A Study of Systemic Risk Spillover in China's Financial Market Based on TVP-VAR Modeling

Xiangyi Hou*
China Jiliang University, Hangzhou, Zhejiang, China
**Corresponding Author*

Abstract: This study employs a Time-Varying Parameter Vector Autoregression (TVP-VAR) model to analyze systemic risk spillovers across China's money, bond, stock, and foreign exchange markets from 2008 to 2023. The results reveal dynamic interdependencies, with risk transmission exhibiting time-varying patterns. The money market, bolstered by central bank interventions, shows the strongest resilience, while the bond market acts as a stabilizer during turbulence. Conversely, the stock market is highly vulnerable to external shocks, with delayed policy responses. The foreign exchange market, influenced by global capital flows, displays intermediate sensitivity. These findings highlight the need for targeted regulatory measures to mitigate systemic risks, particularly in volatile markets. The study provides empirical insights into financial stability mechanisms in emerging economies.

Keywords: Systemic Risk Spillover; TVP-VAR Model; Financial Markets; Time-Varying Analysis; Risk Resilience

1. Introduction

In recent years, amid China's rapid economic development and increased openness, its financial market has experienced significant growth. Concurrently, however, the increasing complexity of financial system correlations stemming from market advancements has increased the likelihood of cross-market, cross-channel, and cross-regional transmission and amplification of financial risks. The prevention and resolution of systemic financial risks have thus emerged as pivotal and inescapable topics. The 2023 Central Financial Work Conference further emphasized the need to enhance systemic risk identification mechanisms, fortify the financial regulatory framework, and uphold the bottom line of avoiding systemic risks. These policy directives reflect the CPC Central Committee's profound emphasis on preventing systemic financial risk.

Additionally, the 2008 global financial crisis and recent turbulence in international and domestic financial markets have underscored the significance of systemic risk research for effective risk mitigation and resolution. This paper examines systemic risk spillovers in China's financial market using a time-varying parameter vector autoregression (TVP-VAR) model, based on diverse data indicators from four representative financial markets. The analysis aims to ascertain the impact of industry volatility changes on systemic risk spillovers across industries and evaluate their respective strengths and weaknesses in risk resistance, ultimately deriving pertinent findings.

2. Literature Review

Systemic financial risk spillover was initially quantified using VaR; however, as circumstances evolved, VaR's inefficacy in capturing expected losses in extreme scenarios became apparent, hindering regulatory prevention and control efforts. To enhance measurement accuracy, extensive research has examined the nexus between financial institutions and systemic risk, yielding three primary mainstream methodologies: In 2011, Conditional Value at Risk (CoVaR) by Adrian et al.[1], in 2016, Systemic Financial Risk Index (SRISK) by Brownlees et al.[2], and in 2017, Marginal Expected Loss (MES) by Acharya et al.[3]. These approaches are utilized to assess risk spillovers among financial institutions and subsequently analyze the mechanism of financial risk contagion.

In recent years, numerous scholars have integrated VaR models with other methodologies to offer additional insights into the measurement of systematic risk spillover, with numerous empirical tests confirming that hybrid models exhibit enhanced measurement accuracy. In 2021, Liu Guangying et al. employed the deep learning long short-term memory (LSTM) model in VaR risk management, constructing the LSTM-RV-EVT risk management VaR model, which significantly improved model performance[4]. In 2023, Zhang He et al. employed the GARCH-VaR model to evaluate the risk of fintech in China, concluding that, compared to traditional finance, emerging fintech innovations exhibit a greater propensity for extreme losses, as indicated by comparing VaR values across different yield series[5].

However, although the method above enhances the accuracy of the original model to a certain degree, it fails to capture the dynamic and time-varying characteristics of the market adequately. Empirical research suggests that TVP-VAR models can more precisely account for market changes through dynamic parameter adjustments, providing a more flexible and accurate assessment of risk.

The TVP-VAR model has been widely utilized across various domains. In financial markets, In 2024, Chen Weiguo et al. formulated a spillover index utilizing the TVP-VAR model to examine risk spillover effects among financial markets, successfully demonstrating a robust correlation between diverse markets, with internal risk spillover typically exceeding inter-market spillover[6]. Amidst the "Carbon Peak and Carbon Neutral" initiative, China is systematically advancing the green financial system. In 2024, Zhang Guofu et al. focus on the pivotal role of green bonds, employing the TVP-VAR frequency domain spillover model to analyze spillover transfer mechanisms between green bonds and other financial markets across different frequencies, revealing risk spillover relationships. We investigate spillover transfer mechanisms between green bonds and other financial markets at varying frequencies, using the TVP-VAR frequency domain spillover model to uncover risk spillover relationships[7]. Recently, the impact of climate risk on financial markets has emerged as a pivotal research area in finance and a concern for policymakers. In 2024, Bian Yuchen et al. empirically assess the time-varying impacts of climate risk on cross-border capital flows and transmission channels by constructing a TVP-VAR model, thereby identifying a connection between the two[8]. Furthermore, in the agricultural products sector, in 2023, Guo Fan et al. investigated the impact of economic policy uncertainty on agricultural product prices using a TVP-VAR model, finding that agricultural product price fluctuations exhibit time-varying characteristics in response to economic policy uncertainty shocks, with alternating positive and negative trends[9]. This highlights the practical application of the TVP-VAR model across various fields.

Based on the TVP-VAR model, this study aims to capture the dynamics and time-varying characteristics of the market and examine systemic risk spillovers within the Chinese financial market.

3. Model Construction and Data Description

3.1 Model Construction

In this paper, we develop a TVP-VAR model to investigate the systematic risk spillover effect within China's financial market, initially defining a traditional VaR model.

$$Ay_t=F_1y_{t-1}+...+F_sy_{t-s}+\mu_t,t=s+1, ..., n \quad (1)$$

In Eq. (1), t is the time, s is the lag order, A and F_1 , ..., F_s is the K×K dimensional lower triangular coefficient matrix, y_t is the k×1 dimensional observation vector, and μ_t denotes the k×1 order vector consisting of structural shocks, is the perturbation term, and $\mu_t \sim N(0|\sum\sum)$.

Primiceri initially incorporated time-varying parameters into the VaR model[10], subsequently refined and expressed as:

$$y_t=X_t\beta_t+A_t^{-1}\sum_t\varepsilon_t,t= s+1,2,...,n \quad (2)$$

In Eq. (2), the coefficients β_t, parameters A_t, and $\sum_t$ are all time-varying. ε_t are residual terms, assuming that all parameters in the model obey a stochastic wandering process, with a stochastic volatility matrix $\beta_{t+1} = \beta_t + \mu_{\beta_t}$, $a_{t+1} = a_t + \mu_{a_t}$, $h_{t+1} = h_t + \mu_{h_t}$, stipulating that the μ_{β_t}, μ_{a_t} and the μ_{h_t} are the disturbance terms for each of the parameters and assuming that:

$$\begin{pmatrix}\varepsilon_t\\ \mu_{\beta_t}\\ \mu_{a_t}\\ \mu_{h_t}\end{pmatrix}=N\left(0,\begin{pmatrix}I & 0 & 0 & 0\\ 0 & \sum\beta & 0 & 0\\ 0 & 0 & \sum a & 0\\ 0 & 0 & 0 & \sum h\end{pmatrix}\right) \quad (3)$$

where equation (3) must satisfy $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0})$, $\alpha_{s+1} \sim N(\mu_{\alpha_0}, \Sigma_{\alpha_0})$, $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$, t = s+1,...,n. And $\sum\beta$, $\sum\beta$, $\sum h$ are diagonal matrices, indicating that the contemporaneous relationships among distinct equations are mutually independent. Regarding model estimation, drawing on TVP-VAR-related literature, the use of the Markov chain Monte

Carlo (MCMC) simulation method for estimation can mitigate measurement error arising from the endogeneity problem to some extent, thereby enhancing the accuracy of model estimation results.

3.2 Data Selection and Description

In this paper, the four primary markets—money market, traditional bond market, stock market, and foreign exchange market-are considered representative of financial markets for data selection. This is a reference to the division of the financial industry into four subsectors in the article by Ouyang Zisheng [11]. For measurement convenience, when selecting representative indicators for each market, this study refers to Wu Yonggang: the money market utilizes the interbank offered rate (Shibor), the bond market employs the China Bond Composite Index (zz), the stock market adopts the CSI 300 Index (hs300), and the foreign exchange market selects the RMB-dollar median price (cu) using the direct markup method[12]. Specifically, the median price of RMB against the US dollar (cu) is chosen for the foreign exchange market. Monthly data spanning from January 2008 to December 2023 are utilized. To eliminate seasonal trends, the Census X-12 seasonal adjustment is applied to all data sourced from Wind.

To eliminate data discrepancies, this paper standardizes the data across four indicators. The CSI 300 Index and the China Bond Composite Index, exhibiting relatively stable distributions, utilize the Z-score standardization method. The RMBUSD, typically fluctuating within a stable range, employs the Min-Max standardization method. The Interbank Offered Rate (IBOR), which contains obvious outliers, employs robust standardization.

4. Empirical Results and Analysis

4.1 ADF Smoothness Test

The construction of the TVP-VAR model requires ensuring that each variable follows a smooth sequence. Initially, the variables undergo the ADF smoothness test, with results presented in Table 1. Examination of these results reveals that the CSI 300 index (HS300), the RMB against the dollar (CU), and the Chinese bond composite index (ZZ) achieve smoothness after the first-order difference. Additionally, the original series of the interbank offered rate (Shibor) is smooth and remains so after the first-order difference, qualifying it for cointegration testing. The results of the cointegration test are displayed in Table 2.

Table 1. Unit Root Test for Variables

variables	ADF test value	P value	conclude
hs300	-2.332	0.1632	Unstable
D(hs300)	-12.641	0.0000	stable
cu	-2.365	0.1533	Unstable
D(cu)	-8.289	0.0000	stable
zz	0.892	0.9953	Unstable
D(zz)	-10.357	0.0000	stable
shibor	-2.979	0.0387	stable
D(shibor)	-12.020	0.0000	stable

4.2 Johansen Test

Table 2. Cointegration Test Results

original hypothesis	eigenvalue	trace test statistic	P value
None*	0.343	182.974	0.0000
At most 1*	0.199	104.826	0.0000
At most 2*	0.177	63.498	0.0000
At most 3*	0.136	27.210	0.0000

The results from the Johansen cointegration test reveal a long-term stable equilibrium relationship among the variables. Table 2 demonstrates that, under the null hypothesis of "None," the trace test statistic attains a value of 182.974 (P = 0.0000), decisively rejecting the absence of a cointegration relationship. Subsequent hypotheses ("At most 1" to "At most 3") all result in P-values of 0.0000, further affirming the presence of at least four cointegration vectors. This finding underscores the long-term stable equilibrium relationship exhibited by the four variables in question.

Therefore, grounded in the theoretical underpinnings furnished by cointegration analysis, the utilization of the original series for simulation, without the necessity for differencing, is warranted. This approach mitigates information loss and enhances the precision in capturing long-term dynamic interrelationships among variables, thereby establishing a solid basis for subsequent analytical endeavors.

4.3 Model Optimal Lag Test

Before constructing the TVP-VAR model, this paper initially establishes the optimal lag order of the model as the 2nd order, based on the Akaike Information Criterion (AIC), as illustrated in Table 3.

Table 3. Optimal Lag Order Test Results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2644.756	NA	23615882	28.32894	28.39805	28.35694
1	-1410.166	2403.158	51.64721	15.29589	15.64147*	15.43592
2	-1377.889	61.44668*	43.40609*	15.12181*	15.74384	15.37386*
3	-1367.927	18.53999	46.32918	15.18638	16.08487	15.55045
4	-1361.667	11.38145	51.47314	15.29055	16.46550	15.76664
5	-1351.892	17.35464	55.11540	15.35713	16.80854	15.94524

4.4 Analysis of Model Parameter Estimation Results

In this paper, the Monte Carlo simulation method (MCMC) is employed to procure samples for parameter estimation. The MCMC iteration count is set to 10,000, with the initial 1,000 iterations discarded to ensure a valid sample set. The parameter estimation outcomes are presented in Table 3. Setting the significance level at 5% yields a critical value of 1.96. Table 4 displays Geweke diagnostic values below 1.96, suggesting that parameter estimation convergence in the posterior distribution cannot be rejected, indicating good model convergence. Additionally, all null factors, except for sh2, are substantially less than 100, demonstrating that the lagged second-order TVP-VAR model can generate valid samples, and all parameter estimates lie within a plausible range.

The three rows, from top to bottom in Figure 1, depict the trend of the sample autocorrelation coefficient, the sample value path, and the density of the sample posterior distribution, respectively. In terms of the sample autocorrelation coefficient, subsequent samples, after discarding the first 1000, converge primarily around 0, exhibiting an oscillatory trend, suggesting that the MCMC method effectively mitigates autocorrelation in parameter estimation. The sample value path also exhibits stability, with the sample posterior distribution density adhering closely to a normal distribution, indicating higher concentration. A conjoint analysis of Table 4 and Figure 1 confirms the efficacy of the MCMC sampling method.

Table 4. Parameter Estimation Results

variables	Mean	standard deviation	Lower 95% confidence interval	Upper 95% confidence interval	Geweke value	ineffective factor
sb1	0.0228	0.0027	0.0184	0.0288	0.010	12.68
sb2	0.0230	0.0027	0.0184	0.0290	0.877	13.25
sa1	0.0637	0.0425	0.0309	0.1674	0.409	11.86
sa2	0.0571	0.0402	0.0303	0.1571	0.767	14.30
sh1	0.3542	0.0963	0.1948	0.5588	0.251	46.89
sh2	0.4896	0.1081	0.2784	0.7100	0.000	131.83

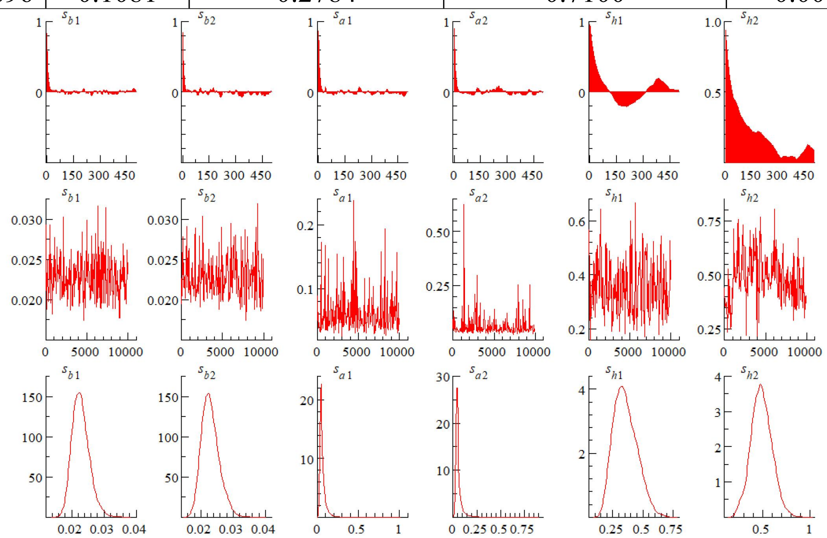

Figure 1. Autocorrelation Coefficient, Fetch Path, Posterior Distribution Density

4.5 Impulse Response Analysis

4.5.1 Analysis of equal interval impulse response

Firstly, the equal-interval impulse response amongst the variables is examined, with impulse response curves for 4, 8, and 12 periods in advance designated to signify short-term, medium-term, and long-term impact mechanisms, respectively. Figs. 3, 4, 5, and 6 depict the shocks that the money market, bond market, foreign exchange market, and stock market exert upon themselves in response to fluctuations in the remaining three markets. The solid line signifies a lag of 4, the long dashed line a lag of 8, and the short dashed line a lag of 12. A positive impulse response denotes that volatility results in an augmentation of one's own risk, whereas a negative impulse response signifies that volatility mitigates an increase in one's own risk. Consequently, the influence of volatility changes in diverse markets on systemic risk spillovers from other markets and the robustness of their respective risk tolerance can be discerned.

Overall, the shock curves exhibit distinct time-varying properties, where short-term shocks are more significant and volatile than medium- and long-term shocks. Notably, the long-term shock curves, with a 12-period lag, demonstrate the least temporal volatility, indicating that the impact of shocks diminishes after 12 periods, regardless of the timing. A detailed analysis of the effects of volatility in other markets on the four markets is presented below.

Figure 2 illustrates the influence of volatility in the stock market, foreign exchange market, and bond market on the money market.

In 2008-2009, China's stock market experienced high volatility due to the global financial crisis, with the CSI 300 index declining by approximately 25% in October 2008. The impulse curve displayed a notably positive trend, indicating that severe stock market fluctuations increased the risk in the money market. Following the implementation of a 4 trillion stimulus plan in November 2008, the curve rapidly reverted, suggesting that central bank intervention can mitigate money market volatility. This is consistent with Ouyang Zisheng's argument in 2023, that economic policy uncertainty has a significant positive effect on systemic risk in financial institutions[13]. Concurrently, the bond market experienced an influx of safe-haven funds, resulting in an increase in the China Bond Aggregate Index and a positive impulse curve. During the 2010-2015 period, the stock market was relatively stable, maintaining the impulse curve in the negative range, which implied reduced impact of stock market volatility on the money market. Positive shocks in the foreign exchange market continued to escalate, significantly elevating currency market risk. In 2015-2016, influenced by the stock market crash, the impulse curve temporarily turned positive before quickly reverting to negative following the August implementation of market-based pricing in the "8-11 exchange reform." In the foreign exchange market, the positive shock weakened as the exchange reform progressed. During the stock market crash, bond market inflows were evident, resulting in a notable positive shock to the economy. In 2020, the outbreak of the COVID-19 pandemic led to a significant decline in the US stock market, which subsequently affected A-shares. The impulse curve briefly increased, but the central bank's actions subsequently reduced it. In the FX market, a global dollar shortage caused RMB depreciation, resulting in a temporary rise in the impulse curve before it declined due to the central bank's rate cut. The bond market shifted from negative to positive; however, except for the period above, its impact on the money market was largely negative, suggesting that the bond market can somewhat attenuate money market risk increases during more stable periods.

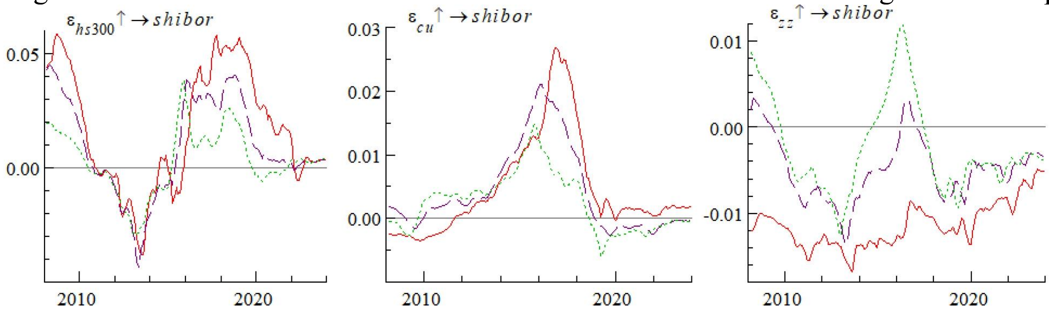

Figure 2. Equally Spaced Impulse Response to Money Market

Figure 3 illustrates the influence of volatility in stock, foreign exchange, and currency markets on the bond market.

Between 2008 and 2010, the stock and bond markets exhibited contrasting movements across the financial system, driven by the risk-averse nature of bonds. Influenced by the global economic crisis, stock market fluctuations led to capital transfers from stocks to bonds during these periods, rendering the bond market positive while the impulse curve was negative, indicative of a typical risk aversion effect. Before 2014, the foreign exchange market observed a negative impulse curve in the context of the bond market's double surplus. Following August 2015, government measures to tighten liquidity led to a "stock and bond dual decline," with the impulse curve briefly turning positive in the bond market relative to the stock market. This positivity was transient. In the foreign exchange market, foreign exchange reserve losses totaled nearly $1 trillion, and the 10-year bond yield surged 70 basis points within a month, significantly shifting the curve positive. From 2015 to 2017, deleveraging policies elevated interest rates, causing the money market-to-bond market curve to trend upward continually. In 2018 and thereafter, trade wars and associated factors intensified foreign exchange market volatility, driving the curve upwards. During the 2020 epidemic outbreak, the equity market experienced a "double dip," and the curve turned positive. In the money market, refinancing measures were implemented to combat the epidemic, coupled with the establishment of a market-oriented deposit rate adjustment mechanism and responses to Federal Reserve interest rate hikes. Consequently, the high impulse curve maintained by these measures heightened money market volatility, thereby increasing bond market risks. In 2023, following a prolonged period of low interest rates, funds flooded into the bond market, enhancing its adverse effects and reducing risk.

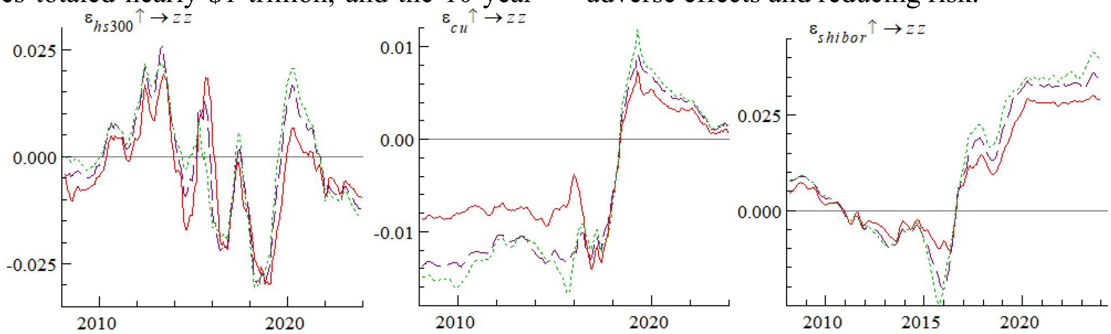

Figure 3. Equally Spaced Impulse Responses to Bond Markets

Figure 4 illustrates the influence of volatility in stock, bond, and currency markets on the foreign exchange market.

Between 2008 and 2010, the stock market volatility curve on the foreign exchange market exhibited a negative trend, indicating hedge fund stabilization of the exchange rate. By 2015, the internationalization of the RMB in the bond market had facilitated foreign capital inflows, resulting in a curve that was initially negative but subsequently turned positive. The impulse curve from the money market to the foreign exchange market generally fluctuated in the vicinity of the 0-axis, demonstrating relative stability. During 2015-2016, stock market shocks induced capital outflows, causing the curve to rise sharply. From 2016 to 2017, Fed interest rate hikes and China's economic recovery pushed bond yields upward in the bond market, prompting foreign investors to increase their holdings of Chinese bonds. This benefited the bond market and led to a negative yield curve. Between 2018 and 2019, continued Fed interest rate hikes, China's quota and interest rate reduction policies to combat the economic downturn, and RMB depreciation pressure resulted in the CNY/USD falling below 7.0 for the first time since 2008. Coupled with sharp fluctuations in foreign investment, the risk in the foreign exchange market increased again. In the early stages of the 2020 pandemic, stock market volatility led to a negative foreign exchange market curve. In 2022, following aggressive Fed interest rate hikes, US bond yields surged, capital outflow pressure caused RMB depreciation, and foreign exchange reserves came under strain, turning the curve positive. Although short-term central bank regulation controlled foreign exchange market risk in the currency market, the medium and long-term risk outlook has been elevated.

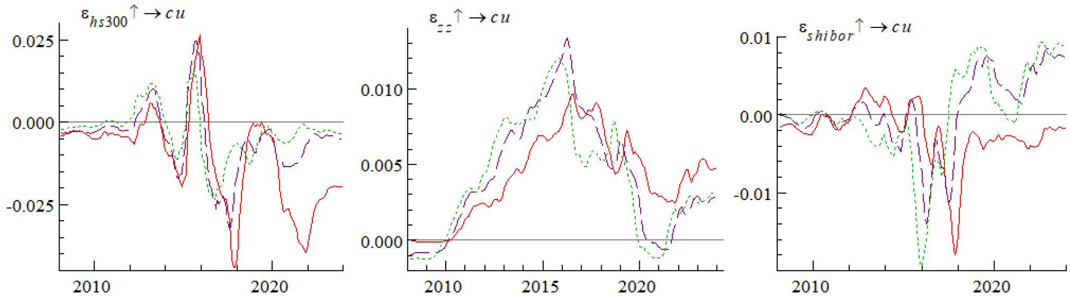

Figure 4. Equally Spaced Impulse Response to the Foreign Exchange Market

Figure 5 illustrates the influence of volatility in foreign exchange, bond, and currency markets on stock market performance.

Overall, within the period spanning 2008-2023, the volatility of foreign exchange, bond, and currency markets exhibited a positive impulse response to the stock market, suggesting heightened sensitivity of the stock market to these market fluctuations, coupled with diminished risk-resistance. Additionally, the stock market demonstrated a certain degree of lag in its response to central bank regulatory policies. For instance, following the 2015 stock market crash, the central bank adopted a loose monetary policy aimed at stabilizing both the stock and bond markets concurrently. However, the initial beneficiaries were the money and bond markets; the money market led the way in reducing rates and enhancing market liquidity, followed by the bond market's response to the rate reductions. Conversely, the stock market lagged, reacting last, as evidenced by the delayed timing of nodes within the overall decline of the impulse curve.

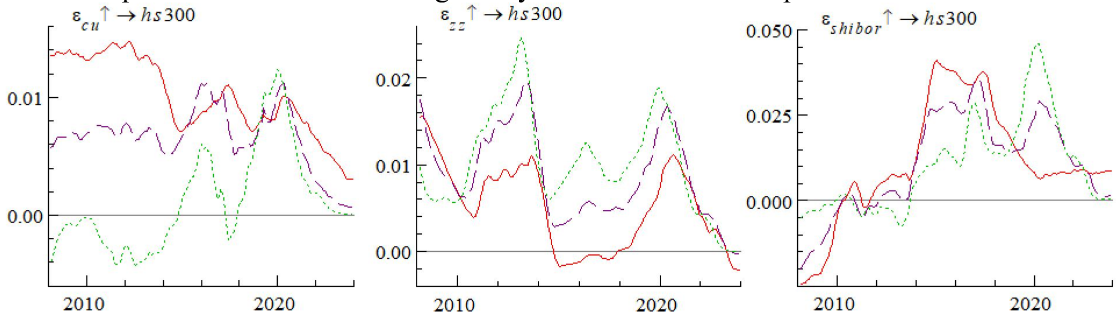

Figure 5. Equally Spaced Impulse Responses to the Stock Market

In summary, a tentative conclusion can be drawn that, within the financial market, the resistance to volatility and risk decreases in the following order: currency market, bond market, foreign exchange market, and stock market.

4.5.2 Temporal analysis of impulse response at specific time-points

Figure 7 illustrates the outcomes of the time-point impulse response among the stock market, foreign exchange market, bond market, and money market. Unlike the equal interval impulse response, the time-point impulse response facilitates the analysis of time-varying effect characteristics at various time points. This study selects October 2008, August 2015, and March 2020 as representative time points for the time-point impulse response. Specifically, in October 2008, China faced a financial risk exposure dilemma due to the global economic crisis; in August 2015, the stock market crash induced significant turbulence in China's financial markets, accompanied by substantial capital outflow pressure; and in March 2020, the COVID-19 pandemic led to a global financial market plunge, impacting China's financial market as well.

Figure 6's first column illustrates the impact of shocks on the stock market at three time points, resulting from the volatility of the other three markets.

October 2008: Foreign exchange and bond market volatility exacerbated stock market risk, whereas money market suppressed risk due to central bank regulation. August 2015: The foreign exchange and money market initially had a positive impact on the stock market, followed by a decline; the short-term risk in the bond market was suppressed due to easing monetary policy. Which is also consistent with Ruan Sumei's paper in 2020,that showed the negative shock effect of “price-based” monetary policy on systemic financial risk, i.e., by regulating the level of interest rates, it can have a dampening effect on systemic financial risk[14]. March

2020: All three markets had a positive impact on the stock market, with gradually weakening effects; the foreign exchange market shock persisted the longest. Column 2: Foreign Exchange Market Impact. October 2008: No significant impact from other markets. August 2015: All markets exacerbated risk before retreat; the money market eventually dampened risk. Equity markets are more influential than bond markets. March 2020: Currency and equity markets favored the FX market in the short term; bond markets exacerbated risk due to foreign selling, while long-term risks retreated with the economic recovery.

Column 3: Bond Market Impact. October 2008: Stock and FX fluctuations promoted capital inflows, thereby suppressing risk. 2015 August: Currency market first to inhibit risk; FX impact on bond market positive initially, quicker to turn negative; stock market last to react. March 2020: All markets had a positive effect on the bond market. Column 4: Money Market Impact. October 2008: The stock market crash increased liquidity demand (heightened risk); FX and bond markets dampened risk due to central bank intervention and inflows. August 2015: Stock and bond markets dampened short-term risk, while increasing long-term risk; the FX market's impact was initially positive but then declined. March 2020: The bond market initially responded to central bank policy, followed by the FX market, which dampened FX risk. The stock market was most affected, positively impacting the money market, but initially exacerbating risk, which weakened over time.

Through the preceding analysis, it is evident that the four markets exhibit substantial interconnectedness, with fluctuations in one market having a significant influence on several others. Additionally, the sensitivity of policy responses and the capacity for timely adjustments to counteract such fluctuations vary, specifically in the order of the money market, bond market, foreign exchange market, and stock market, aligning with the conclusions derived from the impulse response analysis conducted in Section 4.5.1.

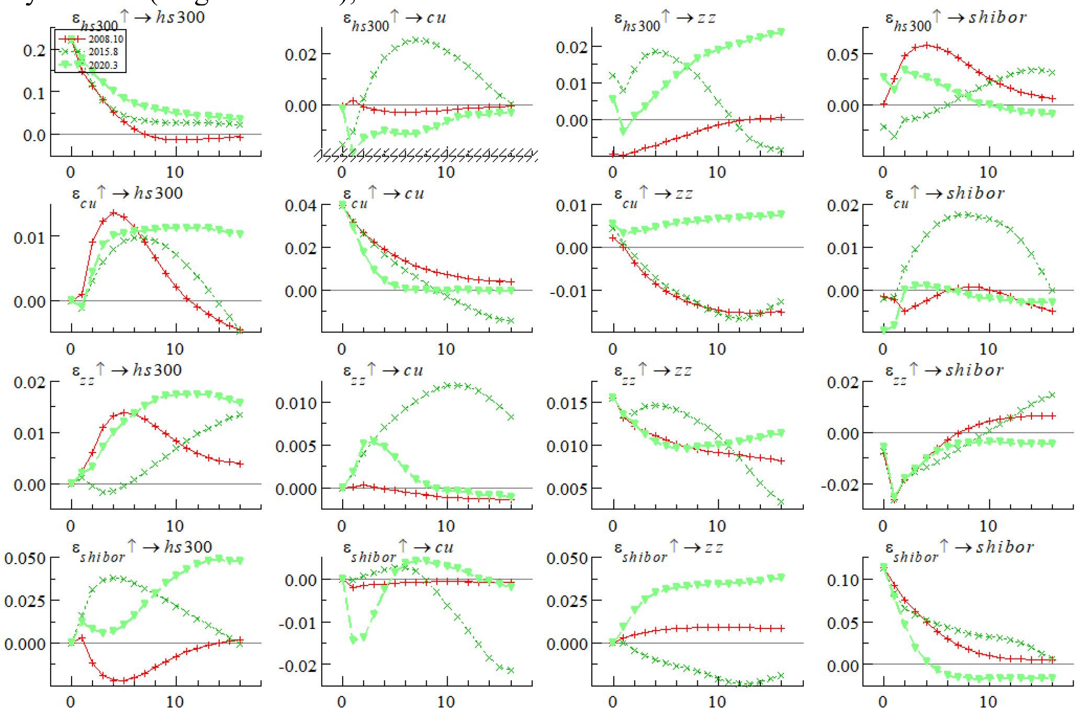

Figure 6. Impulse Response at Different Time Points

4.5.3 Further Analysis of Lag Effects in Stock Markets and Negative Impulse Responses within the Money Market

1. Factors Contributing to Policy Response Delays in the Stock Market

(1) Market Structural Attributes

Stock market participants consist predominantly of retail investors, whose behavior is susceptible to emotional influences, resulting in diminished policy signal transmission efficiency relative to institutionally dominated money and bond markets. Specifically, during the 2015 stock market crash, despite prompt actions by the central bank to reduce the reserve requirement ratio for liquidity injection, retail investors' panic selling hindered market recovery (as illustrated in Figure 5, wherein the pulse curve exhibited a 2–3 period lag before decline).

(2) Analysis of Variations in Investor Behavior

Institutional investors in money and bond markets can promptly respond to policies utilizing tools including interbank lending and government bond repurchase agreements. Conversely, retail investors in the stock market must indirectly respond via secondary market transactions, giving rise to a "policy institutions → retail investors" chain reaction that exacerbates the temporal lag. During the initial phase of the 2020 pandemic, money market interest rates aligned with the central bank's reserve requirement ratio cut on the same day; however, stock market stabilization occurred a week later upon the return of foreign capital (refer to the third column in Figure 6).

(3) Attributes of Policy Tools

Monetary policy, particularly reserve requirement ratio cuts, directly influences interbank liquidity, exerting immediate impacts on the money market. Conversely, the stock market necessitates a multistage transmission mechanism of "liquidity release → decreased financing costs → enhanced corporate profits → valuation revitalization," inherently entailing a lag.

5. Factors Driving Negative Impulse Responses in the Money Market

5.1 Safe-Haven Capital Flow Mechanism

When stock or foreign exchange markets exhibit increased volatility, as observed during the 2008 financial crisis or the 2015 exchange rate reform, institutions often reallocate their funds towards money market instruments, including short-term government bonds and interbank certificates of deposit. This process results in a negative feedback mechanism: "risk asset sell-off → money market capital inflow → interest rate decline → risk suppression." Instances of this phenomenon include the decline in the curves depicted in Figure 2 during November 2008 and August 2015.

5.2 Directness in Policy Transmission

The Money Market: The Central Venue for Central Bank Open Market Operations, with Rapid Transmission of Policy Interventions via the Banking System. For instance, upon the Federal Reserve's interest rate hike in March 2020, the People's Bank of China promptly mitigated dollar liquidity pressures in the money market by increasing the foreign exchange deposit reserve ratio, resulting in the swift manifestation of adverse effects from the foreign exchange shock (Figure 4).

5.3 Homogeneity Among Market Participants

The money market is predominantly controlled by large financial institutions, notably commercial banks, exhibiting homogeneous risk preferences and heightened sensitivity to policy adjustments, thereby facilitating the establishment of consensus expectations. Conversely, the heterogeneity among retail investors in the stock market diminishes the synergistic impact of policy initiatives.

6. Conclusion

6.1 Conclusion

Based on the TVP-VAR model, this study captures the time-varying and dynamic features of the market and examines systematic risk spillover in China's financial market. The research findings indicate the presence of a systematic risk spillover effect across China's stock market, bond market, foreign exchange market, and currency market. As time progresses, the TVP-VAR model facilitates precise observation of dynamic variations and influence mechanisms among variables at various lags and critical time points, leading to the following conclusions:

Different financial markets are intimately interconnected, whereby fluctuations in one market exert an influence on the risk volatility of several others, exhibiting time-varying characteristics and demonstrating both positive and negative trends. A comparison of various markets after shocks induced by the volatility of other markets reveals differing degrees of resilience to volatility, risk tolerance, and policy response speed among individual financial markets.

Money markets, which primarily trade short-term, high-liquidity instruments and are directly regulated by the central bank, exhibit the most excellent stability. In the event of stock market crashes or bond market turbulence, they are the first to be controlled by central bank policies, thus recovering swiftly from fluctuations or impacts. Bond markets, due to their fixed-income and risk-averse attributes, typically serve as havens for funds during stock market or foreign exchange market turbulence. Their anti-volatility and policy response rates are second only to money markets, performing relatively well. The foreign exchange market, influenced by macroeconomic factors and international capital flows, experiences higher volatility than bond markets. Although the central bank can intervene to stabilize it in the short term, there is a certain lag. As a typical risky asset, the stock market is most sensitive to changes in liquidity, interest rates, and capital flows, possessing the weakest risk-resistant ability. It is highly susceptible to fluctuations and violent shocks from other markets, and its impact on policy transmission is also the most lagging.

6.2 Insights and Recommendations Section

Given the disparities in risk-bearing capacity and the speed of policy responses among diverse financial markets, this paper advances the subsequent recommendations to foster targeted enhancements in market risk prevention. These can be condensed into the establishment of a “layered defense + precise regulation” financial safety net.

(1) Enhance further the function of the money market as a "financial stabilizer"

The money market, directly regulated by the central bank, exhibits the utmost risk-resilience and responsiveness to policy adjustments. In future scenarios,

The central bank ought to further hone its monetary policy instruments to augment regulatory precision, thereby facilitating prompt and efficacious adjustments to money supply and liquidity levels in response to market volatilities. Moreover, it should vigorously foster market innovation. In 2024, Yuan Guofang et al. mentioned that modern technology should be further utilized effectively. In the process of preventing systemic financial risks, the theory of science and technology is indispensable. It is thanks to the rapid development of financial technology that financial data processing has become more convenient and transparent, and the efficiency and stability of the financial market have been improved[15]. In 2023, An Qiguang et al. also mentioned that fintech development has a significant impact on systemic risk[16]. Governments should incentivize the evolution of a more diversified array of short-term, highly liquid financial instruments to further strengthen the money market's function as a "financial stabilizer."

(2) Augment the risk-hedging capability of the bond market and refine its market infrastructure

The bond market, possessing superior risk-hedging attributes, is capable of assimilating risk-hedging funds amidst market turbulence. In future endeavors, the utilization of instruments including government bond futures and credit derivatives ought to be expanded, accompanied by diversification of bond types to accommodate varying investor demands, thereby deepening the bond market and further augmenting its risk-hedging functionality. Furthermore, initiatives should be undertaken to stimulate foreign investors to augment their holdings of RMB bonds, mitigating panic selling and bolstering the bond market's resistance to international disturbances. Regarding market infrastructure development, emphasis should be placed on fortifying custody, clearing, and settlement infrastructures to enhance market operational efficiency and diminish transaction costs.

(3) Deepening Reforms in the Foreign Exchange Market and Enhancing International Cooperation

In the foreign exchange market, further refine the floating exchange rate system, augment exchange rate flexibility, empower the market to assume a more prominent role in exchange rate determination, and bolster the adaptability and stability of the market. In 2023, Yang Zihui et al. mentioned that with the further opening up of China's financial sector, the connection between China's financial market and global economies has become more and more close, and the level of interconnection between domestic and foreign markets has gradually risen, which makes the improvement of the financial regulatory coordination mechanism and the prevention of the impact of international financial risks become an important issue that needs to be researched urgently at this stage of China's life[17]. So we should actively engage in international financial cooperation, collaborating with other nations and international organizations to address concerns related to cross-border capital flows, thereby fostering a conducive external environment for the development of the foreign exchange market.

(4) Enhancing Stock Market Supervision and Optimizing the Internal Market Environment

The stock market exhibits the poorest performance regarding risk resistance and policy response speed. Future endeavors should aim to optimize the existing circuit breaker mechanism and price limit system, intensify supervision, or establish a synchronized monitoring mechanism with currency and bond markets to preemptively identify potential risks. Additionally, emphasis should be placed on refining the internal market environment, including strengthening investor protection and confidence, improving the quality of listed companies, and conducting periodic regulatory audits.

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