

## Original Paper

# Co-movement and Risk Spillover Effects between CSI 300 Stock Index Futures and Spot Markets

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### **Abstract**

*The binary investment behavior of retail and institutional investors may lead to structural differences in the risk transmission between the futures and spot markets in China's capital market. This paper decomposes the heterogeneity of volatility spillovers between futures and spot markets: (1) There is a distinct binary effect in risk spillovers: the short-term (1-5 days) spillover is the strongest, showing a "net input" pattern driven by individual investor sentiment from the spot market to the futures market; in the long-term (more than 20 days), it reverses to a "net output" pattern dominated by institutional investors from the futures market to the spot market. (2) Major crisis shocks will trigger "full-frequency resonance", which simultaneously intensifies short-term emotional contagion and long-term risk pricing, significantly increasing the complexity of systemic risks. (3) The futures market plays the role of a "pricing anchor" and "net outputter" of systemic risks in the long run. This study reveals the micro-mechanism of risk contagion under China's specific investor structure, and provides theoretical basis and empirical evidence based on the dual dimensions of "behavior-frequency" for the implementation of differentiated and precise macro-prudential supervision.*

### **Keywords**

*Risk Spillover, Binary Effect, Co-movement, Stock Index Futures*

### **1. Introduction**

Stock index futures serve as important instruments for investors to conduct risk management and price discovery. Their relationship with the spot market also bears on the stability of the financial market. As China's financial market has developed, the CSI 300 stock index futures have played an increasingly critical role. Events such as the 2015 stock market crash show that risk transmission between the futures and spot markets is not static. It changes with market conditions and may present distinctly different

patterns across different time horizons, such as short-term speculation and long-term investment <sup>[10]</sup>. Existing studies commonly measure market connectedness using the volatility spillover index developed by Diebold & Yilmaz (2012). However, such methods only provide an overall average and cannot distinguish between short-term volatility of risk contagion within several days and long-term trends over months. China's stock market has a large share of retail investors, who are easily affected by market sentiment and news and conduct frequent short-term transactions. As a result, short-term sentimental trading and long-term fundamental investment may lead to completely different risk transmission channels <sup>[3][4][5]</sup>. Distinguishing between these two types of risk has long been a difficult issue. Barunik & Křehlík (2018) proposed an approach that uses frequency-domain methods to decompose the total mixed risk spillover into different time scales, including short-term, medium-term and long-term. Price changes at different frequencies correspond to the behaviors of different investor groups <sup>[6][7][8]</sup>. For example, high-frequency price movements mainly reflect sentiment-driven and frequent short-term speculative trading by individual investors, while low-frequency fluctuations more closely represent prudent trading by institutions, funds and potentially rational investors based on their expectations of fundamental trends. Therefore, it is of great significance to explore whether risk contagion in China's market, where retail investors and institutional investors coexist, shows a dual effect and its related characteristics.

Risk contagion in financial markets is a critical issue for ensuring the stability of the financial system. Early studies typically employed methods such as correlation coefficients to analyze intermarket linkages, but these methods struggle to accurately measure the direction and intensity of risk spillovers <sup>[10]</sup>. The spillover index (DY index) proposed by Diebold & Yilmaz (2012) provides a standardized tool for assessing overall risk contagion, but this method has limitations in distinguishing the characteristics of risk transmission across short-, medium-, and long-term time horizons <sup>[5]</sup>. To address this issue, Barunik & Křehlík (2018) proposed a frequency-domain spillover framework that decomposes risk spillover across different time scales, thereby revealing risk dynamics across various cycles; this framework has been widely adopted in international research <sup>[3][11]</sup>.

In domestic research on this topic, most scholars continue to rely primarily on time-domain methods. Although previous studies have confirmed that stock index futures play a dominant role in the overall market, systematic frequency-domain analyses remain scarce, and there has been insufficient attention paid to the characteristics of spillover structures as they evolve over time <sup>[1][2]</sup>. China's capital market exhibits a distinct "retail-institutional" dual structure, with retail investors engaging in frequent trading and being more prone to emotional driving, while institutional investors focus more on fundamentals and long-term allocation. These behavioral differences may result in a "layered" pattern of risk contagion—where different types of investors dominate risk transmission across different time scales <sup>[4]</sup>. However, current research has yet to integrate the "dual-effect" theory with frequency-domain analysis to deeply explore the micro-level risk transmission mechanisms in the Chinese market.

Therefore, this paper applies the Barunik–Křehlík (BK) frequency-domain framework to China's stock index futures and spot markets, incorporating a rolling window method for dynamic analysis. The aim is

to reveal the multiscale structure and evolutionary characteristics of risk contagion from a dual “behavior-frequency” perspective, thereby providing insights for understanding market risk transmission mechanisms and informing policy-making [3][7].

This paper addresses three key questions:

- 1) How does risk spillover between CSI 300 futures and spot markets differ across the short, medium, and long terms? Does this difference support the “behavioral stratification” hypothesis?
- 2) How does this hierarchical structure change during crises such as stock market crashes, trade frictions, and pandemics?
- 3) What roles do the futures and spot markets play, respectively, across different time scales?

We hope this paper will provide a research framework to reveal the unique mechanisms of market risk transmission in China in greater detail, and offer guidance for market regulators to implement more precise oversight.

## 2. Theory and Models

### 2.1 Time-Domain Spillover Effect Measurement Methods

This study employs Vector Autoregression (VAR), Forecast Error Variance Decomposition (FEVD), Total Contagion Index (TCI), and frequency-domain spillover (Baruník–Křehlík, 2018) methods to analyze the spillover effects between IF futures and the CSI 300 Index returns.

The Vector Autoregression model VAR(p) is defined as follows:

$$y_t = c + A_1 y_{t-1} + \dots + A_p y_{t-p} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma) \quad (1)$$

where

$$y_t = \begin{pmatrix} r_t^{IF} \\ r_t^{HS300} \end{pmatrix} \quad (2)$$

$r_t^{IF}$  and  $r_t^{HS300}$  represent the returns of the IF futures and the CSI 300 Index on day  $t$ , respectively. Here,  $c$  is a constant vector,  $A_1, \dots, A_p$  is the VAR coefficient matrix, and  $\varepsilon_t$  is the covariance matrix of the error term  $\Sigma$ . The VAR model captures the dynamic interrelationships among returns and serves as a standard method for studying spillover effects in financial markets.

Forecasted Error Variance Decomposition (FEVD) is used to measure the contribution of shocks from each variable to the variance of itself and other variables. Let  $\Phi_h$  denote the  $h$ -step impulse response matrix; then the variance contribution of variable  $i$  to variable  $j$  at forecast horizon  $H$  is given by:

$$\theta_{ij}(H) = \frac{\sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma \Phi_h' e_i)} \quad (3)$$

Where  $e_i$  is the selection vector for the  $i$ th variable.

This can be used to calculate the Total Spillover Index (TCI) to measure the overall spillover effect of the system. TCI is defined as:

$$TCI = \frac{\sum_{i \neq j} \theta_{ij}(H)}{K} \times 100 \quad (4)$$

where  $K$  is the number of variables in the system, and  $\theta_{ij}(H)$  are the elements of the FEVD matrix. A higher TCI indicates stronger overall connectivity within the system.

To effectively characterize and visualize the dynamic evolution of overall market interdependence over time, this paper employs two complementary measurement methods:

- 1) The Total Contagion Index (TCI) based on Forecast Error Variance Decomposition (FEVD), whose full-sample calculation results provide the average level of interdependence;
- 2) Time-varying trend analysis based on rolling-window correlation coefficients. Specifically, we calculate the 60-day rolling Pearson correlation coefficients for the daily return series of CSI 300 futures and spot markets. Although this indicator differs from TCI in its methodological origins, the time-varying trends in market co-movement it depicts—particularly the heightened correlation during crises—align with financial theory and the conclusions of extensive empirical research, enabling clear and intuitive identification of periods of “risk resonance.”

## 2.2 Frequency-Domain Spillover Effect Measurement Methods

Total spillover is driven by two distinct groups of investors: one consists of investors who are susceptible to sentiment and news and excel at short-term trading, contributing to the high-frequency components in the frequency domain; the other comprises fund managers and institutional traders, whose strategies are rooted in long-term fundamental investing, contributing to the lower-frequency components in the frequency domain. Based on this framework, Baruník–Křehlík (2018) employed a frequency-domain spillover approach to distinguish between short-term and medium-to-long-term spillover.

Let the VAR transfer function be  $F(\omega)$ . Then, the frequency-domain variance contribution is  $\Gamma_{ij}(\omega)$ , and the cumulative variance contribution in the frequency band  $d$  is:

$$\theta_{ij}^d = \int_{\omega \in d} \Gamma_{ij}(\omega) d\omega \quad (5)$$

Following Baruník & Křehlík (2018) and subsequent financial applications (e.g., Tiwari et al., 2022), this paper defines three frequency bands aimed at capturing the time scales of three typical investor behaviors in the Chinese market

Short – term:  $0 \leq \omega \leq \pi/3$  Corresponding to market sentiment and speculative trading (1-5 trading day)

Medium – term:  $\pi/3 < \omega \leq 2\pi/3$  Corresponding to corporate earnings seasons and policy digestion periods (5-20 trading days)

Long – term:  $2\pi/3 < \omega \leq \pi$  Corresponding to economic cycles and the evolution of systemic risk (20 trading days or more)

Frequency-domain spillovers can reveal the characteristics of market risk transmission across different investor time scales. Short-term spillovers primarily reflect trader behavior or market noise, medium-term spillovers indicate macroeconomic shocks, and long-term spillovers embody systemic risk. Combined with rolling window analysis, one can observe the dynamic changes in the TCI and net spillover metrics to capture the patterns of market interdependence as they evolve over time. The core of the BK method

lies in using the Fourier transform to decompose the variance of prediction errors in the time domain and project it into the frequency domain. The economic intuition is that fluctuation components at different frequencies correspond to the behavior and information of different investors. High-frequency (short-term) fluctuations primarily reflect the instantaneous reactions of liquidity traders and noise traders to microstructural market shocks; low-frequency (long-term) fluctuations correspond to asset pricing by fundamental traders and long-term investors based on macroeconomic and market information.

### 3. Empirical Analysis

#### 3.1 Data and Descriptive Statistics

This study uses the daily closing prices of the CSI 300 Index Futures main contract (IF) and the CSI 300 Spot Index (HS300) from January 1, 2015, to November 30, 2024, as the sample. The sample period covers multiple major shocks, including the abnormal stock market volatility of 2015, the U.S.-China trade friction of 2018, and the global COVID-19 pandemic of 2020, providing favorable conditions for studying the time-varying characteristics of risk contagion under different market conditions.

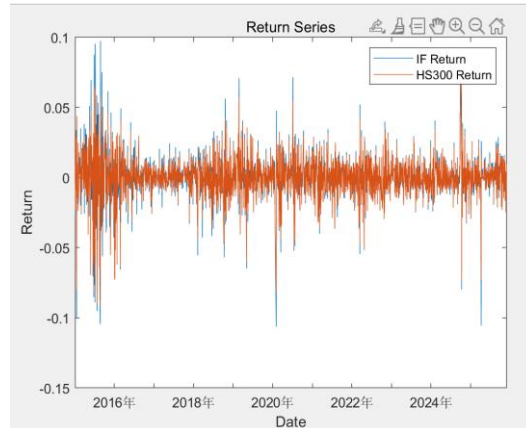
**Table 1. Distribution Characteristics of the CSI 300**

	IF	HS300
Mean	0.000173	0.000174
Std	0.015079	0.013546
Min	-0.106357	-0.091542
Max	0.097371	0.081420
Median	-0.000098	0.000216
Skewness	-0.471	-0.624
Kurtosis	12.119	9.261
JB	11,737.6*	5692.0*
ADF	0.001*	0.001*
PP	0.001*	0.001*

Table 1 reports the descriptive statistics for the daily return series of IF and HS300. The standard deviation of IF returns (1.51%) is higher than that of HS300 (1.35%), indicating that the futures market is more volatile. Both series exhibit left-skewed, leptokurtic, and heavy-tailed characteristics, and the Jarque-Bera test significantly rejects the normal distribution. The results of the ADF and PP tests ( $p = 0.001$ ) confirm that the series are stationary, satisfying the requirements for subsequent modeling. These statistical characteristics provide a suitable data foundation for analyzing the volatility spillover effects between the futures and spot markets.

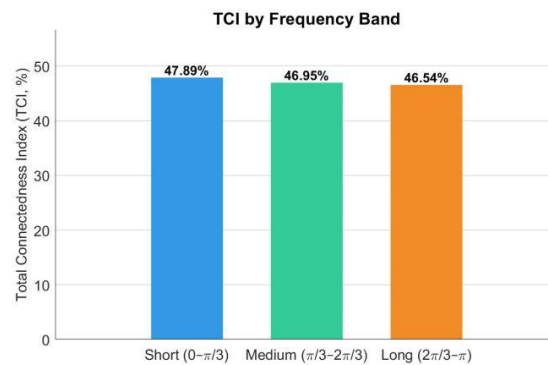
A preliminary examination of the yield time series plots (Figure 1) reveals that the two series exhibit a

high degree of synchronization; however, during periods of extreme volatility (such as mid-2015 and early 2020), the amplitude of IF yields was significantly larger, suggesting that the futures market may be more sensitive to information shocks.



**Figure 1. Time Series and Distributions of IF and HS300 Yields**

To analyze the dynamic interaction between IF futures and HS300 spot yields, this paper constructs a bivariate VAR(2) model. Based on this, we examine static aggregate spillover:



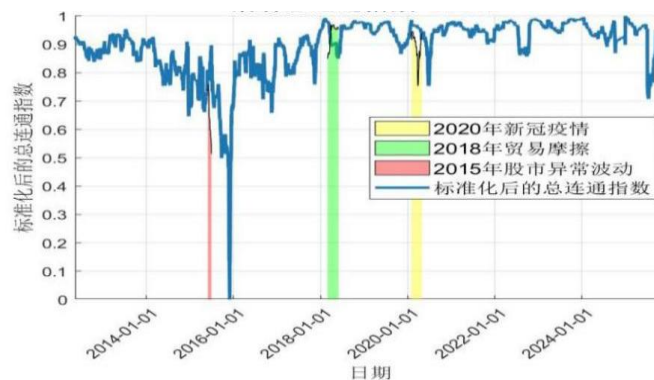
**Figure 2. Comparison of Aggregate Spillover Intensity Across Frequency Bands**

The results show significant differences in total spillover intensity across short-, medium-, and long-term frequency bands. Spillover is strongest in the short term and relatively weaker in the medium and long terms, indicating that the market responds rapidly to shocks, while the long term exhibits a certain degree of self-absorption mechanism.

The finding that “short-term spillovers are strongest” is closely related to the unique microstructure of China’s financial markets. The short-term (1–5 days) band dominates risk contagion, which is highly consistent with the characteristics of China’s market: a high proportion of retail investors, active sentiment-driven trading, and sensitivity to policy news. This implies that market sentiment and noise trading are the primary channels through which risk spreads rapidly between futures and spot markets. In

the long-term frequency band, futures markets become net risk spillover sources, revealing the dominant role of institutional investors and their informational advantage. Over time scales spanning weeks or months, information reflecting macroeconomic trends, policy expectations, and systemic risks is primarily priced in the futures market and transmitted to the spot market. This confirms the core role of stock index futures in medium- and long-term price discovery and risk pricing.

To further reveal the time-varying characteristics of market linkage intensity, a time series plot of the Total Contagion Index (Rolling TCI) under a 60-day rolling window was constructed (Figure 3). The figure shows that the intensity of risk contagion between markets is not constant but fluctuates continuously in response to the macroeconomic environment, policy adjustments, and market sentiment.

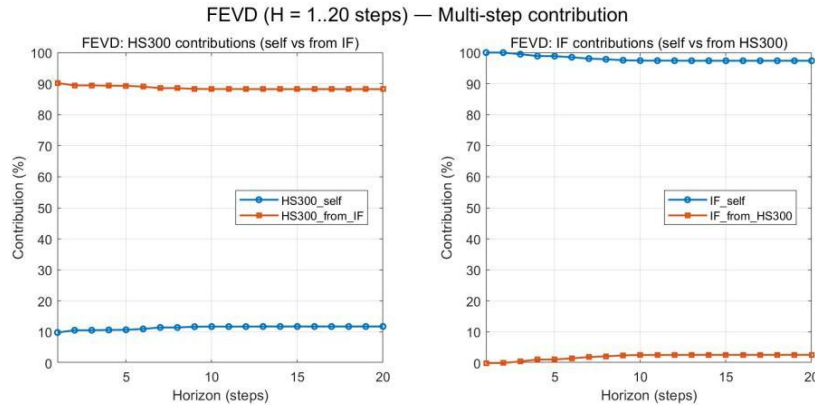


**Figure 3. Time-varying Chart of the Rolling Total Contagion Index**

During major crises such as the abnormal stock market fluctuations in 2015, the U.S.-China trade friction in 2018, and the COVID-19 pandemic in 2020, the Rolling TCI exhibited significant peaks. This visually confirms that extreme external shocks sharply intensify the risk transmission channels between futures and spot markets, forming a tight “risk resonance” network. This finding corroborates the conclusions drawn from the full-sample TCI based on FEVD, jointly establishing the empirical foundation for the increased market correlation during crisis periods.

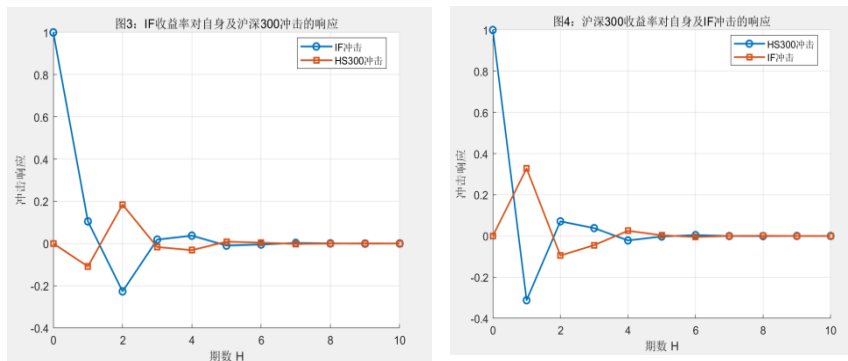
### 3.2 Micro-level Pathways of Shock Transmission: FEVD and Impulse Responses

To further examine the dynamic details and asymmetries of cross-market shock transmission, this paper plots impulse response functions over a 10-trading-day horizon.



**Figure 4. Variance Decomposition of FEVD**

Figure 4 shows that, within the variance of the HS300 forecast error, the endogenous contribution accounts for approximately 88–90%, while the contribution from the IF accounts for approximately 10–12%; conversely, within the variance of the IF forecast error, the endogenous contribution accounts for the vast majority (97–100%), while the contribution from the HS300 is extremely low (0–3%). This indicates that futures have significant explanatory power for spot price volatility, while the feedback from spot prices to futures is weak, supporting the view that the futures market plays a dominant role in risk transmission.



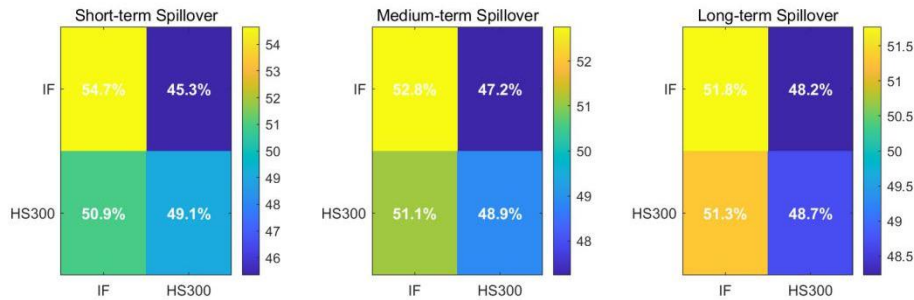
**Figure 5. Impulse Response Functions**

The results show that a positive one-standard-deviation shock to the IF return immediately triggers a co-directional response in the HS300 return, with this effect gradually fading over approximately five trading days; conversely, the impact of the HS300 on the IF is relatively weak and fades more rapidly. This asymmetric dynamic path confirms, from the perspective of shock transmission, the dominant role of the futures market in information transmission and its faster reaction speed.

The rapid response of the IF to shocks reflects the futures market’s high liquidity and strong information efficiency; the lag in the HS300’s response may reflect the spot market’s investor structure, which is dominated by individual investors, whose speed of digesting and adjusting to information is relatively slow, and where emotional trading may prolong the duration of the shock. The asymmetry in impulse

responses reveals the different roles of the two markets in risk absorption and transmission.

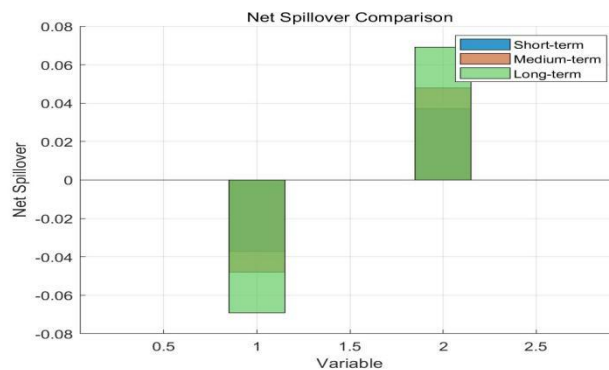
### 3.3 Hierarchical Effects of Risk Transmission



**Figure 6. BK Multiband Spillover Matrix**

The results of the BK Multiband spillover matrix (Figure 6) reveal a distinct structural feature: the spillover intensity in the short-term frequency band (1–5 days) reaches as high as 54.7%, significantly exceeding that of the medium- and long-term bands. This is not a universal global phenomenon, but rather a direct reflection of China’s “retail-institutional” dual structure: emotional trading by individual investors is the primary source of short-term volatility, while algorithmic trading in the futures market acts as an “amplifier,” forming a short-term contagion loop of “spot market sentiment → futures leverage acceleration → feedback reinforcement.”

By comparing the direction of net spillover across different time bands (Figure 7), we have captured decisive evidence supporting the “behavioral stratification” hypothesis.



**Figure 7. Net Spillover Directions Across Frequency Bands**

In the short-term (1–5 days) frequency band, the HS300 is a net exporter of risk (negative net outflow in the IF), indicating that market volatility over several days is primarily driven by trading sentiment in the spot market and is transmitted unidirectionally to the futures market.

In the long-term (20+ days) time frame, the roles undergo a fundamental reversal, with the IF market becoming a net exporter of risk (positive net spillover), indicating that on a timescale relevant to

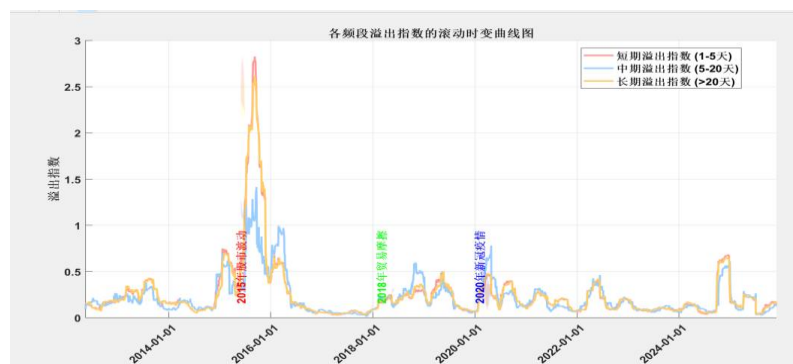
macroeconomic trends and systemic risk, the dominance in risk pricing shifts to the futures market, reflecting the core function of institutional investors in long-term asset allocation and risk pricing through futures.

In the medium-term timeframe, net spillover approaches equilibrium, potentially corresponding to a transitional phase in which policy signals and macroeconomic data are gradually digested and adjusted by both markets.

The above findings constitute the core empirical evidence for the “behavioral stratification” effect: short-term risk contagion is driven by retail investor sentiment, following a “spot → futures” path; long-term risk pricing, however, is driven by institutional investors, following a “futures → spot” path.

### 3.4 Dynamic Evolution Under Crisis Shocks

To examine the dynamic response of the “behavioral stratification” structure under extreme stress, we calculated time-frequency domain spillover indices using a rolling window. The results are shown in Figure 8.



**Figure 8. Time-varying Curves of Spillover Indices across Frequency Bands**

Full-frequency-domain resonance effect: During major crises such as those in 2015, 2018, and 2020, the spillover indices across the short-, medium-, and long-term frequency bands all exhibited synchronous and sharp surges. This “full-frequency-band resonance” indicates that extreme external shocks simultaneously intensify short-term emotional panic, medium-term expectation disruptions, and long-term fundamental concerns, leading to the simultaneous overload of risk transmission channels across all time scales. This greatly increases the complexity of systemic risk and the difficulty of regulation.

The impact of crisis heterogeneity: Comparing different crises reveals variations in the frequency bands that dominate risk transmission. For example, during the 2015 stock market crash—primarily driven by domestic leverage and sentiment—the surge in short-term spillovers was most pronounced; whereas under the global pandemic shock of 2020, the rise in long-term spillovers proved more persistent. This suggests that the microstructure of risk contagion is not static but evolves dynamically according to the nature of the shock’s origins.

## 4. Discussion

### 4.1 Conclusions

Based on the frequency-domain spillover model (BK model), this study analyzes the volatility transmission characteristics between China's stock index futures (IF) and the spot market (HS300), reaching the following main conclusions:

- (1) The futures market plays a dominant role in price discovery and exerts a significant net spillover effect on the spot market, serving as the primary source of volatility transmission.
- (2) Risk spillovers exhibit distinct spatiotemporal heterogeneity: short-term (1–5 days) spillovers are strongest, driven primarily by trading sentiment and noise trading; in long-term spillovers, the futures market acts as a net transmitter of systemic risk.
- (3) Market interconnectivity exhibits significant time-varying and crisis-resonance characteristics: during major external shocks, the overall level of spillover rises sharply, and short-, medium-, and long-term spillovers intensify simultaneously, exacerbating the spread of systemic risk and complicating regulatory efforts.

### 4.2 Policy Recommendations

Based on the findings regarding the aforementioned spatiotemporal heterogeneity, this paper proposes the following targeted policy recommendations:

- (1) Implement frequency-differentiated, targeted regulation. Given the dominance of short-term, high-frequency spillovers, regulatory efforts should focus on curbing noise trading and sentiment-driven herding effects. Consider establishing a dynamic margin adjustment mechanism based on volatility frequency identification, and implement more granular real-time monitoring of algorithmic trading.
- (2) Incorporate low-frequency indicators from the futures market into the systemic risk monitoring framework. Given that futures act as net risk transmitters in the long run, it is recommended that low-frequency information such as the term structure of stock index futures and basis changes be included in the macroprudential early warning system as leading indicators for assessing medium- and long-term market risk sentiment.
- (3) Develop cross-frequency risk response plans for crisis periods. In the face of risks of cross-frequency spillover and resonance under major shocks, regulators should design joint stress tests covering both futures and spot markets, simulate extreme scenarios where short-term liquidity shortages and long-term pessimistic expectations reinforce each other, and use these to improve cross-market liquidity coordination and rescue mechanisms.

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## Appendix

### 1. HHT + BK Joint Analysis

To verify the robustness of the research conclusions, this paper conducts a joint HHT–BK analysis on the IF and HS300 return series, extracting the total connectivity (TCI) and net spillover (NET) of IF at each IMF level. The results are shown in the table.

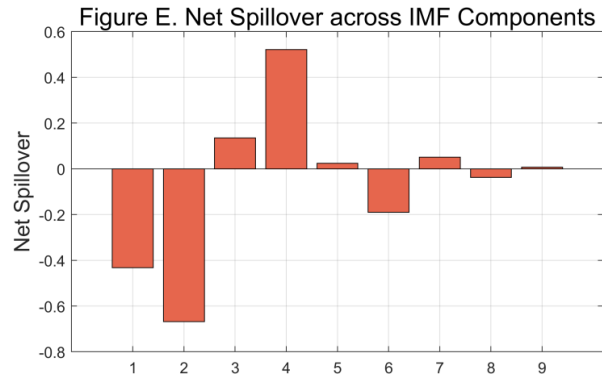
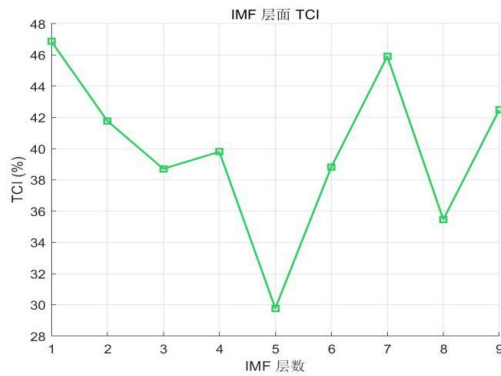
**Table 2. Frequency-Domain Connectivity at the IMF Level and IF Net Spillover**

IMF	TCI (%)	IF_NET	Explanation
1	45.65	-0.0656	High-Frequency → IF is a net risk taker
2	42.28	-0.0451	High-frequency → IF is a net risk-taker
3	37.25	-0.0544	Mid-frequency → IF is a net risk taker
4	47.65	-0.0684	Mid-frequency → IF is a net risk taker
5	43.26	0.2164	Mid-frequency → IF is a net risk contributor
6	41.09	-0.3257	Low-frequency → IF is a net risk taker
7	48.32	-0.0797	Low-frequency → IF is a net risk taker
8	37.75	-0.0202	Low-frequency → IF is a net risk taker
9	43.10	0.6226	Low-frequency → IF is a net risk exporter

\*IF\_NET < 0 indicates that IF is a net risk recipient; IF\_NET > 0 indicates that IF is a net risk exporter.

Analysis:

- 1) In the high-frequency IMF (IMF1–2), the IF is a net risk taker, indicating that in short-term fluctuations, the futures market passively absorbs risks from the spot market;
- 2) In the low-frequency IMF (IMF9), the IF is a net risk exporter, indicating that in long-term trends, the futures market acts as a risk transmitter to the spot market;
- 3) The performance of the medium-frequency IMFs (IMF3–5) shows volatility, which may reflect medium-term market adjustments or sporadic events;
- 4) The TCI index shows that, regardless of frequency, there is a significant correlation between the futures and spot markets.



The figure on the left visually illustrates the strength of the linkage between the futures and spot markets at different frequency levels. It can be observed that the high-frequency IMF (1–2) and low-frequency IMF (7–9) exhibit strong linkage, while the medium-frequency IMF (3–6) shows lower volatility.

The figure on the right visually illustrates the behavioral stratification between short-term net imports (IMF1–2) and long-term net exports (IMF9).

Conclusion:

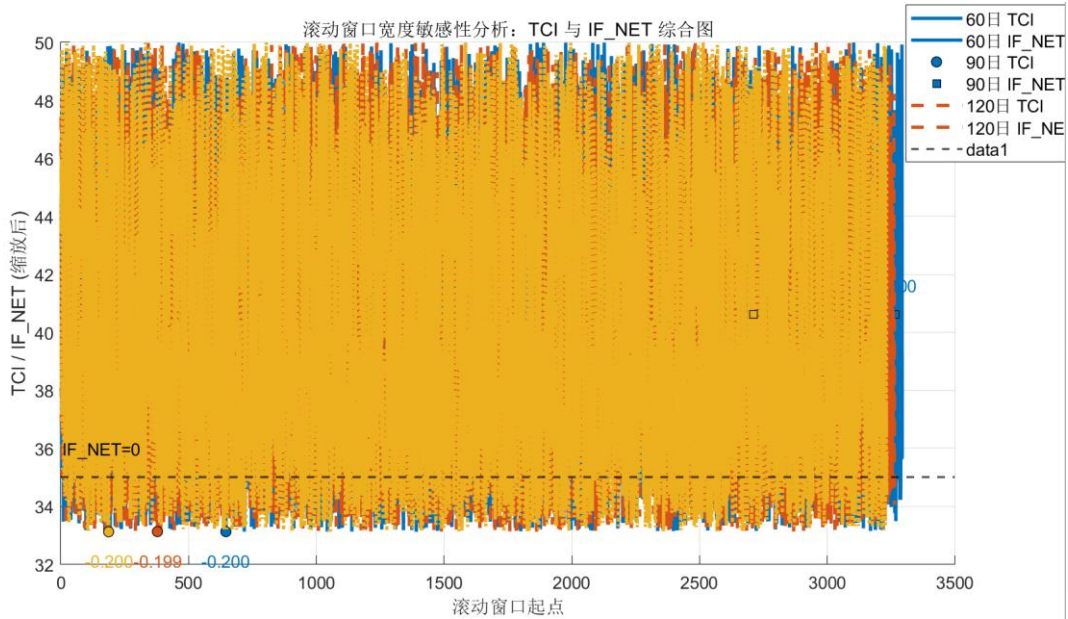
- 1) In high-frequency IMF (IMF1–2), the IF acts as a net risk absorber, indicating that the futures market passively absorbs spot market risk during short-term fluctuations;
- 2) In low-frequency IMFs (IMF9), the futures market acts as a net risk exporter, indicating that the futures market transmits risk to the spot market during long-term trends;
- 3) Medium-frequency IMFs (IMF3–5) exhibit volatility, which may reflect medium-term market adjustments or sporadic events;

The TCI index indicates that significant intermarket linkages exist between futures and spot markets, regardless of frequency.

In summary, the results of the HHT–BK joint analysis are highly consistent with the conclusions of the frequency-domain decomposition in the main text, further validating the robustness of this paper’s “short-term passive—long-term dominant” behavioral stratification hypothesis.

## 2. Sensitivity Analysis of Rolling Window Width

To test the robustness of this paper’s conclusions regarding the choice of rolling window length, the rolling window length was adjusted from 60 days to 90 days and 120 days, respectively, and the time-frequency domain spillover indices (TCI and IF\_NET) were re-estimated. The results show that the core pattern remains stable, as detailed in the analysis below.



\*X-axis: Rolling window start point

\*Y-axis: TCI and IF\_NET (IF\_NET has been scaled to align with TCI on the same axis)

The short-term minimum (net inflow) and long-term maximum (net outflow) of IF\_NET are labeled in the figure.

The zero line in the figure represents IF\_NET = 0, used to distinguish between net risk absorption and net risk output.

**Table 3. Text Results**

Rolling Window Length	Average TCI (%)	Short-term IF_NET Minimum	Long-term IF_NET Maximum
60 days	42.55	-0.199	0.598
90 days	42.60	-0.200	0.598
120 days	42.41	-0.199	0.600

**Robustness Conclusions:**

- 1) Regardless of whether the window length is 60, 90, or 120 days, the minimum value of short-term IF\_NET is approximately -0.20, indicating that the futures market remains passive in absorbing spot market risks in the short term;
- 2) The maximum value of long-term IF\_NET is approximately 0.60, indicating that the futures market plays a dominant role in risk transmission to the spot market over the long term;
- 3) The average TCI remains stable at around 42, indicating that the overall connectivity between the futures and spot markets is unaffected by changes in the rolling window length;

Therefore, the core conclusions of this paper demonstrate robustness regarding the selection of rolling window lengths, and the behavioral stratification pattern of short-term passivity versus long-term dominance is further validated.