

Article

Financial Stability and Economic Activity in China: Based on Mixed-Frequency Spillover Method

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Abstract: To improve financial sustainability and promote economic stability, it is important to understand the intricate relationship between finance and macroeconomy. Thus, focusing on financial stress and macroeconomic sectors, this paper investigates macro-financial spillovers in China. First, we develop a high-frequency financial stress index based on eight daily financial indicators to measure the stability of China's financial markets. Through event identification, we find that China's Financial Stress Index can effectively reflect the stress situation of China's financial market. Then, given that the traditional co-frequency method fails to deal with financial stress index and macroeconomic data with different frequencies, we employ the mixed-frequency spillover method to evaluate macro-financial spillovers to examine the connectedness between China's financial market and the real side of the economy. We find that financial stress is the leading net risk output and primarily affects the loan sector; deterioration of economic conditions can lead to more apparent fluctuations in spillover effects, with spillovers from financial stress to others being the most susceptible; within the sample, the 2015 stock crash, U.S.–China trade friction, and COVID-19 have the most impact on macro-financial spillover effects. In addition, we track the results of different risk events on spillover effects across sectors.



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1. Introduction

Several financial crises have shown that an unstable economic and financial environment can lead to a rapid spread of risks between financial markets and macroeconomic sectors, severely impeding economic growth. At the current juncture of intertwined changes and a pandemic both unseen in a century, the economic situation has become graver and more complicated. Therefore, measuring the stability of financial markets, analyzing risk spillovers between finance and macroeconomy, and tracking the impact of risk events on economic and financial connectedness, are essential for preventing significant risks and stabilizing economic development.

Previous studies on the definition of financial stability have focused on the desired stability and instability perspectives [1,2]. We understand financial stability as lower financial stress, implying less uncertainty [3]. Various indices have been developed to measure financial stability [4,5]. Among these indices, the financial stress index (FSI) is widely used in financial stability-related research [6–9]. The FSI measures the overall stress level of the financial system due to uncertainty and instability. It accurately identifies financial stress events in Canada by tracking the factors influencing financial market stress [10]. Since the financial crisis in 2008, it has attracted considerable interest from academics and financial regulators in developing FSIs. Several central banks and international financial organizations use the FSI as a critical metric to measure financial risk. For instance, there is the Kansas Financial Stress Index [11], the St. Louis Financial Stress Index [12], and the European Financial Stability Index [13].

In addition, scholars have developed various FSIs with different frequencies, different financial indicators, and different econometric models. Ravi et al. employed a monthly frequency FSI for emerging markets with five variables to capture credit conditions in banking, securities, and exchange markets [14]. Louzis et al. developed a monthly frequency FSI for Greece with data from economic fundamentals, the banking market, banking balance sheets, stock markets, and money markets [15]. Roye derived a monthly frequency FSI component of indicators from Germany's bank, capital market, and foreign exchange market [16]. Apostolakis et al. calculated a monthly FSI by the equal variance-weighted average of six variables [17]. Chadwick et al. created a weekly frequency FSI for Turkey with indicators selected from five markets: currency, bond, foreign exchange, stock, and bank [18]. Some scholars have also constructed FSIs for China. Apostolakis measured the FSIs of five emerging Asian countries (China, South Korea, Malaysia, the Philippines, and Thailand) [19]. Yao et al. developed a daily FSI from the perspective of interconnectedness to capture real-time stress in China's financial market [20].

The volatility of FSI is usually correlated with risk events. Apostolakis et al. found that the co-movement and spillover effects of financial stress are positively associated with financial crisis and uncertainty among the G7 economies [7]. Based on the MSVAR and TVAR models, combining information from CLIFS and industrial production, Duprey et al. identified financial market stress events that significantly negatively impacted the real economy and provided a chronology of systemic financial stress episodes in 27 EU countries [21]. Cardarelli et al. proposed that financial turbulence characterized by banking distress is more profound and more prolonged, and economies with more arm's-length financial systems are more vulnerable to contractions in economic activity following financial stress [22].

The connectedness between the FSI and real economic activity has also been extensively analyzed. Cevik et al. found that an increase in financial stress can lead to significant spillovers and systemic risks, constraining the ability of financial intermediaries to extend credit and impact economic activity adversely [23]. Proaño et al. demonstrated that, for EMU countries, debt-to-GDP ratios hurt economic growth mainly in periods of high financial stress, and high debt-to-GDP ratios do not necessarily seem to impair growth if financial markets are stable [24]. Tng et al. observed that increased financial stress has led to tighter credit conditions and reduced economic activity in the ASEAN-5 economies (Indonesia, Malaysia, Philippines, Singapore, and Thailand) [25]. Through a Markov-switching VAR model, Stona et al. investigated the interaction between the FSI and economic activity, inflation, and monetary policy in Brazil, pointing out that financial shocks have a more significant impact on the real economy and inflation during periods of instability, while traditional monetary policy may not be the most effective response to a financial crisis [26]. Polat et al. suggested that a deterioration in financial conditions would lead to a plummet in industrial production and a surge in the consumer price index [27]. By capturing Granger causality in quantiles, Saliminezhad et al. indicated that the dynamic causal relationship between financial stress index and economic activity is significantly negative in the UK and Germany [28]. It is evident that financial stress, in addition to causing risk spillover shocks within financial markets, also has a significant impact on the macroeconomy, and the negative feedback from macroimbalances can exacerbate the spread of risk [29].

Compared with low-frequency variables, high-frequency variables contain more helpful information. Therefore, models that take into account high-frequency variables can examine the information in the system more effectively and better portray the dynamics of the economy [30]. However, macrodata are usually sampled at a low frequency compared to accessible high-frequency financial data. Moreover, in studying the relationship between finance and economic activity, data at different frequencies cannot be directly used with traditional approaches, which severely restricts the employment of high-frequency financial data [31]. Accordingly, high-frequency FSIs tend to be used only in financial markets. In constant, most of the FSIs used to study macro-financial linkages are low-frequency or are converted from high-frequency. Low-frequency FSIs have a certain lag and difficulty

reflecting immediate risk shocks. Therefore, using low-frequency FSIs to assess the interrelationship between financial risks and macroeconomic sectors will produce apparent biases. Macro policies formulated and implemented on this basis will deviate from reality and fail to meet expectations.

With the development of econometric methods, models have been developed to study the interactions between mixed-frequency variables. The mixed-data sampling (MIDAS) and mixed-frequency vector autoregressive (MF-VAR) proposed by Ghysels [31,32] can effectively utilize high-frequency data and improve the accuracy of estimation and prediction. However, such models incorporate potential low-frequency shocks, making it impossible for researchers to quantify precisely the strength of shocks between financial markets and the macroeconomy from the perspective of network correlation analysis. Subsequently, Ghysels et al. [33] proposed a new estimation method for the MF-VAR that addressed the failure of previous models to decompose forecast error variance. Combining the MF-VAR model and the DY spillover approach [34,35], Cotter et al. [36] presented a method to measure macro-financial spillovers. The macro-financial spillover method quantifies risk spillovers directly using financial and macro data at different frequencies. Similar to the DY spillover index, the macro-financial spillover index is directional to determine whether the units are more on the spillover or receiver side. Compared to the co-frequency approach, the mixed-frequency method can more accurately track the spillovers between financial markets and the real side of the economy [37].

Based on previous research, we developed a daily-frequency China's Financial Stress Index (CFSI) focusing on systemic financial risk using a dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model. The CFSI comprises eight financial stress measures based on the essential segments of China's financial system: the interbank market, stock market, bond market, and foreign exchange market.

Unlike previous studies discussing the relationship between low-frequency FSI and economic activities, we consider the potential information in the high-frequency FSI. We attempt to capture the spillovers between macroeconomy and finance by employing the mixed-frequency spillover method, which places the high-frequency CFSI and low-frequency macroeconomic data in one framework. By analyzing the macro-financial spillover effects, we reveal the impact of historical risk events on macro-financial spillovers and trace the risk transmission between financial markets and the macroeconomy.

We find that the spillover effects observed in the mixed-frequency financial spillover approach are significantly higher than those in the traditional co-frequency approach, financial markets are the main risk spillover output, and macro-financial spillover effects are more significant when the financial and economic environment is unstable.

The remainder of this paper is organized as follows: Section 2 describes the methodology and data. Section 3 evaluates the CFSI and gives the empirical results on the macro-financial spillovers in China. Section 4 concludes and discusses.

2. Data and Methodology

2.1. Construction of China's Financial Stress Index

The calculation of CFSI can be divided into two steps. The first step is to obtain sub-indices corresponding to interbank, stock, bond, and foreign exchange markets. We map the raw indicators to [0, 1] by normalization. With the normalized metrics, the sub-indices are obtained by simple arithmetic averaging. The formula is as follows:

$$S_{i,t} = \frac{1}{m} \sum_{j=1}^m X_{i,j,t} \quad (1)$$

In Equation (1), $S_{i,t}$ denotes the financial stress of market i in period t , $i = 1, 2, 3, 4$, and m is the number of indicators of market i .

According to the basic portfolio theory, financial stress is more systemic and thus more dangerous for the economy if financial instability spreads widely across the whole

financial system [13]. Therefore, we choose the correlation coefficient as the weight of each sub-market stress. Referring to [27], we choose the dynamic conditional correlation to weigh the four submarket stresses in the second step. A larger CFSI indicates a more unstable financial system and a more severe impact caused by the corresponding risk event. The CFSI calculation is as Equation (2):

$$\text{CFSI}_t = s_t C_t s_t' \quad (2)$$

In Equation (2), s_t denotes the financial stress in the four financial submarkets, and C_t is the matrix of time-varying correlation coefficients $\rho_{ij,t}$ between financial submarkets i ($i = 1, 2, 3, 4$) and j ($j = 1, 2, 3, 4$). As Equation (3) shows:

$$C_t = \begin{pmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \rho_{24,t} \\ \rho_{13,t} & \rho_{23,t} & 1 & \rho_{34,t} \\ \rho_{14,t} & \rho_{24,t} & \rho_{34,t} & 1 \end{pmatrix} \quad (3)$$

In Equation (3), C_t is estimated by the DCC-GARCH model proposed by Engle [38]. The DCC-GARCH method with multivariate series r_t can be given as Equation (4):

$$r_t | \varphi_{t-1} \sim N(0, D_t R_t D_t) \quad (4)$$

$$D_t^2 = \text{diag}\{\omega_i\} + \text{diag}\{k_i\} \circ r_{t-1} r_{t-1}' + \text{diag}\{\lambda_i\} \circ D_{t-1}' \quad (5)$$

In Equation (4), D_t is a diagonal matrix of conditional volatilities, and R_t is a matrix of time-varying conditional correlations. R_t can be defined by a positive definition matrix Q as Equation (6):

$$R_t = \text{diag}\{Q_t\}^{-1} Q_t \text{diag}\{Q_t\}^{-1} \quad (6)$$

$$Q_t = S(1 - \alpha - \beta) + \alpha \varepsilon_{t-1} \varepsilon_{t-1}' + \beta Q_{t-1} \quad (7)$$

In Equation (6), S is the unconditional correlation matrix of the epsilons, and $\varepsilon_t = D_t^{-1} r_t$. The log-likelihood function that maximizes the parameters of the model can be expressed as:

$$L = -\frac{1}{2} \sum_{t=1}^T \left(\ln \log(2\pi) + 2 \log |D_t| + r_t' D_t^{-1} D_t^{-1} r_t - \varepsilon_t' \varepsilon_t + \log |R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t \right) \quad (8)$$

Through the DCC-GARCH model, we estimate the dynamic correlation among financial markets and calculate the daily CFSI. The larger the CFSI, the stronger the risk in the financial markets.

A rational measure of financial stress in each market is an essential prerequisite for analyzing the stress situation in China's financial markets. Hakio and Keeton note that financial stress events tend to be characterized by: (1) increased asset uncertainty; (2) reduced willingness to hold risky or illiquid assets; (3) more disorderly investor behavior; (4) increased information asymmetry [11]. Therefore, combining the characteristics of financial stress and the actual situation of China's financial market, we mainly consider four submarkets: interbank market, stock market, bond market, and foreign exchange market. Referring to the existing literature on CFSI and considering data availability, we select the following indicators that can promptly reflect the stress status [11,20,39].

(1) Interbank market:

The volatility of the 3-month Shanghai Interbank Offered Rate (SHIV): The high volatility of the 3-month SHIBOR, China's money market benchmark interest rate, reflects flight to quality and flight to liquidity due to increased uncertainty in the short-term interbank market. This indicator tries to capture the volatility of sentiment in the currency market and is obtained with GARCH (1,1).

The TED spread (TED): The indicator attempts to capture counterparty risk dominated by bank lending. This spread represents the risk premium associated with lending to commercial banks and thus reflects overall liquidity risk. It is calculated as:

$$\text{TED Spread} = 3\text{mSH} - 3\text{mTB}, \quad (9)$$

In Equation (9), 3mSH represents 3-month SHIBOR, and 3mTB means 3-month Treasury bill rates.

(2) Stock market:

The volatility of the CSI 300 Index (CSIV): The indicator reflects uncertainty caused by stock market volatility and is obtained with GARCH (1,1).

CMAX for CSI 300 (CMAXC): The cumulative maximum loss (CMAX) over a moving 1-year window for CSI 300 tries to capture systemic risk in the stock market and is calculated as:

$$\text{CMAX}_t = 1 - \frac{S_t}{\max[S \in (S_{t-j} | j = 0, 1, \dots, T)]} \quad (10)$$

In Equation (10), S_t denotes the value of CSI 300 at the time t . Due to the availability of data in a natural year, the real-time window is chosen to be 250.

(3) Bond market:

The volatility of ChinaBond New Composite Net Price Index (CCNV): This indicator reflects the volatility risk of the bond market. It is obtained with GARCH (1,1).

Treasury yield spread (TYS): This indicator reflects the market's risk aversion and is in a form of 30-day moving average. The indicator is calculated as:

$$\text{Treasury yield spread}_t = \left(\frac{1}{30}\right) \sum_{i=0}^{29} (10y_{t-i} - 3m_{t-i}) \quad (11)$$

In Equation (11), $3m_{t-i}$ is the 3-month Treasury yield while $10y_{t-i}$ is the 10-year Treasury yield.

(4) Exchange market:

The volatility of the RMB/USD exchange rate (UER): The U.S. dollar is the most used currency in the world market. Thus, the volatility of the RMB/USD exchange rate is used to determine one of the dominant risk factors in the foreign exchange market. This indicator is measured by GARCH (1,1).

The volatility of the RMB/EUR exchange rate (EER): The EUR ranks second in the use of international currencies worldwide. Therefore, the volatility of the RMB/EUR exchange rate is also one of the main risk factors in the foreign exchange market. The indicator is obtained with GARCH (1,1).

2.2. Mixed-Frequency Spillover Methodology

Following the mixed-frequency model proposed by Ghysels et al. [33], we observe a $K = K_H + K_L$ dimensional mixed-frequency process. The mixed-frequency process contains K_H high-frequency financial variables $\{x_{H,i}(\tau_1)\}_{i=1}^{K_H}$ and K_L low-frequency macroeconomic variables $\{x_{L,j}(\tau_1)\}_{j=1}^{K_L}$. For each low-frequency period, every high-frequency financial series is observed m times. Dividing into m groups for each low-frequency period, the high-frequency variables can be expressed as follows.

$$x_{H,i}(\tau_1) = [x_{H,i}(\tau_1, 1), \dots, x_{H,i}(\tau_1, m)]', i = (1, 2, \dots, K_H) \quad (12)$$

Aggregating the low- and high-frequency variables, a $K_x = mK_H + K_L$ dimensional stacked vector can be obtained as:

$$x(\tau_1) = [x_{H,1}(\tau_1), \dots, x_{H,K_H}(\tau_1), x_L(\tau_1)]' \quad (13)$$

Writing Equation (13) as an MF-VAR(p) model:

$$x(\tau_1) = A_0 + \sum_{j=1}^p A_j x(\tau_1 - j) + \varepsilon(\tau_1) \quad (14)$$

In Equation (14), A_0 and $\varepsilon(\tau_1)$ are K_x -dimensional parameter and error vectors, A_j is a $K_x \times K_x$ dimensional matrix, and $j = 1, \dots, p$. Equation (14) is mathematically equivalent to the standard VAR. According to Pesaran et al. [40], the generalized forecasting error variance decomposition (GFEVD) matrix of K_x -dimensional MF-VAR is obtained as:

$$\begin{bmatrix} \theta_{11}(H) & \cdots & \theta_{1K_x}(H) \\ \vdots & \ddots & \vdots \\ \theta_{K_x 1}(H) & \cdots & \theta_{K_x K_x}(H) \end{bmatrix}, H = 1, 2, \dots \quad (15)$$

In Equation (15), $\theta_{ij}(H) = \lambda_{ij}(H) / \mu_i(H)$. $\lambda_{ij}(H) = \sigma_{jj} \sum_{h=0}^{H-1} (e_i' B_h \Sigma e_j)^2$ is the forecasting error variance of variable i due to the shock of variable j . $\mu_i(H) = \sum_{h=0}^{H-1} (e_i' B_h \Sigma B_h' e_i)$ is the total H -step prediction error variance of variable i .

Following Cotter [36], we transform the K_x -dimensional GFEVD matrix into the K -dimensional matrix as follows to study the K -dimensional mixed-frequency process:

$$\begin{bmatrix} \psi_{11}(H) & \cdots & \psi_{1K}(H) \\ \vdots & \ddots & \vdots \\ \psi_{k1}(H) & \cdots & \psi_{kK}(H) \end{bmatrix}, H = 1, 2, \dots \quad (16)$$

Each element $\psi_{kl}(H)$ in the K -dimensional GFEVD matrix can be calculated as:

$$\psi_{kl}(H) = \frac{\sum_{i \in I_k, j \in J_l} \lambda_{ij}(H)}{\sum_{i \in I_k} \mu_i(H)}, k, l = 1, \dots, K; H = 1, 2, \dots \quad (17)$$

In Equation (17), I_k and J_l are, respectively, the sets of data in the mixed-frequency model and the K -dimensional GFEVD matrix.

As $\sum_{j=1}^K \psi_{kl}(H) \neq 1$, to facilitate the analytical interpretation of the spillovers, we follow Diebold [34] to normalize $\psi_{kl}(H)$ as:

$$\tilde{\psi}_{ij}(H) = \frac{\psi_{ij}(H)}{\sum_{j=1}^K \psi_{ij}(H)} \quad (18)$$

In Equation (18), $\sum_{j=1}^K \tilde{\psi}_{ij}(H) = 1$, and $\sum_{i,j=1}^K \tilde{\psi}_{ij}(H) = K$. Thus, the spillover from variable i to variable j is given by:

$$S_{ij}(H) = \frac{100}{K} \tilde{\psi}_{ij}(H) \quad (19)$$

The total spillover index to measure the overall level of spillovers is computed as:

$$S(H) = \frac{100}{K} \sum_{\substack{i,j=1 \\ i \neq j}}^K \tilde{\psi}_{ij}(H) \quad (20)$$

The gross directional spillover index of all other variables to variable i and variable i to all other variables can be calculated as follows:

$$S_{Ti}(H) = \frac{100}{K} \sum_{\substack{j=1 \\ j \neq i}}^K \tilde{\psi}_{ji}(H) \quad (21)$$

$$S_{Fi}(H) = \frac{100}{K} \sum_{\substack{j=1 \\ j \neq i}}^K \tilde{\psi}_{ij}(H) \quad (22)$$

The net spillovers of variable i to all other variables can be calculated as follows:

$$S_{Ni}(H) = S_{Ti}(H) - S_{Fi}(H) \quad (23)$$

Following Yang [41], monthly data on Industrial Added Value (IAV), Total Retail Sales of Consumer Goods in China (TRS), Investment in Fixed Assets (IFA), New Yuan Loans (NYL), and Broad money (M2) are selected to represent the macroeconomic sectors of production, consumption, investment, loans, and currency. These data are obtained from the National Bureau of Statistics of China, China Bond Information Network, and the Wind database. SHIBOR is an essential variable in the calculation of CFSI in this paper. However, SHIBOR was officially operational in January 2007. Due to data availability, the sample period of this paper is 1 January 2007 to 31 December 2021. Descriptive statistics of financial market variables are presented in Table 1. Descriptive statistics of macroeconomic variables are presented in Table 2.

Table 1. Descriptive statistics of financial market variables.

Variable	Mean	Sd	Min	Max	Mid
SHIV	0.003	0.031	0.000	1.000	0.000
TED	0.421	0.201	0.000	1.145	0.371
CSIV	0.140	0.151	0.000	0.963	0.084
CMAXS	0.225	0.209	0.000	1.000	0.183
CCNV	0.064	0.103	0.000	0.974	0.030
TYS	0.506	0.209	0.000	1.000	0.483
UER	0.090	0.114	0.000	0.992	0.052
EER	0.093	0.115	0.000	0.962	0.055

Table 2. Descriptive statistics of macroeconomic variables.

Variable	Mean	Sd	Min	Max	Mid
IAV	0.003	0.031	0.000	1.000	0.000
TRS	0.421	0.201	0.000	1.145	0.371
IFA	0.140	0.151	0.000	0.963	0.084
NYL	0.225	0.209	0.000	1.000	0.183
M2	0.064	0.103	0.000	0.974	0.030

3. Results

3.1. China's Financial Stress Index

3.1.1. Evaluation of China's Financial Stress Index

This paper develops a daily CFSI through dynamic conditional correlation with equally weighted market indicators to measure systemic risk in Chinese financial markets. Figure 1 presents the CFSI from 4 January 2007 to 31 December 2021. The larger the financial index, the more unstable the financial market and the higher the financial risk.

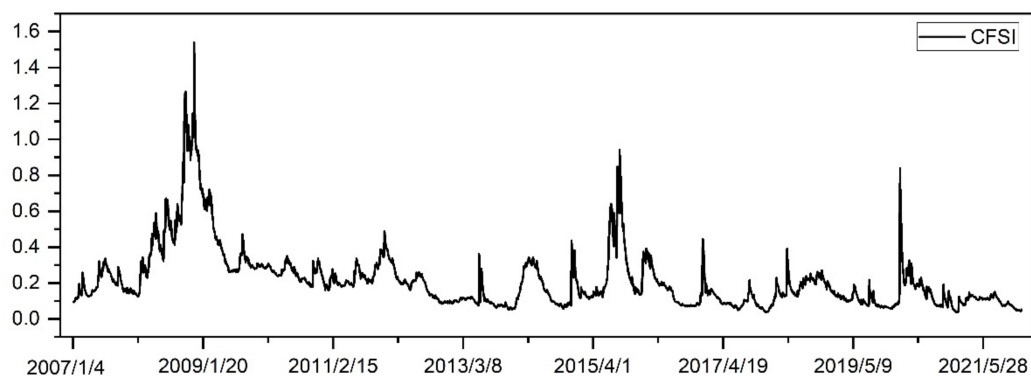


Figure 1. China's Financial Stress Index.

CFSI has a mean value of 0.22 and a standard deviation of 0.17 and is fluctuated below 0.6 most of the time, usually in a low-stress state during the sample period. Three peaks of CFSI above 0.6 are observed in Figure 1. The first and highest peak (1.54) corresponds to

the global financial crisis in 2008, the second peak to the stock market crash in 2015, and the third peak to the outbreak of COVID-19 in 2020.

3.1.2. Identification of stress events

A good FSI should reflect stressful events in a timely and effective manner. The response of the FSI to past financial stress events can be used to evaluate the performance of the index [11,13,27]. Likewise, we analyze the performance of CFSI in terms of its response to financial stress events. The peak of China's financial stress index corresponds to the following financial stress events: a, Lehman Brothers went bankrupt, and the financial crisis broke out on 15 September 2008; b, Fitch International downgraded Greece's long-term sovereign credit rating from "A−" to "BBB+" on 8 December 2009; c, The State Council issued ten measures to curb the rapid rise in house prices and real estate on 17 April 2010, and banking sectors fell sharply; d, the stock market plunged on 12 November 2010; e, Asia-Pacific Economic Cooperation leaders issued a statement on 14 November 2011 saying that the global economy is facing significant downside risks due to the impact of the European debt crisis; f, the "money shortage" event on 20 June 2013; g, Premier Li Keqiang first mentioned "steady growth" on 19 March 2014; h, stock market crash on 15 June 2015; i, the "Circuit Breaker" was introduced in China's A-shares on 1 January 2016; j, Treasury futures fell by the daily limit on 15 December 2016; k, the central bank announced lower required reserve ratios on 18 April 2018; l, China initiated level I response to significant public health emergency to prevent the COVID-19. As shown in Figure 2, the CFSI constructed in this paper provides appropriate signals for well-known stress events.

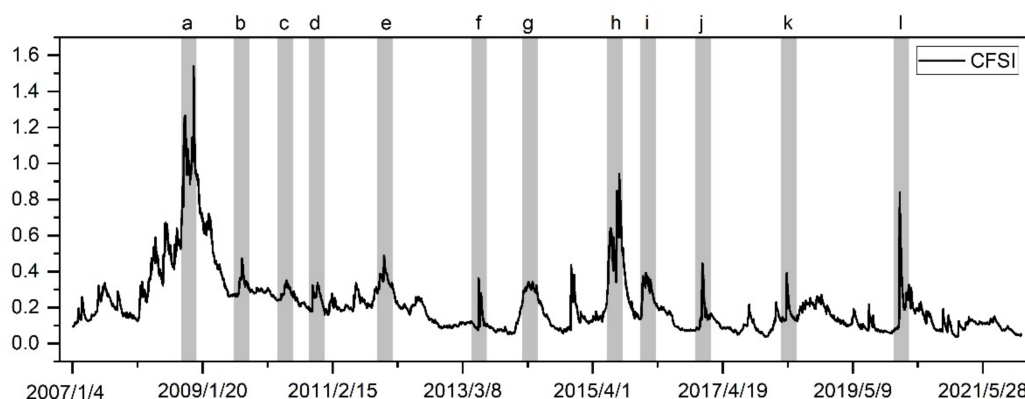


Figure 2. China's Financial Stress Index and stress events.

Following Ma [42], we identify periods of high financial stress as those in which the financial stress index deviates by more than twice its standard deviation. The validity of the financial stress index is further proved by testing whether periods of high financial stress effectively reflect significant risk events. The results show that the Chinese financial market experienced three high financial stress periods. They are June 2008 to March 2009, corresponding to the 2008 global financial crisis, June 2015 to September 2015, corresponding to the Chinese stock market crash, and February 2020, corresponding to the outbreak of COVID-19. Overall, CFSI effectively identifies important stress events during the sample period and validates the effectiveness of the Financial Stress Index.

3.1.3. Dynamics of Financial Stress in China

By observing the trend of CFSI in Figure 1, we can roughly divide China's financial development into three phases during the sample period, from January 2007 to December 2012, from January 2013 to December 2019, and from January 2020 to December 2021. In conjunction with the financial submarket stress index in Figure 3, we analyze the dynamics of CFSI and related economic events.

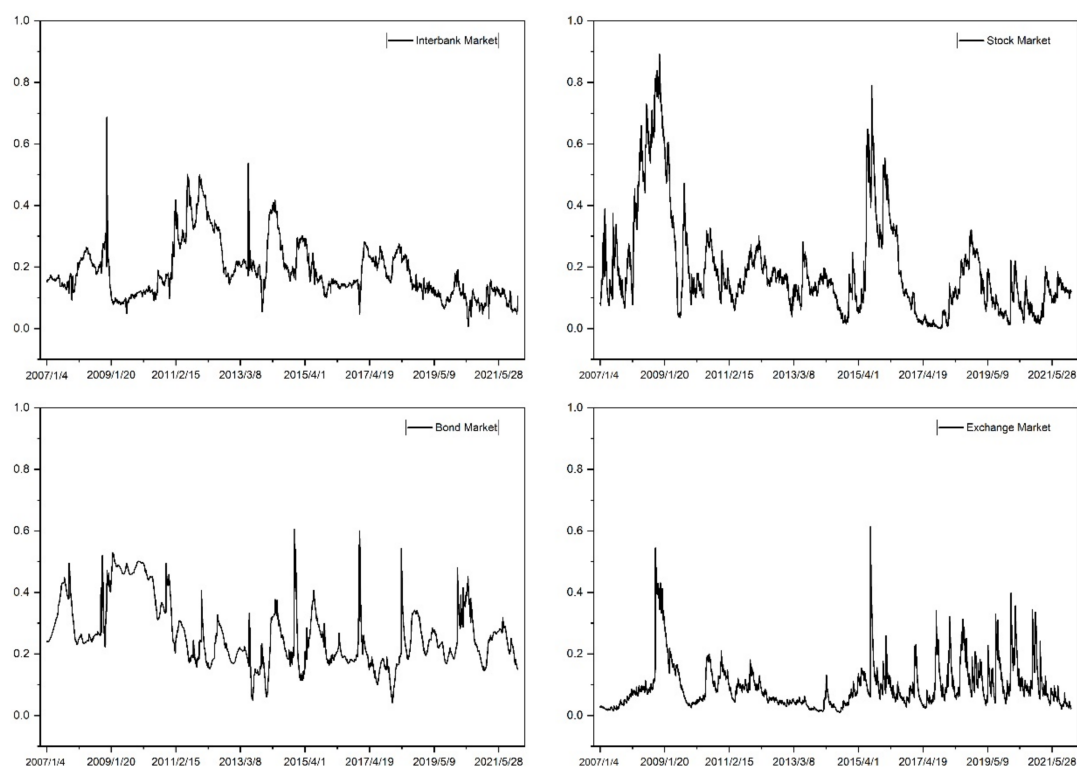


Figure 3. Financial stress in sub-markets.

In the first phase, starting in 2007, CFSI began to oscillate upward and peaked in December 2008, then quickly fell to a low level in August 2009. The pressure on China's financial system came mainly from abroad during this period. In August 2007, the U.S. housing market indicators deteriorated, and the subprime mortgage crisis began to spread globally. With the bankruptcy of Lehman Brothers in 2008, the international financial crisis broke out. The financial crisis was a storm caused by the bankruptcy of subprime mortgage lenders, forced closure of investment funds, and violent stock market shocks, which led to a crisis of illiquidity in major financial markets around the world and hit the Chinese financial market severely. Subsequently, the Greek debt crisis that started at the end of 2009 triggered the European debt crisis. The deepening of the European debt crisis complicated China's domestic and international economic and financial situation, adversely affecting financial markets and institutions. As a result of the European debt crisis, China's stock market was turbulent, with estimated stock price fluctuations. In addition, the continued appreciation of the RMB against the Euro caused international hot money to enter the Chinese market for speculation and risk aversion, continuously impacting the Chinese financial market. Confronted with the financial crisis, China took active measures to cope with it. In November 2008, China published the "four trillion plan" to expand domestic demand and boost the economy while implementing a moderately loose monetary policy to provide liquidity support. The financial crisis was adequately dealt with, and the financial stress was effectively released.

In the second phase, starting in early 2013, although CFSI was generally at a low level, there was a significant increase in volatility. During this period, China's financial reform accelerated, and problems in financial markets increased, thus making financial stress more unstable. The interbank market suffered from liquidity pressure, the stock market saw the pressure of volatility, the bond market suffered from liquidity stress, and the foreign exchange market was affected by the 2015 stock market crash.

In the interbank market, in June 2013, funds were idle in the financial system or flowed to restricted areas, leading to liquidity constraints in the banking sector and an outbreak of money shortages. Panic quickly spread to the entire financial market, during which the

stock market fell sharply, and bond market rates rose rapidly. In the first quarter of 2014, affected by the “money shortage” in June 2013, investors’ sentiment was fragile, and the market was pessimistic about monetary policy, resulting in a slight downward trend in interest rates.

In the stock market, from November 2014 to September 2015, the CSI 300 saw a sharp rise and fall. China has an extremely high proportion of resident savings that cannot be effectively converted into investment. Furthermore, corporations are excessively indebted due to a lack of access to financing. To improve the corporate financing environment, The Third Plenary Session of the Eighteenth Central Committee put forward the goal of capital market reform to increase the proportion of direct financing. The positive news drove the stock market higher. However, the dramatic increase in investor capital leverage and inappropriate guidance from the mainstream media led to an inflating asset bubble. Then, when the speculation bubble reached its limit, the stock market began to plummet. In response to the overheated stock market, in June 2015, the China Securities Regulatory Commission (CSRC) rectified the over-the-counter (OTC) placement market and proactively released risks through deleveraging. Many stocks entered the forced liquidation process contemporaneously, liquidity dried up, and the stock market entered a downward cycle. In just three months, the CSI 300 Index fell from a high of 5380.43 points to 3025.69 points, and the phenomenon of “thousand shares limited down” occurred many times. Since February 2018, the escalating trade dispute between the U.S. and China, coupled with the continued depreciation of the RMB and a large number of capital outflows from the stock market, has caused the stock market to plunge throughout the year and increased financial stress on the stock market.

In the bond market, the “Opinions on Strengthening the Management of Local Government Debt” issued by the State Council in October 2014 represented the official launch of local debt cleanup. Subsequently, on 8 December 2014, “Opinions on Strengthening the Management of Corporate Bond Repurchases” were issued, which led to the loss of pledge eligibility and liquidity of some corporate bonds and a liquidity crisis as credit bond valuations rose sharply. In response, 10-year government bonds with better liquidity were sold off first, moving up about 30 basis points in three trading days. In the fourth quarter of 2016, U.S. Treasury yields rose, the RMB depreciated rapidly, and pressure on foreign reserve outflows increased, causing the bond market to plunge. The 10-year Treasury rate spiked to 3.37% from 2.87% at the beginning of the year, before falling back to 3.01%. In April 2018, the volatility of the bond market increased. The bond price index and treasury interest rate volatility were significantly higher than the previous month. On 17 April, the central bank announced lower required reserve ratios (RRR), which triggered market sentiment fluctuations. On the first day after the announcement of the RRR downgrade (18 April), the bond market strengthened across the board, with the bond price index rising sharply and the Treasury rates of all maturities moving downward. Subsequently, the bond market gradually calmed down, overlaid with tight funding, the bond price index fell significantly, and 1-year and 10-year Treasury rates rose consistently.

In the foreign exchange market, to promote the internationalization of the RMB, the central bank of China announced the adjustment of the RMB/USD exchange rate mid-price quotation mechanism on 11 August 2015. This was the “811 Exchange Reform” for short. This reform effectively promoted the marketization of the RMB exchange rate and made the RMB exchange rate more accurately reflect the current supply and demand in the foreign exchange market. However, the introduction of the “811 Exchange Reform” coincided with the 2015 stock market crash, which caused rapid depreciation of the RMB and a considerable loss of foreign exchange reserves. In August 2017, the RMB exchange rate showed an appreciation trend, ending the unilateral decline of the RMB against the U.S. dollar after the “811 Exchange Reform”. In September, the RMB exchange rate accelerated its appreciation and began fluctuating in two directions, up and down.

In the third phase, China’s financial markets received only a brief shock in early 2020. At this stage, the stress on China’s financial markets briefly increased due to a “black

swan" event—COVID-19. Affected by COVID-19, the 3-month SHIBOR fell from 3.04% in December 2019 to 1.39% in April 2020, the CSI 300 index plunged 7.88% on 3 February 2020, the RMB exchange rate fluctuated widely, and RMB depreciation widened. China actively took preventive measures in the face of the epidemic's impact and effectively prevented financial risks. Overall, although the shock of COVID-19 on Chinese financial markets was significant, it was relatively short-lived.

The above analysis shows that three phases characterize CFSI. CFSI is consistent with trends in economic events over the sample period. The corresponding peaks accurately identify important stress events, indicating that CFSI can effectively monitor financial risks.

3.2. Analysis of China's Financial Stress and Macro Spillover

3.2.1. Static Analysis of Spillovers

We use CFSI to measure risk in financial markets and adopt the mixed-frequency approach to study the spillovers between finance and macroeconomy. When calculating the spillover indices, we mainly consider the forecast horizons of 1 to 10 months. However, we find no significant sensitivity of the estimates to changes in the forecast horizon over 3 months. Therefore, only the results of 5 months' horizon are reported. The "input-output" spillover indices of financial stress and the macro sectors across the entire sample are reported in Table 3. The ij th element is a measure of spillover from market j to market i . The elements of the row labeled "to" are the sums of off-diagonal columns, which estimate directional spillovers from the elements to others. The elements of the column labeled "from" are the off-diagonal row sums, which are the directional spillovers from the others to the elements. The elements in the row "net" indicate the net spillovers. The total spillover index appears in the lower right corner.

Table 3. Full-sample macro-financial spillovers.

	CFSI	IAV	TRS	IFA	NYL	M2	From
CFSI	13.53	0.23	0.84	0.98	0.59	0.49	3.14
IAV	2.93	8.33	1.36	0.87	0.87	2.30	8.34
TRS	2.51	2.93	7.18	2.23	0.39	1.43	9.49
IFA	1.00	1.80	2.48	10.05	0.44	0.90	6.62
NYL	9.03	0.28	0.84	0.40	5.37	0.74	11.30
M2	4.10	2.03	1.23	0.87	0.91	7.54	9.13
to	19.58	7.27	6.75	5.35	3.19	5.87	48.01
net	16.44	−1.07	−2.74	−1.27	−8.10	−3.26	

Note: IAV is industrial added value, TRS is total retail sales of social consumer goods, IFA is the completed investment in fixed assets, and NYL is new RMB loans from financial institutions.

We first observe the directional spillovers of financial stress. The spillover from financial to macro is 19.58, and the swap is 3.14, indicating that risk spreads mainly from financial markets to the macroeconomy, which also indicates to some extent that systemic financial risks have not seriously affected the stable operation of China's economy. From the "to" row, we can see that the gross spillover index from IAV to others is relatively large at 7.27, followed by the TRS sector with 6.75. We can also see from the "from" column that the gross spillover index from others to NYL is comparatively large at 11.30, followed by the TRS sector and the M2 sector at 9.49 and 9.13. As for the net directional spillovers, it can be found that the financial market, consumption, and investment are net exporters of risk. At the same time, industrial added value, loans, and currency are net receivers of risk. The largest is from the CFSI sector to others ($19.58 - 3.14 = 16.44$) and from others to the NYL sector ($3.19 - 11.30 = -8.10$).

We can learn from Table 3 that the overall connectedness between financial markets and macroeconomic sectors was weak during 2007–2021, suggesting that China's economic and financial regulatory policies have effectively prevented and mitigated risks and promoted stable and healthy development of China's economy. In addition, the spillover index of

CFSI to NYL is 9.03, much larger than the spillover to other sectors, showing that the loan sector is the main transmission of financial risk to the economy.

3.2.2. Dynamic Analysis of Spillovers

Given the rapidly changing economic and financial environment, spillover indices based on full-sample data, while providing an overview of “average” spillover behavior, cannot capture the movement of spillovers over time and assess the impact of risk events on spillover effects. To address this issue, we select a forecast horizon of 10 months and use “rolling sample estimation” with a 60-month window to calculate the total spillover index, gross directional spillover index, net gross spillover index, and pairwise directional spillover index to identify the risk events affecting China’s economic development and analyze the impact of different risk events. In this way, the sample size is sufficient to allow accurate estimation of the parameters of the MF-VAR model while capturing the dynamics of the spillover effects [36,41].

(1) Dynamic Analysis of Total Spillovers

The total spillover indices from the mixed-frequency (MF) and common-frequency (CF) approaches are plotted in Figure 4. As can be seen, the total spillover indices estimated by both methods move in roughly the same trend over the sample period, which indicates that the spillover indices are significant. However, the total spillover index estimated by the mixed-frequency method is mostly higher than that of the traditional common-frequency way (with one or two exceptions) and is more unstable. This is because some short-term effects that high-frequency financial data detect may not be observed by low-frequency financial data [43,44]. Using low-frequency financial data or aggregating high-frequency financial data with low-frequency can ignore or underestimate spillover effects [36]. Therefore, this paper analyzes macro-financial spillover effects based on the mixed-frequency spillover approach.

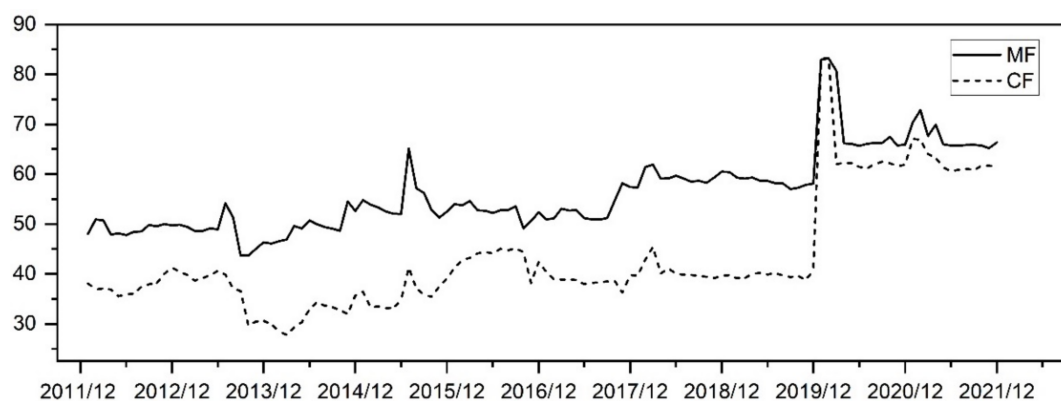


Figure 4. Total spillover index between financial and macro sectors.

In Figure 4, it can be observed that the total spillover index has exhibited many changes and an upward trend. Some of the changes burst and subside, while others continue for a long or short term. We can identify three phases in the total spillover plot in terms of total spillover levels.

In the first phase, from January 2012 to September 2017, the total macro-financial spillover index mostly fluctuated between 45 and 55. Starting at 48 in the first window, the index was relatively flat before dropping in the second half of 2013. Then, along with the stock market rallying and falling, the total spillover index climbed to 65 in June 2015. Later, the index returned to around 50 in late 2015. The high level of the total spillover index in this phase corresponds to the money shortage event in 2013 and the stock market crash event in 2015. Therefore, we tentatively deduce that the increase in spillovers in the first phase was mainly influenced by increased stress in financial markets.

In the second stage (October 2017–December 2019), the aggregate spillover index is higher than most of the first stage. In September 2017, the aggregate spillover index started to increase. The total spillover index reached 61.40 in February 2018 and stayed above 55 until 2020. The rise in the total spillover index in this phase is mainly due to the adjustment of foreign exchange risk reserves by the Chinese central bank at the end of 2017, which led to increased volatility in the RMB exchange rate and the trade dispute between China and the U.S. in 2018, which hit the Chinese manufacturing sector. Therefore, we tentatively judge that the increase in total spillovers in this phase is mainly influenced by the increase in spillovers from the financial market and the real economy.

After a relatively calm period from the second half of 2018 to 2019, the total spillover index in the third phase arrived at a higher level than the previous. The total spillover index recorded a significant upward movement in the first half of 2020. It climbed from 58 in late 2019 to 83 in February 2020 due to the outbreak of COVID-19. With a series of prevention and control measures taken by the Chinese government, the epidemic was quickly and effectively managed. The total spillover index fell back to around 66 in mid-2020. The high level of the main total spillover index in this period corresponds to the outbreak of COVID-19 in the first quarter of 2020, which coincides with the Chinese New Year, the peak consumption period in February 2020. However, due to COVID-19, offline consumption stagnates, and the real economy stops working and production. Therefore, we tentatively judge that the increase in total spillover effects during this period is mainly influenced by the increase in spillover effects from the real economy, consumption, and investment.

It can be seen that financial instability leads to an increase in total macro-financial spillovers. Sudden external shocks such as the U.S.–China trade frictions and the new crown pneumonia epidemic can also cause an increase in aggregate macro-financial spillovers.

(2) Dynamic gross spillovers

The total spillover index measures changes in spillovers at a high level of aggregation but fails to capture which sector is affected by the risk event leading to an increase in total spillover. Therefore, we use the gross directional spillover indices corresponding to the “to” row (given by $S_{Ti}(H)$ in Equation (21)) and “from” column (given by $S_{Fi}(H)$ in Equation (22)) mentioned above in Table 3, to analyze which sector drove the increase in the total spillover index.

In Figure 5, we present the gross directional spillovers from each of the six sectors to others (corresponding to the “to” row in Table 3). The dynamics of the gross directional spillover index across sectors show that fluctuations in financial stress spillover effects are the leading cause of fluctuations in total spillover effects during the sample period. In June 2013, China’s financial markets experienced a “money shortage” event, with liquidity tightening and interest rates surging in a short period, which led to a significant increase in corporate financing costs and a particular impact on the real economy. The total CFSI spillover to other sectors increased from 21.31 in June 2013 to 29.05 in July 2013 due to the money shortage. In 2014, local government debt management was further strengthened, many AA-rated bonds could not be pledged for financing, and the bond market experienced a liquidity crisis. This led to a passive contraction of corporate financing capacity, and the real economy received a short-lived shock. As a result, CFSI’s spillover index rose from 23.19 in October 2014 to 31.77 in November 2014. In June 2015, China’s stock market crashed, blocking direct financing channels for enterprises, evaporating investor assets, and hitting real economic development hard. The spillover index of CFSI to other sectors reached 37.35 in July 2015.

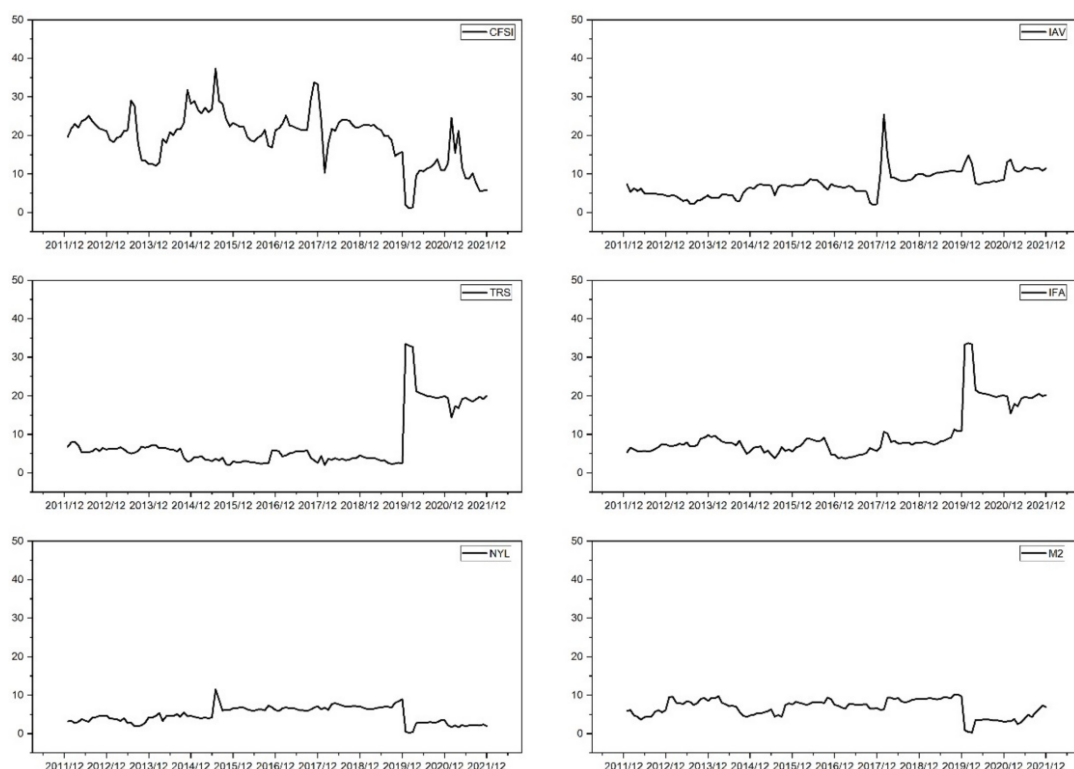


Figure 5. Gross directional spillover indexes from six sectors to others.

In addition to the financial sector, the increase in spillovers from the industrial sector in February 2018 and from the consumption and investment sectors in February 2020 drives the growth in total spillovers. In 2018, trade friction between China and the United States intensified. The increase in tariffs raised the cost of exporting products, and manufacturing companies that depended on the U.S. market were more affected. As a result, the spillover index for the industrial sector reached 25.45 in February 2018. In 2020, the COVID-19 pandemic brought a big shock to the economic operation, and industry, consumption, and investment growth rates dropped significantly. Influenced by this, the consumption and investment spillover indices reached 33.46 and 33.32 in January 2020.

Figure 6 presents the gross directional spillovers from others to each of the six sectors (corresponding to the “from” column in Table 3). The spillovers from others vary less significantly over time than the directional spillovers to others. Spillover from others fluctuated mainly in June 2015, February 2018, the first half of 2020, and the first half of 2021. Spillovers from others to NYL experienced a cycle from May 2013 to September 2013, and spillovers to IFA experienced a cycle in the first half of 2021.

In addition, we focus on the net gross spillover index. Each point in Figure 7 is obtained by Equation (23), corresponding to the “net” row of Table 3. Figure 7 shows that the net spillover index for CFSI fluctuates more frequently and with greater magnitude during the sample period. The net spillover indices for the other five sectors are more stable, fluctuating between 10 and -10 most of the time. However, the net spillover index shows a significant change in February 2018 and 2020. CFSI shifted to a net risk input in the first half of 2020, and the net premium index turned negative. The IAV net premium index was significantly higher in February 2018. The TRS and IFA net premium indexes were significantly higher in the first half of 2020. As a result of the U.S.–China trade dispute in February 2018, the net spillover index for IAV increased from -13.22 to 18.05, whereas the net spillover indices of CFSI decreased. COVID-19 in the first half of 2020 caused the net spillover indices of TRS and IFA to rise by 32.06 and 21.54. From December 2020 to February 2021, the net spillover index of CFSI increased by 14.45.

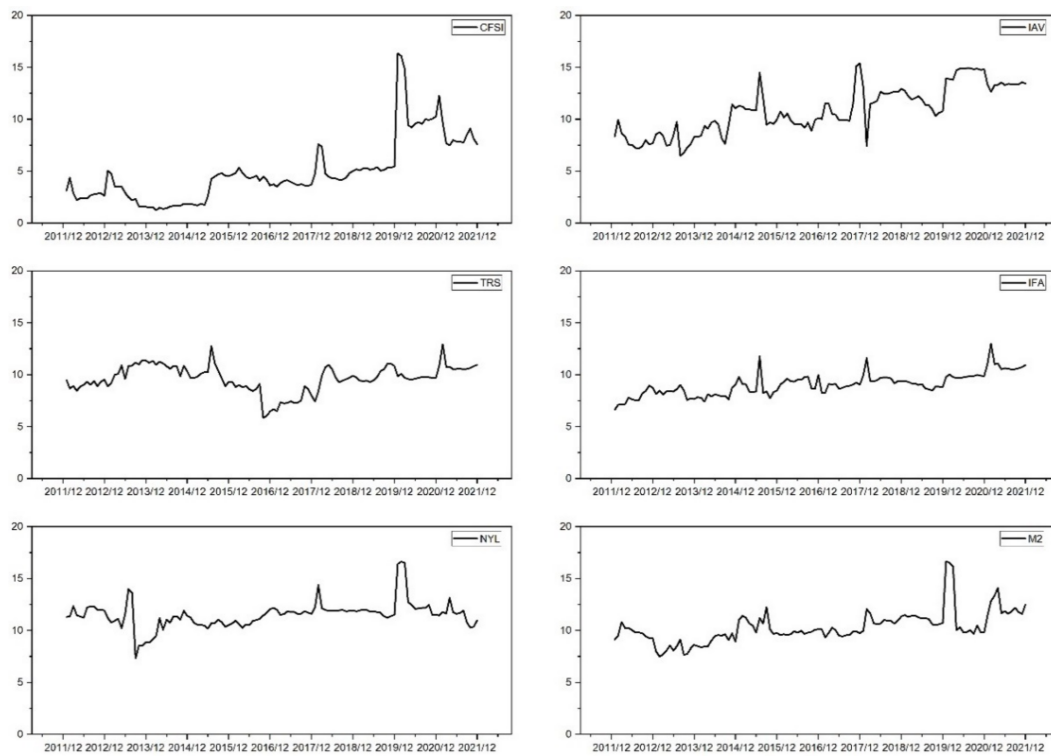


Figure 6. Gross directional spillover indexes from others to six sectors.

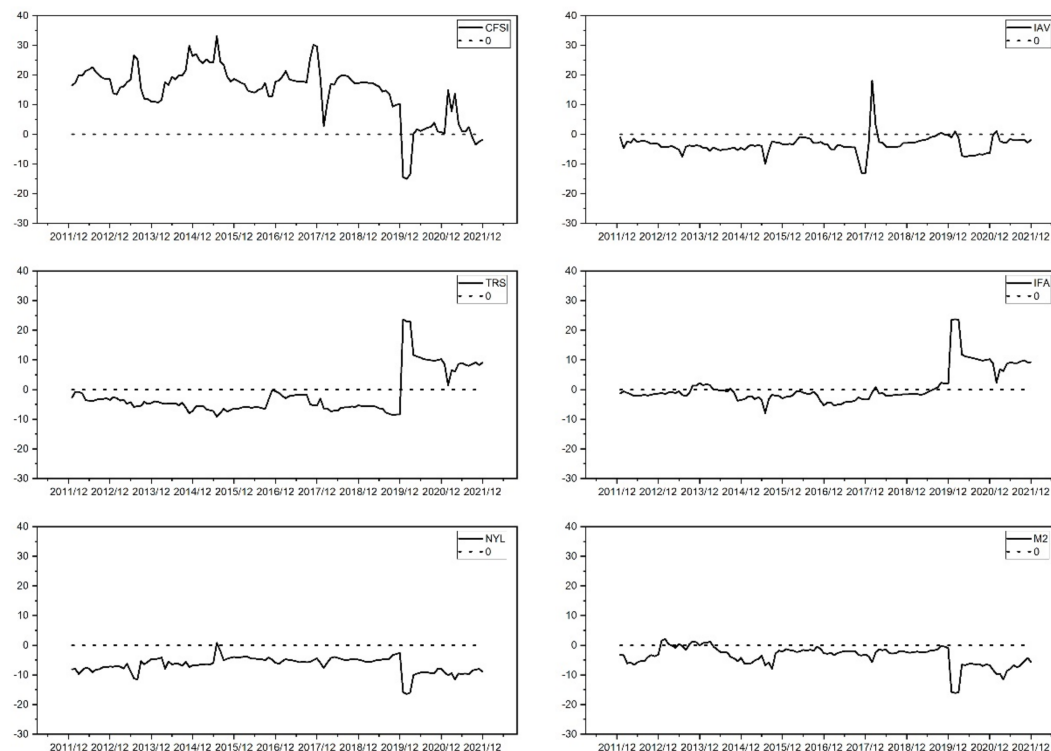


Figure 7. Net gross spillover indexes of six sectors.

(3) Dynamic pairwise directional spillovers

Above, we briefly discussed the total spillover index, the gross directional spillover index, and the net gross directional spillover index. To further study how risk events affect spillover effects among macro and financial sectors, we decompose the gross directional

spillovers into their component pairwise directional spillovers (given by $S_{ij}(H)$ in Equation (19)). Figures 8 and 9 show the dynamic pairwise directional spillovers between CFSI and the macroeconomic sectors.

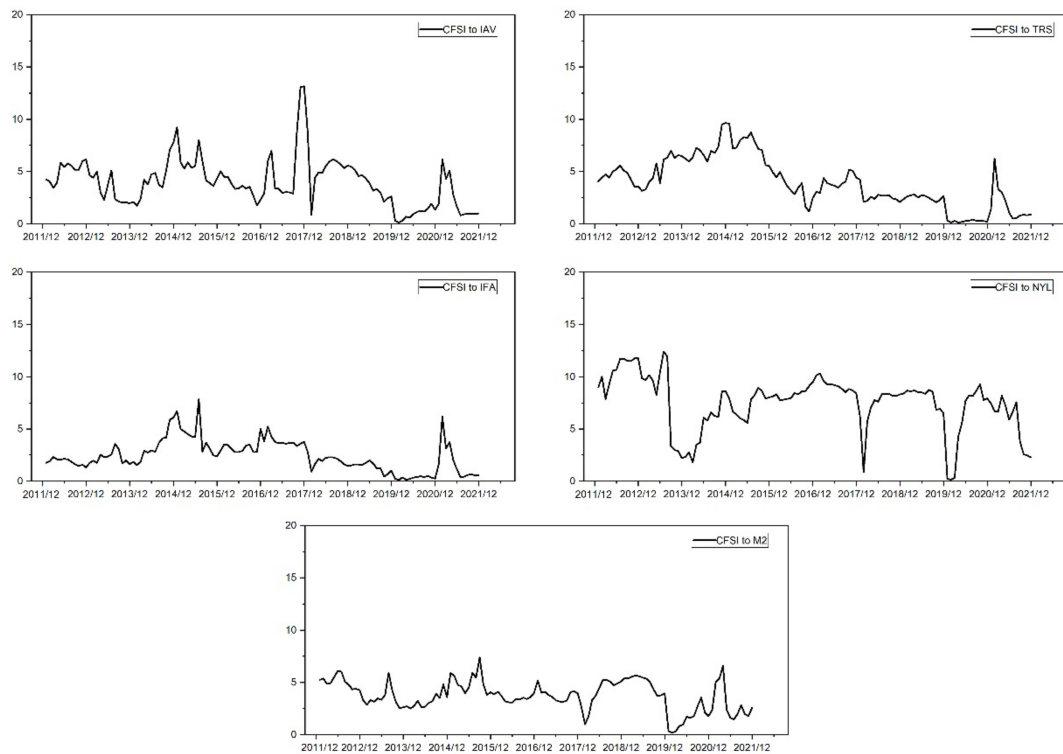


Figure 8. Pairwise directional spillover indexes from CFSI to others.

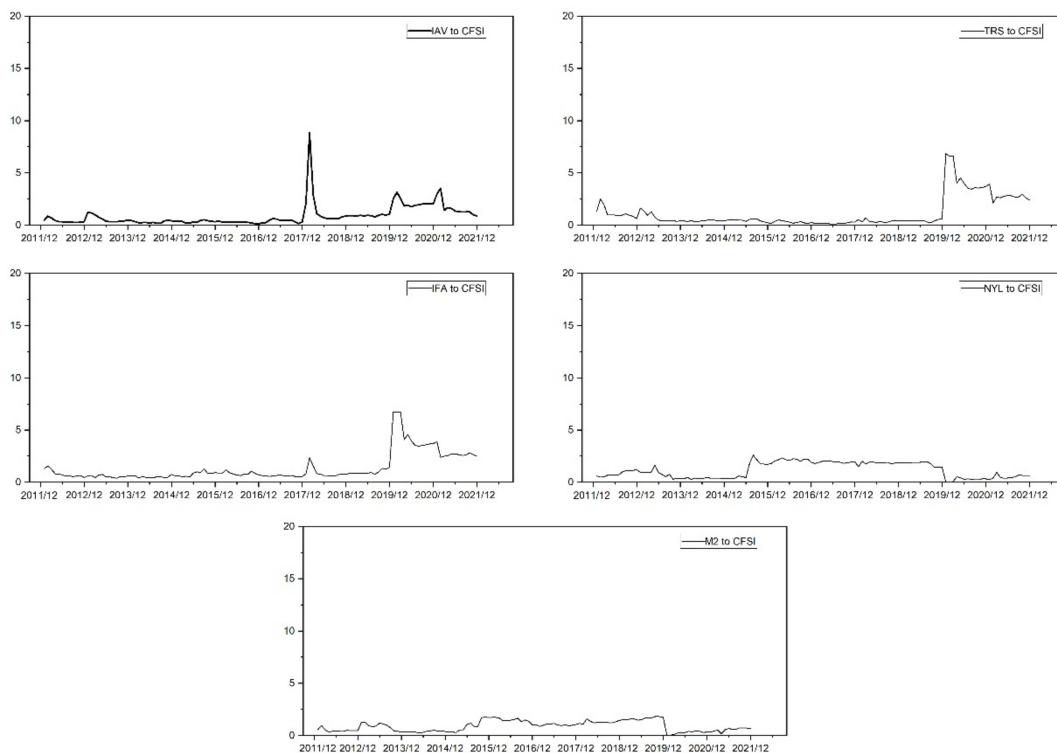


Figure 9. Pairwise directional spillover indexes from others to CFSI.

First, we give a plot of the spillover indices from CFSI to others in Figure 8 to analyze how different risk events drive an increase in the gross directional spillovers of CFSI.

In June 2013, the “money shortage” caused China’s stock and bond markets to plunge, pushing up lending rates and increasing funding costs. The net spillover index of CFSI reached 26.56, and the spillover index of CFSI to IAV, NYL, and M2 increased by 2.68, 3.72, and 2.54. The lack of funds in the real economy caused by improper financial regulation and control, and the outflow of funds generated by fluctuations in international markets, are the main reasons for this “money shortage”. The “money shortage” in 2013 reflected the lack of flexibility in China’s capital market regulation and the inability of the market to handle financial market fluctuations through the effective allocation of funds. After the money shortage, the ability of monetary policy to regulate and stabilize banking system liquidity and market interest rates was further enhanced, with a financial regulatory framework with dual pillars of monetary policy and macroprudential policy introduced, and the spillover effects of CFSI declined. It can be seen that a liquidity crisis in the interbank market can increase the spread of financial risks to the real economy, lending, and monetary sectors.

In December 2014, as many bonds could not be collateralized for financing, market liquidity contracted, and bond rates rose. As a result, financing costs for corporations and local governments increased, and debt service payments took a hit. Spillovers from CFSI to all other sectors increased, including a 3.77 increase in the spillover to IAV. It is thus evident that a liquidity crisis in the bond market increases the spread of financial risks to the real sector of the economy.

In June 2015, the Chinese stock market experienced a “stock market crash” that hit the financial market and the real economy hard. The stock market can effectively reallocate investors’ capital as one of the essential financing channels for the real economy. However, a stock market plunge can block the stock market’s financing function and the ability to allocate capital efficiently, leading to slow economic growth. A decline in the stock market can also lead to a significant reduction in asset values, reducing the willingness and ability to consume and weakening economic development. At the same time, a stock market crash will also impact investment. When the market value of the stock is lower than the replacement cost, the scale of corporate investment and willingness to invest will be weakened. When the stock price falls, the net value of the company decreases, the company’s ability to raise capital in the capital market also decreases, and the cost of financing increases, which in turn reduces investment. In addition, the loan and M2 sectors were also affected by the deterioration of the market funding supply and demand situation due to the stock market crash. This crash caused the CFSI spillovers to IAV, IFA, NYL, and M2 to increase by 2.65, 3.42, 3.68, and 2.48, respectively. It follows that stock market volatility increases the financial risk to the real economy, consumption, investment, loans, and monetary sectors.

In December 2016, a credit crisis among financial institutions plunged the Chinese bond market. As a result, market interest rates rose, and financing costs increased. The spillover index of CFSI to IAV increased by 3.21. This means that the credit crisis in financial institutions hits the real economy sector.

In February 2021, market expectations declined as economic recovery was hampered by the failure to resolve COVID-19 completely. The spillover effects of CFSI on IAV, TRS, IFA, and M2 increased by 3.56, 4.75, 4.99, and 4.77, respectively. It can be seen that financial market instability increases the spread of financial risks to the real economy, consumption, investment, and monetary sectors.

Then, we give a plot of the spillover indices from others to CFSI in Figure 9. The gross directional spillovers from IAV to others mainly increased in February 2018. The spillover from TRS and IFA to CFSI mainly increased in the first half of 2020.

In February 2018, China’s industry was significantly hit by the trade friction between the U.S. and China, with tariffs imposed on some exports to the U.S., resulting in reduced market demand. In response, China’s industrial value-added fell by 2.12% year-over-year, and China’s fixed asset investment and consumption growth rates dropped significantly to

a 10-year low. In addition, financing's growth rate and size are downward. The spillovers from IAV to CFSI rose by 3.28. This shows that the spillover effect on financial markets increases when the industry sector experiences a downswing due to external shocks.

In the first half of 2020, people were isolated at home, and consumption was significantly reduced due to the epidemic prevention policy. At the same time, the rapid spread of the epidemic led to shutdowns in most industries and financial difficulties for investors. There was a significant decline in investment. Low consumer demand and a sharp decline in corporate financing demand further increased the downward pressure on the economy. The weakening of the real economy generated significant adverse feedback to financial markets. This shows that the impact of COVID-19 on macroeconomics has led to increased risk spillovers from the real economy, consumption, and investment sectors to financial markets.

The above analysis shows that when the stability of financial markets is destabilized, the risk spillover from financial markets to the macroeconomic sector becomes larger. Financial stability can be adversely affected when the macroeconomic sector is subjected to external shocks.

3.3. Robustness Analysis

The MF-VAR model is constructed with a lag of 3 according to the AIC and SC minimization criterion. The spillover index is calculated by selecting the forecast horizon of 5 months. In this section, we check for the robustness of the rolling MF-VAR model results.

We estimate the MF-VAR model with a lag of 2 and a forecast horizon of 5 months, and a lag of 3 and a forecast horizon of 3 months, respectively, and present the total spillover index for different lag orders and forecast periods in Figure 10. It can be seen that the trend of the total spillover index is approximately the same for other lag orders and different forecast horizons.

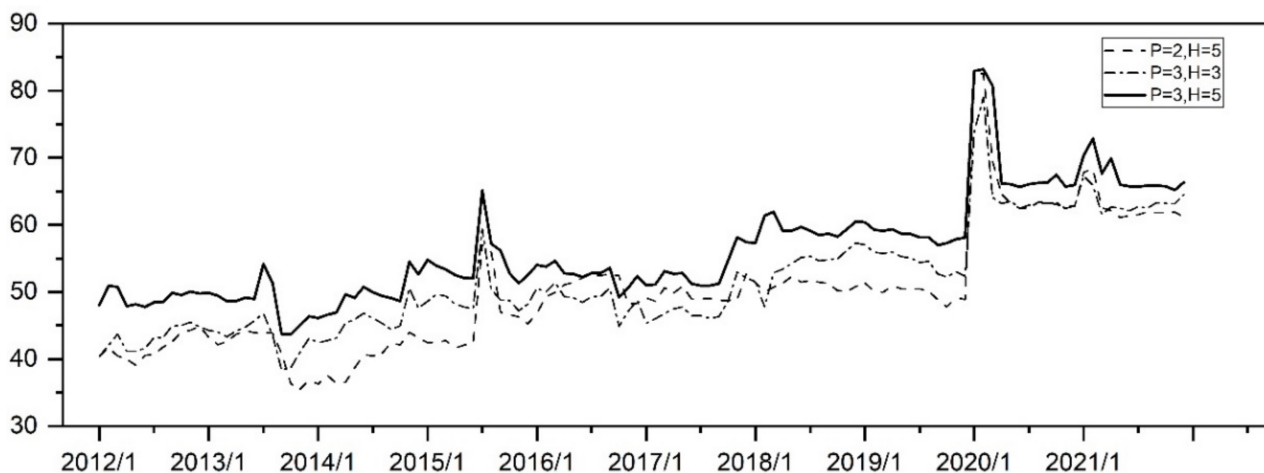


Figure 10. Total spillover index estimated with different lags and forecast horizons.

Moreover, we re-estimate the MF-VAR model to check the robustness of the results. We use China macroeconomic sentiment coincident index (CI) instead of the industrial added-value (IAV) to represent the industrial sector and the consumer confidence index (CCI) instead of the total retail sales of consumer goods (TRS) to represent the consumer sector [41]. We plot the spillover indices for the two sets of indicators in Figure 11. As can be seen, the two aggregate spillover indices are roughly the same. Hence, the empirical results of this paper are robust.

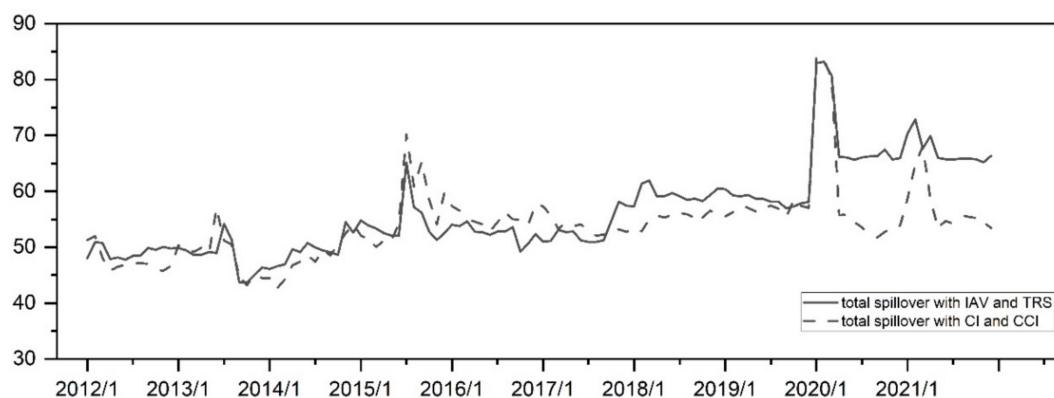


Figure 11. Total spillover index estimated with different indicators.

4. Discussion and Conclusions

Aiming to measure the systemic risk at high frequency, this paper develops a daily financial stress index for China using eight financial market indicators with an application of the weighted average and DCC-GARCH model. Then, this paper empirically investigates the correlation between financial stress and economic activity using a mixed-frequency spillover method.

The CFSI is consistent with the economic development trend, identifies important stress events during the sample period, and can effectively monitor systemic financial risks in China. The dynamics of the CFSI indicate that China's financial stress is overall manageable and is generally at a low level during the sample period. However, extreme risk events can have a profound negative impact on financial operations. Similar to the findings of previous studies [20,41,45], the financial markets in China were in a state of high stress during the 2008 financial crisis and the 2015 stock market crash, indicating instability in China's financial markets. Moreover, the CFSI finds that COVID-19 leads to higher financial stress in China's financial markets in the first half of 2020 than in any previous period.

Empirical studies on the correlation between financial markets and the macroeconomic sectors suggest that financial stability in China is closely related to macroeconomic activities. A full-sample static analysis shows that risks spread mainly from financial markets to the macroeconomic sectors and mainly affect the NYL sector. However, the overall spillover effect between financial markets and macro sectors is moderate, suggesting that China's economic and financial regulatory policies have effectively prevented and resolved the risks and promoted the stable and healthy development of China's economy. It also indicates that China's macroeconomic development environment is conducive to financial stability.

The dynamic analysis of the rolling sample shows that the mixed-frequency spillover index is larger than the traditional co-frequency spillover index. This confirms that the mixed frequency method can observe more information [36]. The mixed-frequency spillover index is significantly higher in periods of macro-financial instability than in periods of stability, suggesting that financial and macroeconomic deterioration amplifies macro-financial spillover effects. This is similar to the finding of Hueng et al. that macro-financial shocks are more significant during periods of high financial stress [46]. The risk events with the most significant impact on China's macro-financial spillover from 2012 to 2021 are the stock market crash in 2015, the China–U.S. trade friction in 2018, and COVID-19 in 2020. The stock market crash in 2015 caused financial stress to macroeconomic sector spillovers, mainly in the form of increased spillovers to the IAV, IFA, NYL, and M2 sectors. The 2018 U.S.–China trade frictions caused increased IAV spillovers to CFSI. The macro-financial spillovers are most prominent in the first half of 2020, which is consistent with the findings of Li et al. [47]. COVID-19 causes increased spillovers from TRS and IFA sectors to CFSI.

We contribute to the related literature in two ways. First, this paper provides a reference for the study of financial stress. Based on the existing literature, this paper constructs

a daily frequency Chinese financial stress index and monitors financial stress, including during the COVID-19 period. Meanwhile, applying the mixed-frequency spillover method in this paper is also a meaningful expansion and attempt at macro-financial spillover research. To our knowledge, this paper is a rare study using high-frequency CFSI and low-frequency macroeconomic data in a mixed-frequency analysis framework to analyze macro-financial spillover effects. Based on the mixed-frequency model, the data information can be mined deeper, and the risk contagion relationship between financial markets and macroeconomics can be screened more accurately. The research on the relationship between financial stress and economic activity in this paper provides essential support for policymakers in formulating policies aimed at achieving economic security.

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