrossRef]
- Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., & de Gracia, F. P. (2023). Dynamic connectedness among the implied volatilities of oil prices and financial assets: New evidence of the COVID-19 pandemic. *International Review of Economics & Finance*, 83, 114–123.
- Basu, P., & Gavin, W. T. (2010). What explains the growth in commodity derivatives? *Federal Reserve Bank of St Louis Review*, 93, 37–48. [CrossRef]
- Belkhir, N., & Abbes, M. B. (2024). Analysis of the impact of COVID-19 on the dynamic volatility spillover network in the Saudi stock market. *International Journal of Asian Social Science*, 14(1), 26–49. [CrossRef]
- Bellman, R. (1966). Dynamic programming. *Science*, 153, 34–37. [CrossRef]
- Chau, K. W., & Zou, G. (2018). Energy prices, real estate sales and industrial output in China. *Energies*, 11(7), 1847. [CrossRef]
- Chen, Y., Yu, L., & Gang, J. (2021). Half-day trading and spillovers. *Frontiers of Business Research in China*, 15, 1. [CrossRef]
- Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66. [CrossRef]
- Dieci, R., Schmitt, N., & Westerhoff, F. (2018). Interactions between stock, bond and housing markets. *Journal of Economic Dynamics and Control*, 91, 43–70. [CrossRef]
- Du, R., & Xu, P. (2024). Time-Varying spillover effects between clean and traditional energy under multiple uncertainty risk: Evidence from the U.S. market. *Sustainability*, 16(21), 9164. [CrossRef]
- Geng, J., Du, Y., Ji, Q., & Zhang, D. (2021). Modeling return and volatility spillover networks of global new energy companies. *Renewable and Sustainable Energy Reviews*, 135, 110214. [CrossRef]
- Gong, X., Liu, X., Xiong, X., & Zhang, W. (2020). Research on China's financial systemic risk contagion under jump and heavy-tailed risk. *International Review of Financial Analysis*, 72, 101584. [CrossRef]

- He, X., & Hamori, S. (2023). Different moments create different spillovers: A study of commodity markets. *The Singapore Economic Review*, 1, 1–22. [CrossRef]
- Hu, G. X., & Wang, J. (2022). A review of China's financial markets. *Annual Review of Financial Economics*, 14, 465–507. [CrossRef]
- Kalli, M., & Griffin, J. E. (2014). Time-varying sparsity in dynamic regression models. *Journal of Econometrics*, 178(2), 779–793. [CrossRef]
- Khalfaoui, R., Mefteh-Wali, S., Dogan, B., & Ghosh, S. (2023). Extreme spillover effect of COVID-19 pandemic-related news and cryptocurrencies on green bond markets: A quantile connectedness analysis. *International Review of Financial Analysis*, 86, 102496. [CrossRef]
- Koop, G., & Korobilis, D. (2013). Large time-varying parameter VARs. *Journal of Econometrics*, 177(2), 185–198. [CrossRef]
- Korobilis, D. (2013). Var forecasting using Bayesian variable selection. *Journal of Applied Econometrics*, 28(2), 204–230. [CrossRef]
- Korobilis, D., & Yilmaz, K. (2018). *Measuring dynamic connectedness with large Bayesian VAR models*. Available at SSRN 3099725. Available online: <https://econpapers.repec.org/paper/kocwpaper/1802.htm> (accessed on 19 April 2025).
- Kumar, S., Singh, G., & Kumar, A. (2022). Volatility spillover among prices of crude oil, natural gas, exchange rate, gold, and stock market: Fresh evidence from exponential generalized autoregressive conditional heteroscedastic model analysis. *Journal of Public Affairs*, 22(4), e2594. [CrossRef]
- Li, T., Ju, Y., & Dong, P. (2023). Investigating the interconnectedness of carbon, fossil energy, and financial markets: A dynamic spillover index approach. *PLoS ONE*, 18(12), e0295363. [CrossRef]
- Liow, K. H., & Song, J. (2021). Interdependence dynamics of corporate equity and public real estate markets. *Journal of European Real Estate Research*, 15(2), 147–178. [CrossRef]
- Liu, N., Liu, C., Da, B., Zhang, T., & Guan, F. (2021). Dependence and risk spillovers between green bonds and clean energy markets. *Journal of Cleaner Production*, 279, 123595. [CrossRef]
- Liu, Q., Xu, C., & Xie, J. (2024). Comparative analysis of spillover effects in the global stock market under normal and extreme market conditions. *International Journal of Financial Studies*, 12(2), 53. [CrossRef]
- Liu, Y., Zhang, J., Guo, N., & Liu, J. (2023). Investor sentiment contagion and network connectedness: Evidence from China and other international stock markets. *The Manchester School*, 91(6), 587–613. [CrossRef]
- Luo, R., & Li, Y. (2007). Some new features of the current relationship between stock market and real estate market. *Southwest Finance*, 9, 31–32.
- Mensi, W., Al Rababa'a, A. R., Vo, X. V., & Kang, S. H. (2021). Asymmetric spillover and network connectedness between crude oil, gold, and Chinese sector stock markets. *Energy Economics*, 98, 105262. [CrossRef]
- Mensi, W., Jiang, Z., Vo, X. V., & Yoon, S. (2023). Asymmetric volatility transmission and hedging strategies among REIT, stock, and oil markets. *Australian Economic Papers*, 62(4), 597–615. [CrossRef]
- Nakajima, J. (2011). Time-varying parameter VAR model with stochastic volatility: An overview of methodology and empirical applications. *Monetary and Economic Studies*, 29, 107–142.
- Ngene, G. M. (2021). What drives dynamic connectedness of the US equity sectors during different business cycles? *The North American Journal of Economics and Finance*, 58, 101493. [CrossRef]
- Nie, D., Li, Y., & Li, X. (2021). Dynamic spillovers and asymmetric spillover effect between the carbon emission trading market, fossil energy market, and new energy stock market in China. *Energies*, 14(19), 6438. [CrossRef]
- Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, 72(3), 821–852. [CrossRef]
- Shahzad, S. J. H., Naeem, M. A., Peng, Z., & Bouri, E. (2021). Asymmetric volatility spillover among Chinese sectors during COVID-19. *International Review of Financial Analysis*, 75, 101754. [CrossRef]
- Smith Stegen, K. (2015). Understanding China's global energy strategy. *International Journal of Emerging Markets*, 10, 194–208. [CrossRef]
- Su, C. W., Wang, Z., Nian, R., & Zhao, Y. (2017). Does international capital flow lead to a housing boom? A time-varying evidence from China. *The Journal of International Trade & Economic Development*, 26(7), 851–864.
- Taruttis, L., & Weber, C. (2022). Estimating the impact of energy efficiency on housing prices in Germany: Does regional disparity matter? *Energy Economics*, 105, 105750. [CrossRef]
- Usman, M., Akhter, W., & Haque, A. (2023). Spillover effects of crash and jump events: Evidence from Chinese market. *China Finance Review International*, 13(4), 599–620. [CrossRef]
- Vo, D. H., & Nguyen, H. L. (2024). Market risk spillover and the asymmetric effects of macroeconomic fundamentals on market risk across Vietnamese sectors. *Financial Innovation*, 10(1), 95. [CrossRef]
- Wang, Q., Wei, Y., Wang, Y., & Liu, Y. (2022). On the safe-haven ability of bitcoin, gold, and commodities for international stock markets: Evidence from spillover index analysis. *Discrete Dynamics in Nature and Society*, 2022(1), 9520486. [CrossRef]
- Wang, X., Bian, S., & Wu, C. (2023). Spillover effects within supply chains: Evidence from Chinese-listed firms. *Journal of International Financial Management & Accounting*, 34(3), 594–632.
- Yang, G., Yin, X., Sun, Z., Bi, P., & Ma, Q. (2024). The spillover effect of real estate boom on stock market efficiency: Evidence from China. *Applied Economics*, 57(24), 3164–3179. [CrossRef]

- Zha, R., Yu, L., Su, Y., & Yin, H. (2023). Dependences and risk spillover effects between Bitcoin, crude oil and other traditional financial markets during the COVID-19 outbreak. *Environmental Science and Pollution Research*, 30(14), 40737–40751. [[CrossRef](#)] [[PubMed](#)]
- Zhang, W., He, X., Nakajima, T., & Hamori, S. (2020). How does the spillover among natural gas, crude oil, and electricity utility stocks change over time? Evidence from North America and Europe. *Energies*, 13(3), 727. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.