The Mutual Contagion Effects of Bank Credit Risk, Consumer Behaviour and Supply Chain Stress - Evidence from China and the United States

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Abstracts

This paper takes China and the United States as the research objects, and based on the macroeconomic monthly data from 2008 to 2024, systematically analyses the dynamic contagion effects and their differences between the credit risk (non-performing loan ratio, 10-year treasury bond yields), consumer sentiment (consumer confidence index, macroeconomic sentiment index), and supply chain finance (supply chain bottleneck index, global supply chain stress index) of the domestic banking sector in the two countries. Through Granger causality test, vector autoregressive model (VAR) and structural equation modelling (SEM), it is found that (1) China's banking credit risk is mainly affected by the lagged impact of supply chain stress index, whereas in the US, it is significantly affected by the bi-directional feedback between consumer confidence and treasury yields; (2) consumer confidence indirectly affects bank risk through supply chain bottlenecks in China's economy, whereas in the US, it (2) Consumer confidence indirectly affects bank risk through supply chain bottlenecks in the Chinese economy, while it directly drives credit market volatility in the United States; (3) there is a closed-loop path of 'supply chain pressure→consumer sentiment→credit risk' in both countries, but the feedback is stronger in the United States. The study reveals the heterogeneity of financial risk contagion mechanisms under different economic structures and provides a theoretical basis for US and Chinese policymakers to differentiate risk blocking strategies.

Keyword：Crisis contagion; banking; supply chain stress; consumers; closing the crisis contagion loop

JEL code：C32; D12; G01; G21; L14

1. Introduction

In the aftermath of the 2008 global financial crisis, cross-sectoral contagion of financial risks has become a central challenge to economic stability. In the context of the development of financial liberalization and economic globalization, with the continuous introduction of financial innovations, financial markets, as well as financial derivatives have become more complex, the links between international financial markets have started to become closer, and the turmoil of the financial system worldwide has been furnished with a more pronounced expression of financial crises already issued and linked. The deepening of global financial integration has made the links between financial markets in different regions more and more close, leading to the risk and crisis of contagion between markets. Pericoli et al. (2003) for the view that financial crisis contagion is 'during the financial crisis, the linkage between the financial markets of different countries and regions is significantly strengthened. Many studies have been conducted on the basis of this definition.

With regard to the argument of financial crisis contagion, Longin et al. (1995) mentioned that financial crisis contagion is usually an increase in the likelihood of a financial crisis in one country leading to a financial crisis in another country, emphasizing the fact that a crisis in one country is caused by a crisis in another country. Typically, a financial crisis that occurs in one country or region is transmitted to other countries or regions through a number of pathways that trigger turmoil in the financial markets of those countries or regions and, through those pathways, feed back into the country where the financial crisis occurred, worsening the economic situation and leading to an even greater financial crisis.

The performance of China's banking sector, the second largest economy in the world, during the COVID-19 epidemic highlights systemic risk and resilience characteristics. Studies have shown that although the epidemic led to a decline in loan growth in the Chinese banking sector, the non-performing loan ratio (NPL ratio) increased significantly, especially as state-owned and large banks effectively controlled their NPL ratios through high-quality capital (Kryzanowski et al., 2023). At the same time, the impact of the epidemic on business operations and supply chains exacerbated macroeconomic volatility, for example, the average NPL ratio of Chinese commercial banks reached 1.94 per cent in the second quarter of 2020, the highest since 2009 (Kryzanowski et al., 2023). This financial stress is further transmitted through consumer confidence indices and supply chain bottleneck indices, creating a complex mechanism of cross-industry risk contagion.

The United States, as the world's largest economy, has a financial system that is uniquely vulnerable to the compounding of COVID-19 and natural disasters. Research has shown that the economic impacts are significantly amplified by ‘complex events’ created by the combination of natural disasters and epidemics (Al Kajbaf et al., 2025), such as the strong correlation between the distribution of PPP loans and regional disaster histories, but with high economic risk areas (e.g., neighbourhoods with high unemployment rates) receiving less aid (Al Kajbaf et al., 2025). This uneven financial support may exacerbate the volatility of supply chain stress indices, which are further transmitted to macroeconomic sentiment indices through consumer sentiment indicators (e.g., confidence indices), creating a closed-loop path of contagion. The US case provides a typical sample for analysing cross-industry risk linkages under multiple crises.

Banks' NPL ratios and the interest rate environment are central factors affecting credit risk. Delis et al. (2014) note that a rise in the ratio of NPLs to total loans can significantly dampen bank credit growth, especially in times of heightened political and economic uncertainty, and that such banks contract their lending more tightly as a result of widening credit risk exposures. For example, it has been found that for every 1 percentage point increase in the NPL ratio, credit growth may decline by about 1.7 per cent (Delis et al., 2014). Gozgor (2018) further adds that systemic risks (e.g., corruption) can indirectly push up the NPL ratio by increasing transaction costs, with the data showing that for every 1 standard deviation (0.94 points) decrease in the level of corruption, private sector credit ratio to GDP can increase by 1.78 per cent. In addition, interest rate differentials (the difference between domestic and international interest rates) have a significant impact on credit supply, with credit growth slowing down due to higher financing costs when domestic interest rates are higher than international rates

(Gozgor, 2018). Although the literature does not directly refer to the 10-year treasury rate, its findings implicitly suggest that the long-term cost of funds has an impact on banks' credit behavior, especially when capital flows are constrained, and instability in the interest rate environment may exacerbate credit risk.

Consumer sentiment, as a key indicator of economic expectations, has a bidirectional impact on credit markets. Delis et al. (2014) find that fluctuations in consumer confidence significantly dampen bank lending growth, especially in times of uncertainty, when low sentiment causes households to scale back their borrowing needs while banks tighten credit standards due to rising default risk. Gozgor's (2018) cross-country study shows that consumer confidence, as an important component of socio-economic conditions, directly drives household credit demand - for every 1 standard deviation (1.7 points) increase in the confidence index, private sector credit as a share of GDP increases by 0.63 percentage points. In addition, consumer sentiment acts indirectly on bank credit supply by influencing the overall economic environment, e.g. low confidence may signal a recession, prompting banks to adjust their risk exposures earlier (Delis et al., 2014). These findings suggest that consumer sentiment is not only a ‘weathervane’ for credit demand, but also a key basis for banks to optimize their asset allocation in a complex environment.

Supply chain finance has a key role in preventing risk contagion and enhancing supply chain stability. Xu Min and Yu Dongdong (2016) found through empirical research that the risk contagion among supply chain member enterprises has bidirectional and jumping characteristics (such as the bidirectional risk spillover between manufacturing industry and electric power enterprises), and it is difficult to cope with systemic risk by simply relying on individual risk management; and supply chain finance can block the risk chain through the integration of financing demand and credit resources (such as accounts receivable financing) to avoid the ‘domino’ effect. Li Xin and Zhu Dongqing (2023) further point out that industry credit risk contagion will push up the cost of corporate debt and weaken the borrowing capacity, leading to commercial credit contraction, while supply chain finance can reduce financing costs, alleviate information asymmetry, and enhance supply chain synergy through the credit endorsement of core enterprises, digital technology empowerment (e.g., blockchain to enhance transparency), and diversified financing tools (e.g., factoring, warehouse receipt pledges) Risk resistance. Together, the two studies show that supply chain finance has become an important mechanism for maintaining supply chain resilience through risk isolation, structural optimization and collaborative governance.

The purpose of this study is to break through the limitations of the traditional "single-link" or "static" contagion analysis, and for the first time organically integrate the three key areas of bank credit risk, consumer (or business) confidence and supply chain stress into the same "closed-loop dynamic contagion" framework. We dynamically capture the positive and negative feedback of each link and their differential performance in the heterogeneous economic structures of China and the United States through multiple methods such as VAR impulse response, rolling window Granger causality test, rolling regression, and closed-loop network visualization, to provide precise empirical support for cross-border cross-sectoral risk management.

The contribution of this article is the establishment of a quantifiable and visualized analytical framework of "three-link closed-loop contagion", which provides a new paradigm for systemic risk research. It reveals that China's "confidence → bank risk → supply chain → confidence" closed-loop mainly relies on the first two loops, while the United States is characterized by the "consumer confidence → bank → supply chain → consumer" feedback, highlighting the essential differences between the two countries' economic structures and policy mechanisms. Moreover, this study is the first to combine rolling window Granger causality, rolling regression and VAR impulse response, and finally obtains the closed-loop network graph.

2. Theoretical background and current state of research

In the aftermath of the 2008 global financial crisis, cross-sectoral contagion of financial risks has become a central challenge to economic stability. In the context of the development of financial liberalization and economic globalization, with the continuous introduction of financial innovations, financial markets, as well as financial derivatives have become more complex, the links between international financial markets have started to become closer, and the turmoil of the financial system worldwide has been furnished with a more pronounced expression of financial crises already issued and linked. The deepening of global financial integration has made the links between financial markets in different regions more and more close, leading to the risk and crisis of contagion between markets. Pericoli et al. (2003) for the view that financial crisis contagion is ‘during the financial crisis, the linkage between the financial markets of different countries and regions is significantly strengthened. Many studies have been conducted on the basis of this definition.

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It is for these reasons and the purpose of the article that we mentioned in the first part as our motivation for this paper to provide strong evidence for the computational and empirical part that will be done later.

The formation and transmission mechanisms of credit risk are closely linked to the dynamics of consumer behavior and supply chain finance, and Rajan (1994) reveals from a behavioral finance perspective that the limited rationality of bankers leads to fluctuations in the credit cycle, e.g., collective credit contraction in crises exacerbates real economic downturns through "cognitive bias," a mechanism that is extended in Hatzius et al. This mechanism is extended in Hatzius et al. (2010) to the indirect effect of "animal spirits" on bank risk - consumer confidence fluctuations map the vulnerability of the banking system. Mian et al. (2017) further integrate household debt into the risk chain: if future income is lower than expected, the debt burden inhibits consumption and backfires on the banking system through the credit channel, creating a vicious cycle of "rising debt → declining confidence → economic slowdown → increasing non-performing loans → tightening credit" (Caglayan & Xu, 2016). empirical evidence on more than 9,000 banks in G7 countries shows that the negative impact of sentiment volatility on credit policy (about 13%) far outweighs changes in sentiment levels (only 1%), and that banks with high capital adequacy ratios (each 1% increase in Tier 1 capital adequacy ratios is associated with a 0.8% improvement in credit stability) are more resilient to such shocks.

Consumer behavior both triggers and mediates credit risk. the economic policy uncertainty index (EPU) constructed by Baker et al. (2016) shows that a 10% rise in EPU leads to a 0.8% decline in consumption growth and pushes up the risk of chain breaks for supply chain SMEs; Ma (2020) empirically empirically finds that for every 1-unit increase in supply chain stress, business confidence falls by 0.6, while consumer confidence rises by 0.2 as a result of a short-term shift to local substitutes, but may reverse in the long run; Platitas et al. (2023) further reveal that transportation delays that push up the price of raw materials by 10% trigger a 5% rise in inflation expectations and a 5% decline in consumption intentions, highlighting the sensitivity of consumer confidence to supply chain pressures. This sensitivity shows differences in cross-country comparisons: Héctor (2024) and Yilmazkuday (2024) find that the negative impact of global supply chain stress on business confidence is pervasive, but that Germany (manufacturing resilience) vs. China (domestic supply chain closure) show resistance to stress.

Supply chain finance acts as a key node of risk transmission, both amplifying credit risk and providing mitigation tools. Diem et al. (2023) demonstrate through Hungarian supply chain network data that defaults in key industries can amplify banks' expected losses by a factor of 5.2 through the chain of transactional relationships, with a rise in value-at-risk (VaR) by a factor of 6.7, necessitating targeted liquidity support through the Financial Systemic Risk Index (FSRI) (0.5% equity support reduces losses by 5%).He et al.'s (2025) climate risk study shows that differences in supply chain concentration significantly affect bank credit pricing: credit spreads of low-concentration firms widen by 51.3 bps, while those of high-concentration firms widen by only 2.7 bps, underscoring the role of supply chain stability on risk pricing.Xie et al.'s (2023) dual-channel financing game model points out that the prioritization design of bank credit and trade credit needs to balance risk contagion - prioritizing bank loan repayment can exacerbate demand risk due to increased order book (intensity is negatively correlated with production cost), while increasing the share of trade credit may inversely amplify the risk. Lan Wang et al.'s (2024) green supply chain credit assessment system further shows that the explanatory power of firms' carbon intensity and the proportion of suppliers' environmental certification for credit risk reaches 35%, and environmental factors become emerging risk variables.

Consumer trust rebuilding is a cornerstone of supply chain resilience. Giampietri et al. (2018) validate that a 1-unit increase in consumer trust in short food supply chains leads to a 0.7-unit increase in willingness to buy, and that 50.4% of respondents switched to fair-trade products due to trust.Nunes et al. (2024) emphasize the need for firms to offset, through transparency in water management (e.g., disclosure of water-saving practices) the Nunes et al. (2024) emphasize the need for companies to offset the negative effects of a high water footprint through water management transparency (e.g., disclosure of water conservation practices) (a 20% drop in brand attitude can be offset by a 15% increase in transparency).Qiu et al.'s (2024) virtual showroom (VSB) strategy drives dynamic pricing adjustments between manufacturers and retailers by filtering for differences in the cost of the consumer experience (the high-cost group tends to be offline) (an 8% increase in profitability when VSB is supported), underscoring the role of consumer behavior as a driver of supply chain finance strategies. The role of consumer behavior in driving supply chain finance strategies is highlighted.

3. Data and Methodology

Data Description

Our analysis uses parallel high-frequency datasets for China and the U.S. (monthly frequency, 2011M1-2024M6). By calculating the 12-month growth rate, we remove some of the seasonal effects. However, we also lose 12 monthly data. Next, we list and present the six core indicators involved in the empirical evidence.

First, from the perspective of financial market and macroeconomic risk transmission, TTBY (Ten-Year Treasury Bond Yield) captures well the dynamic difference in sovereign credit risk premiums between China and the U.S. The Chinese data reflect market liquidity expectations under the anchoring of policy rates. In contrast, the U.S. data characterize the structural variation in global risk-free rates and term premiums. Second is NPL (Non-performing Loan Ratio): a cross-country comparison of apparent NPL pressure, with China focusing on real estate mortgage quality and the US highlighting consumer credit and SME loan risk.

From a Behavioral Economics perspective, the CCI (Consumer Confidence Index) captures heterogeneous behavioral feedback on precautionary savings (China) and debt-driven consumption (US). In addition, the ZEW Economic Sentiment Indicator can map the difference in the transmission efficiency impact of different policy expectations on the real economy in the two countries.

From a supply chain perspective, the GSCPI (Global Supply Chain Pressure Index) measures systemic pressures in cross-country production networks. Further, the Supply Bottlenecks Index (SBI) quantifies the comprehensive pressures of supply-side constraints. The specific manifestation in China is the relationship between plummeting manufacturing capacity utilization and the intensity of policy interventions.

This study's data architecture aims to overcome the limitations of traditional single contagion channel studies through a triple design.

3.1 Stability Test and Covariance Test

ADF test (Augmented Dickey-Fuller Test)

Dickey and Fuller (1979) in the study of unit root tests pointed out that the smoothness of the time series data is the core prerequisite for the construction of valid econometric models (e.g., ARIMA, VAR, cointegration analysis, etc.). If there is a unit root in the data (i.e., the data is not smooth), at this point, if it is modeled directly, it may lead to pseudo-regression. To avoid the seemingly significant relationship between variables is a chance match of data trends, rather than a real causal relationship, we choose to do the ADF test. If the data passes the unit root test (i.e., the null hypothesis is rejected), then the data is smooth and can be further analyzed. In addition, the ADF test is more flexible than other smoothness tests. It supports a variety of model settings including constant terms, trend terms, etc., and adapts to most common deterministic trends in economic data.

The underlying assumptions and formulas for the ADF test are shown as follow.

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

Where:

$\Delta y_t = y_t - y_{t-1}$ is the first-difference operator; α is the drift term; β_t is the time trend component (optional); γ is the Coefficient of interest ($H_0: \gamma = 0$); ϕ_i is the lagged difference coefficients to correct serial correlation; $\sum_{i=1}^{p} \phi_i \Delta y_{t-i}$ is the lagged difference term, which effectively eliminates residual autocorrelation and enhances the effectiveness of the test. p is the optimal lag length determined by Schwarz Bayesian Criterion (SBC).

If the data are found to be non-stationary after the ADF test, they can be transformed to satisfy the model assumptions by differencing, de-trending, or cointegration analysis. The processed data needs to be tested again until the data is smooth.

VIF Test (Variance Inflation Factor)

In multiple regression models, multicollinearity among independent variables can severely distort parameter estimates. For example, the standard errors of the regression coefficients are inflated, leading to underestimation of statistical significance (insignificant t-values); or the coefficient estimates are highly sensitive to small changes in the data, leading to poor model stability; or when faced with the difficulty of distinguishing between the independent effects of a single variable, which undermines the explanatory power of the economy. The VIF test provides an objective basis for the diagnosis of covariance by quantifying the degree of linear dependence between variables. In other words, it enhances the reliability of statistical inference by reducing the variance of parameter estimates through the reduction of covariance.

During model testing, the VIF value can directly reflect the severity of variable covariance (e.g., $VIF \geq 10$ indicates severe covariance). This is the first time that Marquardt (1970) states as a basis for judging severe covariance, making cross-model comparisons more convenient.

Operationally, the VIF test is very convenient. It can be obtained simply by calculating R^2 through auxiliary regression, and most mainstream statistical software has a standardized process built in. Once we have identified high VIF variables in the model, we can optimize the model settings by removing redundant variables, principal component analysis (PCA), and other methods. After excluding highly covariate variables, the retained independent variables are more likely to represent independent economic mechanisms and improve the robustness of subsequent regression models.

The one-sided representation of the VIF test is obtained by calculating the R^2.

For each predictor X_j, VIF is derived from:

$$VIF_j = \frac{1}{1-R^2} \tag{2}$$

where R^2 is the coefficient of determination from regressing X_j on all other predictors. When $VIF < 5$, represents negligible collinearity; When $5 \leq VIF < 10$ represents moderate collinearity; $VIF \geq 10$ represents severe collinearity.

3.2 VAR model construction and impulse response function analysis

In this paper, we propose the use of vector autoregressive models (VAR models) to test the contagion effects of financial crises across markets. In addition, Granger causality test and impulse response analysis are the most used functions in this model.

3.2.1 VAR model

In this paper, we propose the use of vector autoregressive models (VAR models) to test the contagion effects of financial crises across markets. The Vector Autoregressive (VAR) model was first published in 1980. The VAR system can reflect complete information about the system by integrating economic variables into the system and characterizes the dynamics between the variables better than previous traditional methods. The Vector Autoregressive (VAR) model was first published in 1980. The VAR system can reflect complete information about the system by integrating economic variables into the system and characterizes the dynamics between the variables better than previous traditional methods. Sims (1980) proposed the advantage of the VAR model over the traditional single equation or structural model, that is, by "integrating" multiple economic variables into one system, it can capture the rich dynamic relationships and interactive characteristics among the variables without relying too much on priori structures or theoretical limitations. Khalid et al. (2003) proposed that VAR is often used to analyze the dynamic effects of random disturbances on variable systems. Before estimating VAR, it is very important to determine the length of lag. The usual practice is to arbitrarily choose the lag length, allowing enough lag to ensure that the residual is white noise while maintaining the accuracy of the estimate. In addition, using information criteria (such as AIC, BIC) Akaike (1974) determines the appropriate lag length.

To capture the dynamic interactions among multiple variables in the system, we construct a vector autoregression (VAR) model：

$$Y_t = \begin{matrix} y_{1,\ t} \\ y_{2,\ t} \\ \cdot \\ \cdot \\ \cdot \\ y_{6,\ t} \end{matrix}, \tag{3}$$

At this time, the $VAR(p)$ model is:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \tag{4}$$

Where Y_t is the k vector of endogenous variables, A_1,…, A_p are the coefficient matrices to be estimated, and $\varepsilon_t$is the error term vector. Khalid (2003) proposed that these error term vectors may be correlated with each other at the same time but are uncorrelated with their own lagged values and all right-hand-side variables.

3.2.2 Granger Causality Tests

Khalid (2003) proposed that the causal relationship test in the difference VAR may have higher power in a limited sample. Compared with the traditional econometric method, researchers can focus more on the dynamic relationship between variables without worrying about endogeneity and other issues that need to be considered in traditional modeling.

The traditional Granger causality test is used to test whether there are past values of the variable x that significantly enhance the prediction of the current value of the variable Y in the overall sample. The model form is:

$$Y_t = \alpha + \sum_{i==1}^{p} \beta_i Y_{t-i} + \sum_{i=1}^{p} \gamma_i x_{t-i} + \varepsilon_t \tag{5}$$

Test whether the null hypothesis H_0: $\gamma_1 = \gamma_2 = \cdots = \gamma_P = 0$ is true (Granger, 1969).

where Y_t is the current value (point in time t) of the dependent (predicted) variable; α is a constant term that describes the average level of Y_t when all lags are zero; β_i corresponds to the coefficient of Y_{t-i}, which indicates the strength of the effect of its own lag on the current value of Y_t; γ_i corresponds to the coefficient of x_{t-i}, which describes the marginal effect of the exogenous or marginal impact of other variables x on Y_t; p lag order; and ε_t is the random error term, reflecting the portion of stochastic fluctuations that are not explained by the present model, which is usually assumed to have an expectation of 0, finite variance, and to be uncorrelated (or to be white noise relative to past information).

Ren et al. (2025) proposed the time-varying Granger causality test for testing time-varying causal relationships between variables that are considered to be related. This method helps in identifying the key factors that lead to certain behaviors or phenomena for better decision making. Due to the time-varying and fluctuating nature of causality between time series of different variables, the traditional Granger causality test cannot solve this problem, so here the rolling window approach is used to test the Granger causality locally. That is, within each rolling window (here we set the time period as 24 months), the above models are estimated separately, and the corresponding p-values are recorded. When the p-value is less than 0.05 within certain windows, we consider that there is a significant causal transmission effect in that local time period.

3.2.3 Impulse Response Analysis

In this subsection, we will analyze the impulse response. Khalid et al. (2003) mention that the impulse response function traces the effect of applying a one standard deviation shock to an innovation on the current and future values of the endogenous variable. A shock to the ith variable directly affects that variable and is transmitted to all endogenous variables through the dynamic structure of the VAR.

After the VAR model is estimated, we compute impulse response functions (IRFs), which measure the response of each variable in the system to a structural shock that evolves over time. Specifically, for h response after a period of time：

$$IRF(h) = \frac{\vartheta Y_{t+h}}{\vartheta_{\varepsilon_t}} \tag{6}$$

where Y_t is a vector of endogenous variables at the moment of time t; ε_t denotes the structural shock at the moment of time t, which is usually an $n \times 1$ vector. ; $IRF(h)$ (Impulse Response Function at horizon h) denotes that when a unit shock ε_t occurs at time t, in the future period h (i.e., at time $t + h$), how the variables Y_{t+h} change in the system; $t + h$ refers to the number of future periods after the time $t + h$ order, usually h denotes the number of periods in the future 1 period, 2 periods...etc. (e.g., 1 month after, 2 months later, ...); $\frac{\vartheta Y_{t+h}}{\vartheta_{\varepsilon_t}}$ which is a partial derivative notation indicating the sensitivity of Y_{t+h} to ε_t. IRF analysis visualizes the path of the crisis shocks transmitted inside the system and their duration.

3.3 Regression analysis

In this section we will use the Ordinary Least Squares (OLS) method for the initial estimation of the relationship between the variables. Later, to further explore the dynamic relationship between the different domains, we use rolling regression.

3.3.1 Multiple regression analysis

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \epsilon \quad (7)$$

Y is the dependent variable (predicted variable); X_1 to X_k are the independent variables (predictor variables); β_0 is the intercept term; β_1 to β_k are the regression coefficients; ϵ is the error term (obeys a normal distribution with a mean of 0 and a constant variance).

Our model is further characterized by the following form since it passes the unit root test with a lag of one order. That is, our model is the form of the equation for a multiple regression model under first-order differencing (OLS).

$$\Delta Y = \beta_0 + \beta_1 \Delta X_1 + \beta_2 \Delta X_2 + \cdots + \beta_k \Delta X_k + \epsilon \quad (8)$$

Wooldridge (2016) notes that multiple regression can isolate the “net effect” of a single independent variable on the dependent variable by controlling for other variables. Some of the multiple regression results are presented below.

3.3.2 Rolling regression analysis

To further explore the dynamics between the different domains, we use a rolling regression approach. In practice, model instability is a common phenomenon in forecasting, and Timmermann (2006) suggests that one way to cope with this instability is to use rolling or recursive regression to obtain time-varying parameter estimates and subsequently combine these estimates. Timmermann (2006) shows that, in some cases, forecasting combinations based on rolling window estimates can significantly improve forecasting accuracy compared to forecasting combinations based on constant parameter estimates. Combinations can, in some cases, significantly improve prediction accuracy over those based on constant parameter estimates. For the selected combination of variables (e.g., banking sector indicators as dependent variables and consumer and supply chain finance indicators and their interaction terms as independent variables), the following rolling regression model was developed:

$$y_t = \alpha(t) + \beta_1(t)x_{1,t} + \alpha(t) + \beta_2(t)x_{2,t}\alpha(t) + \beta_{12}(t)x_{1,t}x_{2,t} + \varepsilon_t \quad (9)$$

where $\alpha(t)$, $\beta_1(t)$, $\beta_2(t)$, $\beta_{12}(t)$ varies over time, and coefficients and p-values are obtained for each time period using fixed-length window rolling estimates.

The window coefficients were subsequently averaged to represent the average conduction effect in each direction over the entire sample period. Also, the time-varying nature of the transmission effect is visualized by plotting the coefficient and p-value curves from the rolling regression.

3.4 Closed-loop contagion effect analysis and network diagram construction

Glasserman and Young (2016) mention that initial asset shocks to banks may spread to other banks, creating a cascade of default effects. This reflects the basic idea of closed-loop contagion. Tarski's fixed point theorem guarantees that every monotone mapping has at least one fixed point, which immediately implies the existence of a clearing vector that characterizes the cumulative effect of cascading shocks in the network. However, the term "cascading shocks" refers to the phenomenon where shocks from one node are transmitted sequentially to the entire system to form a closed-loop feedback.

Based on the rolling regression results in the previous subsection, we construct closed-loop contagion networks for selected key indicators in the three industries (banking, consumer, and supply chain finance). Example:

Let β_1 be the average impact of consumer indicators on banking sector indicators (e.g., CNCCI → CNNPL), and

β_2 be the average impact of banking sector indicators on supply chain indicators (e.g. CNNPL → GSCPI), and

β_3 be the average impact of supply chain indicators on consumer indicators (e.g. GSCPI → CNCCI).

The overall effect of what constitutes closed-loop transmission can be expressed as the product of these three average coefficients, $\beta_1\beta_2\beta_3$. If this product is significantly non-zero, it indicates that there is a circular transmission effect within the system.

Then the closed-loop conduction effect can be described as:

$$Closed_{Loop} = \bar{\beta}_1\bar{\beta}_2\bar{\beta}_3 \tag{10}$$

In the network diagram, the values shown on each side reflect the direction of the

$\left|\overline{\beta_1}\right|$size, and the thickness of the edge is proportional to that value.

4. Analysis of Empirical Results

The empirical analysis in this paper is realized by MATLAB R2024b, whose advantages are first, it can efficiently deal with complex calculations of high-frequency time series data; secondly, the software has a built-in econometric toolbox, which is especially good at dealing with the optimization of the data containing structural breakpoints; and its scripted process ensures the traceability of the results. Its scripted process ensures that the results are traceable and verifiable. This ensures the replicability of the study and its contribution to the academic community in the direction of crisis contagion modeling.

In the next step, we present the empirical results. First, we show the results of the smoothness test, followed by the covariance test. Then we further show the results of the multiple regression and the interpretation of the main results with the model.

4.1 Results of The Stability Test

Table 4.1 demonstrates the ADF test p-values for each variable after first-order differencing for China and the United States (significance level α=5%):

Table 4.1 The results of Unit root test

ADF test: Steady at first-order derivatives

CN	p-value	USA	p-value
CNNPL	0.047	USNPL	0.0028
CNTTBY	0.0254	USTTBY	0.0178
CNCCI	0.0036	USCCI	0.001
CNZEW	0.0082	USZEW	0.001
GSCPI	0.001	GSCPI	0.001
SBI_CN	0.001	SBI_US	0.001

All variables reject the unit root hypothesis after first-order differencing ($p<0.05$), confirming first-order monotonicity and satisfying the requirements of cointegration analysis and VAR modeling.

Detailed graphs of the smoothness test are shown in Appendices 4.1-4.2.

Among them, we find some interesting facts. The p-value of both China-US GSCPI and SBI is 0.001, indicating that supply chain-related indicators are highly sensitive to policy shocks (e.g., China's “zero-zero” blockade, US port strikes), and the trend component is quickly eliminated after differencing, confirming that supply chain pressures have short-term memory. Appendix Figures 4.1-4.2 demonstrate that the series fluctuates around the zero mean after first-order differencing, verifying smoothness (e.g., China's GSCPI returns to the mean after fluctuating violently during the 2021 blockade).

The p-value of China's non-performing loan ratio (CNNPL) is close to a critical value (0.047), reflecting that state-owned banks mitigate risks through policy rollovers, leading to adjustment inertia; meanwhile, the p-value of USNPL is highly significant (0.0028), reflecting that market-based disposal mechanisms (e.g., asset securitization) accelerate the risk clearance.

The p-value of China's CNTTBY (treasury bond yield) (0.0254) is higher than that of the USNPL (0.0178), as China's interest rates are controlled by the “implicit corridor”, and fluctuations are smoothed by the administration; on the contrary, the USNPL is more responsive to the Fed's hiking cycle and has a stronger smoothening after the differencing.

All in all, after the first-order difference, all the data have long-term trends and smoothness. It makes a certain degree of guarantee for the robustness of the subsequent multiple regression as well as the rolling regression.

Table 4.2: Correlation test for CN

	CNNPL	CNTTBY	CNCCI	CNZEW	GSCPI	SBI__CN
CNNPL	1	-0.38518	0.156516	-0.1064	0.027647	-0.18509
CNTTBY	-0.38518	1	0.275009	0.350158	-0.12414	-0.04125
CNCCI	0.156516	0.275009	1	0.278575	-0.03264	-0.09839
CNZEW	-0.1064	0.350158	0.278575	1	-0.08328	-0.33668
GSCPI	0.027647	-0.12414	-0.03264	-0.08328	1	0.414865
SBI__CN	-0.18509	-0.04125	-0.09839	-0.33668	0.414865	1

From Table 4.2 we observe that GSCPI (Global Supply Chain Pressure Index) and SBI_CN (China Supply Side Bottleneck Index) show a moderate positive correlation (0.41), reflecting the fact that China, as a global manufacturing hub, has synergistic fluctuations between its local supply chain bottlenecks (e.g., energy problems, logistics stagnation) and the global systemic pressures. However, the VIF value (1.47) is below the threshold, suggesting that potential policy interventions partially block the transmission of covariance. Second, the positive correlation (0.35) between CNTTBY (10-year treasury yields) and CNZEW (economic expectations index) reveals the policy-oriented character of China's financial market. When the rise in treasury yields is often accompanied by expectations of easing policy (e.g., LPR cuts), it can instead boost market confidence. This contrasts with the negative "yield-expectation" correlation in the US (see Table 4.3).

Interestingly, the low correlation (0.16) between the CNNPL (non-performing loan ratio) and the CNCCI (consumer confidence index) confirms that China's residential sector is insensitive to bank risks, reflecting the "risk isolation" effect of the deposit insurance system and the implicit guarantee of state-owned banks.

Table 4.3: Correlation test for USA

	USNPL	USTTBY	USCCI	USZEW	GSCPI	SBI_US
USNPL	1	-0.07654	-0.42518	0.004127	0.085323	0.177146
USTTBY	-0.07654	1	0.220187	0.082313	-0.09038	-0.23949
USCCI	-0.42518	0.220187	1	0.118533	-0.17432	-0.24447
USZEW	0.004127	0.082313	0.118533	1	-0.06866	-0.04527
GSCPI	0.085323	-0.09038	-0.17432	-0.06866	1	0.568798
SBI_US	0.177146	-0.23949	-0.24447	-0.04527	0.568798	1

Table 4.3 shows the correlation of the indicators for the U.S. The high positive correlation between GSCPI and SBI_US (0.57) is significantly higher than that of the Chinese sample in the comparison, reflecting the relative vulnerability of the U.S. consumption-driven supply chain. When global pressures arise, they can directly exacerbate local supply chain market bottlenecks. The VIF value (1.61) is not exceeded, but one needs to be wary of covariance amplification effects in subsequent time-varying models. It is worth noting that the USNPL (non-performing loan ratio) has a significant negative correlation (-0.43) with the USCCI (consumer confidence index). This reveals the sensitivity of the "debt-consumption" chain in the US. That is to say, when credit risk rises, it will further inhibit residents' willingness to borrow, forming a potential "risk contraction-demand contraction" vicious cycle. The weak correlation (0.08) between USTBY (US bond yields) and USZEW (economic expectations) implies that the Fed rate hike cycle has had a very limited impact on market expectations. Side by side, this reflects the lag in the transmission of monetary policy.

Table 4.4: The Results of VIF Test

VIF_CN	VIF_US
CNNPL: VIF = 1.3642	USNPL: VIF = 1.2373
CNTTBY: VIF = 1.4696	USTTBY: VIF = 1.1031
CNCCI: VIF = 1.2384	USCCI: VIF = 1.3276
CNZEW: VIF = 1.3717	USZEW: VIF = 1.0239
GSCPI: VIF = 1.2502	GSCPI: VIF = 1.4940
SBI__CN: VIF = 1.4694	SBI_US: VIF = 1.6068

Observing from Table 4.4 we can see that the VIF values of all variables are below 2.0 (the highest in China is 1.47 and the highest in the U.S. is 1.61), which is far below the empirical threshold ($VIF = 5$). It indicates that there is no serious multicollinearity interference in the model setting, which can guarantee the unbiased estimation of regression coefficients.

Further, there are some differences between Chinese and US data that deserve our attention. The VIF value of SBI_US in the US (1.61) is higher than that of SBI_CN in China (1.47), reflecting that its supply chain bottlenecks are more driven by market mechanisms (e.g., ocean freight prices, labor shortage), and the linear dependence between variables is stronger; the VIF value of CNTTBY in China (1.47) is higher than that of USTTBY in the US (1.10), reflecting that the policy interventions (e.g., interest rate regulation) increase the endogenous complexity of the endogenous complexity of interest rate variables.

4.2 Results of The Regression

Figure 4. 1: Partial Results of Multiple Regression for CN

```
========== Regression: CNCCI as Dependent Variable ==========
                    Estimate         SE          tStat        pValue
                   ___________    __________    _______    __________

    (Intercept)      -0.013142     0.0067343    -1.9516      0.052781
    CNNPL              0.19554      0.050331     3.8851    0.00015082
    CNTTBY             0.18419      0.047722     3.8596    0.00016593
    CNZEW              0.18816      0.072423      2.598      0.010275
    GSCPI          -1.5301e-05    0.00050005    -0.0306       0.97563
    SBI__CN          0.0042565      0.008106     0.5251       0.60026
```

After adding the test results for China, our model becomes:

$$\Delta CNCCI = -0.0131 + 0.1955 \cdot \Delta CNNPL + 0.1842 \cdot \Delta CNTTBY + 0.1882 \cdot \Delta CNZEW - 0.000015 \cdot \Delta GSCPI + 0.0043 \cdot \Delta SBI\_CN + \epsilon \quad (5)$$

The multidimensional risk contagion framework embodied here has several explanations. First, for every 1-unit rise in Treasury yields, consumer confidence improves by 0.1842 units. A rise in Treasury yields may suggest a revision in market expectations of policy easing (e.g., the end of the rate-cutting cycle), sending a signal of economic recovery and offsetting the negative impact of tighter liquidity on confidence. Second, for every 1-unit rise in the NPL ratio, consumer confidence improves by 0.1955 units. Reacting to the rise in China's NPL ratio, the state can indirectly boost consumer confidence by adjusting expectations through policy. Third, a 1-unit increase in the economic sentiment index is associated with a 0.1882-unit increase in confidence. Here maps the efficiency of the transmission of policy expectations to the real economy. In an environment of high policy transparency, improving the economic sentiment index effectively reduces the precautionary saving incentive. Fourth, for every 1-unit increase in the supply chain stress index, confidence slightly decreases by 0.000015 units. Here the link between the two is shown to be weak. Finally, a 1-unit increase in the supply-side constraint index is associated with a slight increase in confidence of 0.0043 units.

For China, in terms of p-value, the treasury bond yield, non-performing loan ratio, and economic sentiment index have a significant positive impact on consumer confidence. However, the effect on confidence from the supply chain direction is very limited.

Figure 4. 2: Partial Results of Multiple Regression for USA:

========== Regression: USTTBY as Dependent Variable ==========

	Estimate	SE	tStat	pValue
(Intercept)	0.15801	0.053911	2.931	0.0038869
USNPL	0.14395	0.32111	0.44828	0.65457
USCCI	0.55384	0.26044	2.1266	0.035026
USZEW	0.0047962	0.0067352	0.71211	0.47746
GSCPI	0.0031077	0.0035349	0.87915	0.38067
SBI_US	-0.079768	0.03078	-2.5916	0.01046

After adding the test results for the USA, our model becomes:

$$\Delta USTTBY = 0.1580 + 0.1440 \cdot \Delta USNPL + 0.5538 \cdot \Delta USCCI + 0.0048 \cdot \Delta USZEW + 0.0031 \cdot \Delta GSCPI - 0.0798 \cdot \Delta SBI\_US + \epsilon \quad (6)$$

Each 1-unit increase in the NPL ratio in the United States caused a 0.1440-unit increase in Treasury yields. The demand for Treasuries as a safe-haven asset by investors likely rose because the risk of non-performing loans in the United States (consumer credit defaults) can directly push up the risk premium in financial markets. Second, Treasury yields rise by 0.5538 units for every 1-unit increase in consumer confidence. Increased U.S. consumer confidence will stimulate aggregate demand, and the market expects inflation to heat up with tighter monetary policy, leading to higher long-term interest rates. The weak impact of the economic sentiment index on Treasury yields may be due to the high transparency of U.S. policy expectations, which have been priced in by the market in advance. Also, consider the guidance to the market from the Fed's policy outlook. Global supply chain pressures have a near-zero impact on U.S. bond yields, reflecting the U.S. ability to pass on external shocks under dollar hegemony. Heightened supply-side constraints lead to a 0.0798-unit decline in Treasury yields.

The data comparison between the two countries suggests a systemic divergence in the risk transmission mechanism between China and the United States. Chinese consumer confidence is driven by policy interventions, while U.S. confidence affects Treasury yields through market inflation expectations; Chinese supply chain shocks are administratively isolated, while U.S. supply bottlenecks depress Treasury yields through growth expectations; and U.S. nonperforming loan risk directly pushes up the cost of sovereign financing, while the same type of risk in China inversely boosts confidence due to policy underwriting.

These differences identified in our study can provide the basis for differentiated paths for international policy coordination and crisis management.

4.3 Results of VAR modeling and impulse response analysis

In this section, the results obtained for the VAR model, time-varying Granger Causality test and impulse response analysis mentioned in the methodology section of Chapter 3 are presented and discussed here.

4.3.1 Result of VAR model

After constructing the VAR model, we estimate the dynamic system for the Chinese and US markets separately. For the Chinese sample, we chose 2nd order lag (i.e., p = 2), and thus the model includes two sets of 6×6 AR coefficient matrices $A1$ and $A2$, as shown in Table 4.7; whereas for the U.S. sample, since the information criterion indicates the optimal lag order to be 1, only a set of 6×6 AR coefficient matrices $A1$ are included, as shown in Table 4.8.These matrices visually demonstrate the dynamics of the variables in the system with time. conduction relationship between the variables within the system over time.

Table 4.5 AR matrix of the China VAR model (first order)

	CNNPL(t-1)	CNTTBY(t-1)	CNCCI(t-1)	CNZEW(t-1)	GSCPI(t-1)	SBI__CN(t-1)
CNNPL	1.71663	0.00748	-0.05897	-0.01057	0.00009	-0.00135
CNTTBY	-0.65669	0.97139	-0.01366	0.17621	0.00040	-0.00853
CNCCI	0.03600	-0.07326	0.80806	0.08314	0.00023	-0.00229
CNZEW	-0.34429	-0.08613	-0.05230	1.38178	0.00083	0.00555
GSCPI	65.36504	-0.71963	50.53707	26.88076	-0.16031	7.74052
SBI__CN	-0.36553	0.85254	-0.04755	-6.14477	-0.01384	0.77978

Table 4.6 AR Matrix of China VAR Model (Second Order)

	CNNPL(t-2)	CNTTBY(t-2)	CNCCI(t-2)	CNZEW(t-2)	GSCPI(t-2)	SBI__CN(t-2)
CNNPL	0.00014	-0.00016	-0.00007	-0.00004	0.00934	-0.00011
CNTTBY	-0.00016	0.00257	0.00035	0.00039	-0.14318	-0.00140
CNCCI	-0.00007	0.00035	0.00138	0.00018	-0.03911	-0.00293

CNZEW	-0.00004	0.00039	0.00018	0.00105	0.00279	-0.00205
GSCPI	0.00934	-0.14318	-0.03911	0.00279	148.40173	1.29276
SBI__CN	-0.00011	-0.00140	-0.00293	-0.00205	1.29276	0.28808

Table 4.7 AR matrix for the U.S. VAR model

	USNPL(t-1)	*USTTBY(t-1)*	*USCCI(t-1)*	*USZEW(t-1)*	*GSCPI(t-1)*	*SBI__US(t-1)*
USNPL	0.00490	-0.00188	-0.00110	-0.14951	0.17287	0.02714
USTTBY	-0.00188	0.03062	0.00150	0.14201	-0.10991	-0.02098
USCCI	-0.00110	0.00150	0.01137	0.08291	-0.11053	-0.00629
USZEW	-0.14951	0.14201	0.08291	31.28569	-8.59341	-0.88339
GSCPI	0.17287	-0.10991	-0.11053	-8.59341	134.21710	4.23491
SBI_US	0.02714	-0.02098	-0.00629	-0.88339	4.23491	1.21563

As can be seen from Table 4.5, the CNNPL(t-1) → CNNPL(t): coefficient is positive and has a large value (about 1.71663), suggesting that the current NPL rate has a strong positive continuity to itself, i.e., a higher NPL in the previous period tends to lead to the current period remaining at a high level. For CNTTBY, the autoregressive coefficient of 0.97139 likewise shows a high persistence of 10-year Treasury yields in the short run. The negative (-0.65669) with CNNPL(t-1) indicates that when the NPL ratio increased in the previous period, the current interest rate may be suppressed by some financial market mechanism or policy effect, reflecting the inverse correlation between risk premium and interest rate. Meanwhile, CNTTBY is negatively correlated with CNCCI(t-1) (-0.01366) and SBI__CN(t-1) (Supply Chain Bottleneck Index) (-0.008533), and consumer confidence or supply chain bottlenecks are elevated in the previous period, while the current ten-year government bond yields are slightly downward, which suggests that when the market is highly concerned about changes in the outlook for consumption or supply chain bottlenecks , funds may shift to safer assets, or policy interventions may occur that depress Treasury rates. It may also indicate that when consumption and supply chain indicators are higher, market concerns about future inflation or economic overheating are mitigated to some extent, leading to a fall in long-term interest rates. CNCCI (Consumer Confidence Index) is negatively related to CNTTBY(t-1) (10-year Treasury Yield) (-0.07326) and SBI__CN(t-1) (Supply Chain Bottleneck Index) (-0.00229), and it is highly probable that there is a small negative correlation between the rise in Treasury Yield or Supply Chain Bottlenecks in the previous period and the current consumer confidence. On the one hand, a rise in market interest rates, higher financing costs, or a reflection of some tightening or risk aversion in the economy could weaken consumer confidence; on the other hand, a worsening of supply chain bottlenecks, potential price increases or supply-side risks could dampen consumer confidence in the future. Further observing the rows where the Corporate Zenith Index (CNZEW) is located, we find that its coefficient with the bank non-performing loan ratio (CNNPL(t-1)) in the previous period is -0.34429, and its coefficients with the treasury bond yield (CNTTBY(t-1)) and the consumer confidence (CNCCI(t-1)) are -0.08613 and -0.05230, respectively, which all show negative effects. Such results suggest that the improvements in bank risk, interest rate hikes and consumer confidence in the previous period instead dampened the current level of business sentiment to a certain extent, which may reflect the phenomenon that firms tend to be more conservative in their expectations of future economic growth in the face of higher funding costs or market uncertainty in the process of financial tightening or transmission of risk spillovers. In addition, the coefficients of the Global Supply Chain Stress Index (GSCPI) and the Supply Chain Bottleneck Index (SBI_CN) likewise exhibit significant negative effects. For example, the GSCPI is negatively related to both the previous period's Treasury bond yields and its own previous period, while the Supply Chain Bottleneck Index is negatively related to all variables except for the Treasury bond yields, implying that, in the short term, the rise in these indicators may reflect the market's anticipation of heightened supply-side risks, which in turn leads to an inverse adjustment mechanism between the various related indicators. Overall, the positive coefficients imply that a rise in a variable in the previous period helped to push the current variable up, while the negative coefficients indicate the existence of an inverse, inhibitory effect, reflecting the existence of a complementary, offsetting mechanism in the market's adjustment process.

These findings are consistent with Glasserman and Young's (2016) theory in exploring risk contagion in financial networks, where they state that the strength of risk contagion depends on the positive and negative feedback of the dynamic interactions between nodes, and that feedback in real systems often involves both positive transmission and reverse regulation (Glasserman & Young, 2016, pp. 792-794).

Since the lagged first-order matrix of the VAR model for China is analyzed in detail, the lagged second order as well as the lagged first-order data for the U.S. will be briefly described below. In the second-order lag matrix, the more typical negative effect is reflected in the transmission of CNTTBY(t-2) to GSCPI(t), with a coefficient of -0.14318. This suggests that a rise in the 10-year Treasury yield in the previous period (or more precisely, two periods ago) would currently have some negative impact on the GSCPI. The economic interpretation could be that if Treasury yields were higher two periods ago, it could signal market expectations of future economic risks or liquidity tightening, and such expectations could be driving the supply chain finance indicator lower in the current period to reflect market expectations of a slowdown in supply chain stress. In addition, the coefficients between the remaining variables reveal complex feedback effects between different areas. For example, the combined effect of positive or negative transmission between consumer confidence and bank NPL ratios provides further evidence of the coexistence of short-run information transmission and long-run dynamic adjustment mechanisms in the market (Hamilton, 1994; Lütkepohl, 2005).

For the U.S. sample, due to the choice of a single-order lag for the information criterion, we constructed only a 1st order VAR model with an AR coefficient matrix reflecting the effect of each variable in the previous period on the current value. Again, some typical negative relationships are observed in the U.S. data. For example, in some pairs of key variables, Treasury yields or other financial market indicators in the previous period have a dampening effect on a current economic variable, thus indicating a faster market correction mechanism to shocks in the short run. Overall, the negative transmission effects in the U.S. model suggest that higher levels of the previous period's indicators can have an inverse effect on current economic activity or market sentiment, which may reflect the characterization of risk spillovers and adaptive market adjustments (Acemoglu et al., 2015). Compared to the Chinese data, the U.S. single-order model captures a more immediate response, and the negative effects help mitigate the excessive transmission of some of the shocks in the system.

4.3.2 Result of rolling window Granger causality test

Granger causality tests were conducted for each combination of variables for the two countries separately using the rolling window method. In the overall sample most of the time the causality between the variables is relatively stable and are presented insignificant, but in the specific crisis period, such as 2013-2015, 2016-2017 and 2020-2022, the partial causality is significantly strengthened ($p-value < 0.05$). This suggests that during crises, the interactions between variables may be amplified through financial or economic transmission mechanisms, creating a significant "contagion effect". (See appendix for detailed diagrams)

Table 4.8 Part Result of Granger causality test

	CN		**U.S.**	
	Positive	**Negative**	**Positive**	**Negative**
SAME VARIATION	SBI_CN→CNCCI CNZEW→SBI_CN CNZEW→CNTTBY CNNPL→GSCPI	GSCPI→CNZEW GSCPI→CNTTBY	SBI_US→USCCI USZEW→SBI_US USZEW→USTTBY USNPL→GSCPI	GSCPI→USZEW GSCPI→USTTBY

DIFFERENCE VARIATION	SBI_CN→GSCPI GSCPI→SBI_CN GSCPI→CNNPL CNZEW→CNNPL CNTTBY→CNCCI CNTTBY→CNNPL	GSCPI→CNCCI SBI_CN→CNZEW	SBI_US→USZEW USCCI→USTTBY USNPL→USTTBY	USCCI→GSCPI

1) Explanation of China

Against the background of global economic volatility and geopolitical tensions, the gradual deepening of the impact of SBI_CN on the GSCPI and CNCCI illustrates the key position of China in the global supply chain system. As the global dependence of Chinese manufacturing rises, its internal bottlenecks are quickly transmitted globally, triggering fluctuations in the GSCPI. At the meantime, supply chain bottlenecks compress market supply, triggering higher prices and deteriorating consumer expectations, thereby dampening Chinese consumer confidence.

The enhanced impact of GSCPI on SBI_CN and CNNPL is mainly due to the fact that the tension in the global chain is directly reflected in the rising cost of imports and export constraints, which exacerbates the financial pressure on domestic enterprises and creates a credit risk for the banking system.

CNZEW, as a comprehensive representation of the operating conditions of enterprises, has an enhanced impact on the GSCPI, CNTTBY, and CNNPL, which suggests that the expectations of business operations changes are working inversely on supply chain management, capital market pricing and financial risks. CNTTBY reflects the market’s reaction to macroeconomic trends and inflation expectations and has a deepening impact on CNCCI and CNNPL. High yields often correspond to inflationary expectations or tight credit conditions, which can depress consumer confidence and raise borrowing costs, triggering a rise in non-performing loans. The increased impact of the CNNPL on the GSCPI reflects the potential constraints that the health of the financial system can impose on the functioning of global supply chains — risky lending erodes corporate credit, limiting capacity expansion and raw material sourcing, which in turn affects global supply chains.

It is worth noting that the impact of the GSCPI on the CNZEW, CNCCI and CNTTBY has gradually diminished, suggesting that China's economy is improving its ability to fight against crises and weakening its response to fluctuations in the global supply chain. Chinese gradually constructed domestic macro-circulation system and policy hedging mechanisms have enhanced its buffering capacity against external shocks.

In 2013-2015, China faced economic downward pressure, overcapacity in some industries, debt risk problems gradually became obvious, and foreign exports faced uncertainty in the international market, leading to a significant shock in the Chinese stock market in 2015.In 2016-2017, after macroeconomic adjustments, which led to a more perfect market mechanism and gradually favorable market expectations, which drove dynamic adjustments among the indicators. From the more obvious one-way influence gradually changed to mutual influence. At the same time, the Sino-US trade friction has begun to emerge, and global policy uncertainty has risen, making the supply chain reaction more violent. In 2020-2022, COVID-19 has an unprecedented impact on China and the world, logistics interruption of consumption and investment fluctuations exacerbate economic uncertainty and market risk, and the impact of the indicators has intensified. It is worth mentioning that the impact of CNZEW on SBI_CN is enhanced, while the reverse impact of SBI_CN on CNZEW is weakened, a phenomenon that fully illustrates that digitalization, informatization and the new economic field, represented by CNZEW and GSCPI, are gradually coming to the fore after COVID-19, and the impact of the traditional model, represented by SBI_CN, is increasing, while the feedback from the traditional model is weakening.

2) Explanation of the US

The gradual deepening of the impact of SBI_US on USZEW and USCCI illustrates the real economy's high dependence on supply chain stability. With the increasing trend of manufacturing repatriation and localized production in the US, the direct impact of supply chain disruptions on business operations and consumer expectations is becoming more and more evident. For example, raw material shortages and logistical blockages can lead to higher costs and damaged profits, thus reducing business confidence; at the same time, companies will pass on the increased costs to consumers to raise commodity prices, suppressing consumers' willingness to spend and confidence.

The deepening impact of USZEW on SBI_US and USTTBY suggests that when firms' confidence declines, their behavior in adjusting orders, inventories, and production plans directly exacerbates supply chain volatility. In addition, declining business confidence depresses market interest rate expectations, a change that can lead to adjustments in Treasury yields.

The strengthening influence of the USCCI on the USTTBY suggests that consumer confidence is increasing its impact on interest rates. Stronger confidence usually implies a rise in potential consumption heat, which pushes up inflation expectations and drives long-term interest rates upwards. Conversely, low confidence weakens expectations of future growth, steering yields downward.

The gradual deepening of the USNPL on USTBY is the relationship between the financial system and capital markets. A high USNPL indicates rising credit risk in the banking system, which could trigger expectations of credit tightening and policy easing, thus affecting long-term interest rate movements.

Meanwhile, the diminishing impact of the GSCPI on the USZEW and USTTBY suggests that the US economy is becoming less sensitive to external supply chain volatility. This is closely related to the U.S. promotion of ‘manufacturing repatriation’ and regionalized supply chain layout, which makes it less dependent on global chains.

In additional, the reduced impact of the USCCI on the GSCPI also suggests that the response of US internal demand to changes in the global supply chain has weakened. On the one hand, the U.S. consumption structure has become more diversified; on the other hand, improved supply chain elasticity has made changes in consumption no longer strongly transmitted to the global supply and demand balance.

From 2013 to 2015, the U.S. economy was in the recovery phase after the financial crisis, and the aftermath of the European debt crisis, the plunge in oil prices, and the shift in global monetary policy triggered a rise in economic uncertainty, which strengthened the correlation between the variables. 2020-2022, the new crown epidemic's dramatic impact on the supply chain has amplified the transmission effect, especially in the U.S. domestic health care, consumption, logistics, and many other areas are under pressure to cut off supplies, strengthening the variable linkages between supply chain issues, bank credit risk, and consumers.

3) Comparation

Comparing the impact paths of supply chain-related variables in China and the US, it can be found that there is a high degree of consistency in the significant deepening of the impacts of the two countries during the crisis period (2013-2015, 2020-2022), which indicates that global shocks (such as epidemics, oil price fluctuations, and changes in global financial policies) have an amplifying effect on the fluctuations of indicators in the two countries and the mutual changes between indicators. This indicates that global shocks (e.g., epidemics, oil price fluctuations, global financial policy changes) have an amplifying effect on the fluctuations of the indicators in both countries, as well as on the interactions between them. The impact of supply chain bottlenecks on the CCI and Economic Sentiment Index has been deepening in both China and the US, reflecting the increasing importance of supply chain stability on consumption and business expectations. At the same time, the impact of both the CCI and the Enterprise Prosperity Index on the supply chain bottleneck index of China and the US has been strengthened, indicating that enterprises, as the core nodes in the supply chain, have the ability to inversely regulate their expectations and behaviors on the pressure of the whole chain. The deepening impact of the CCI of China and the US on the yields of their own 10-year treasury bonds also reflects the influence of consumer confidence on macro interest rates.

The difference is that CNNPL has a stronger impact on GSCPI while USNPL has a stronger impact on USTTBY, suggesting that China's financial risks are more likely to spill over into the global supply chain, whereas in the US financial risks are mainly embedded in the adjustment of the domestic capital market. The deepening impact of CNTTBY on both CNNPL and CNCCI reflects the more diversified paths of interest rates as a regulatory tool in China; whereas in the US, USCCI and USNPL are more dominant on USTTBY, showing that market expectations are the most important factor influencing changes in interest rates. In the US, the USCCI and USNPL dominate the USTTBY more prominently, reflecting that market expectations are the most important influence on interest rate changes.

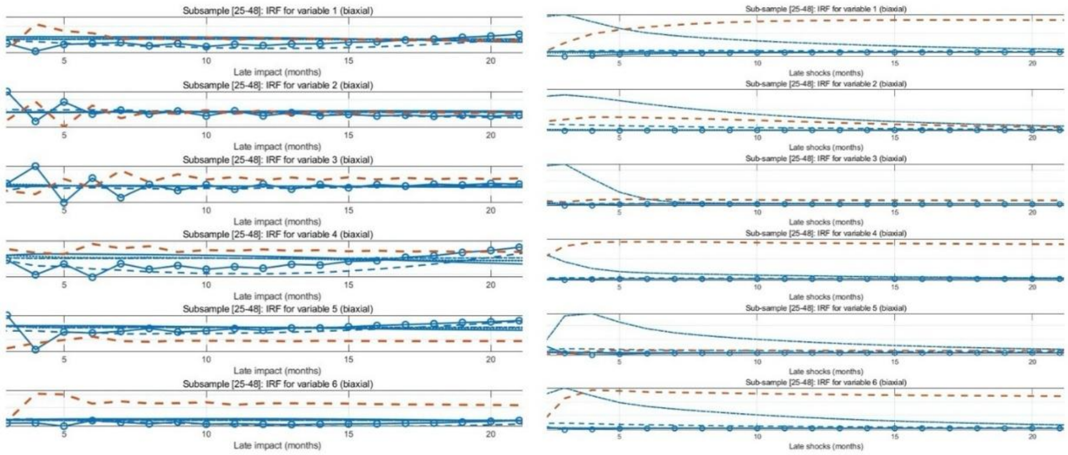
The impact of the GSCPI on the economic sentiment index and Treasury yields has weakened in both China and the US, but it has declined more in the US, a phenomenon that is reflected in the US policy of industrial repatriation and global chain adjustment, while the weakening of the GSCPI in China reflects the gradual effect of the domestic macro-cycling strategy. In addition, the USCCI's impact on the GSCPI diminishes, while the CNCCI is strengthened by the SBI_CN, suggesting that Chinese consumers are more sensitive to the state of the supply chain in their home country.

4.3.3 Impulse response analysis results

Based on the causality test, we find that there is basically a causal relationship between the variables no matter in the period of stability or crisis. On this basis, this section builds an impulse response model for China and the US to calculate the dynamic transmission effects between variables at an information shock of one standard deviation in size. In the figure, each subplot usually corresponds to one explanatory variable, while the figure contains six curves corresponding to 6 variables: variable 1 - CNNPL, USNPL, variable 2 - CNTTBY, USTTBY, variable 3 - CNCCI, USCCI, variant 4 - CNZEW, USZEW, variant 5 - GSCPI, and variant 6 - SBI_CN, SBI_US.

The horizontal coordinates of the graphs indicate the time series from 0 to 24 months after the shocks occurred (2013-2015, 2016-2017, and 2020-2022), while the vertical coordinates reflect the magnitude of the response generated by the explanatory variables to the corresponding shocks (positive or negative indicates upward or downward movement).

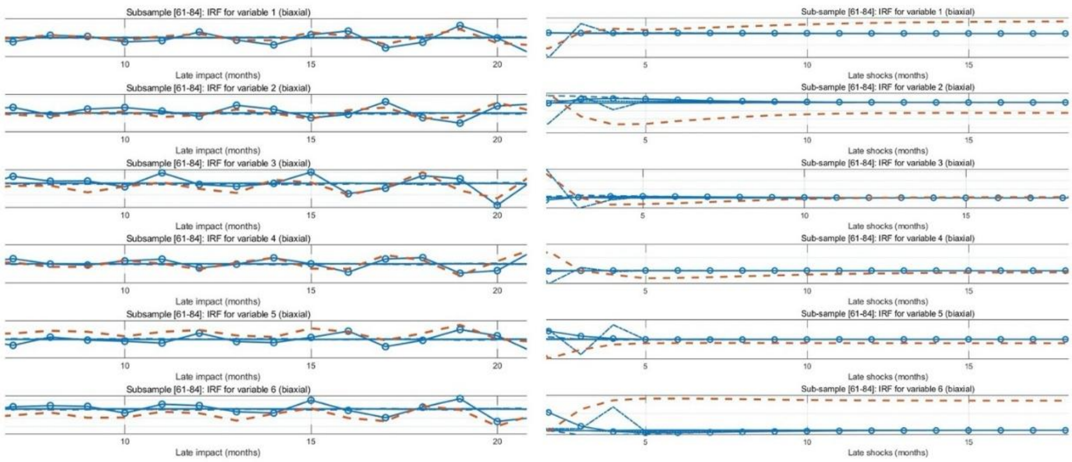
Figure 4.3 2013-2015 Impulse Response Analysis during the China-U. S Crisis



Between 2013 and 2015, variables in both countries showed a rapid response to the shock, with a particularly significant response within the first five months, followed by gradual stabilization, characterized by alternating positive and negative responses, and a shorter overall duration of the shock. The U.S. market adjusted to the shock significantly faster than China's, and the pace of recovery was more rapid.

During this period, Chinese economy faced significant downward pressure, corporate and consumer confidence suffered, market risk sentiment rose, and the stock market shook violently. The figure (left figure) shows that GSCPI and SBI_CN reacted significantly to the shocks, with increased volatility, especially during the crisis. The persistently low CNZEW reflects a lack of confidence in the economy as a whole, and declining business confidence further drives the upward trend in the SBI_CN, signaling intensifying supply chain problems. The US was in the recovery phase after the European debt crisis and was affected by the sharp fall in crude oil and commodity prices, with supply chain pressures remaining relatively low and maintaining an overall stable level in this period. The figure (right figure) shows that the USCCI is more sensitive to shocks, reflecting the rapid feedback of residents' expectations to external shocks under its economic recovery.

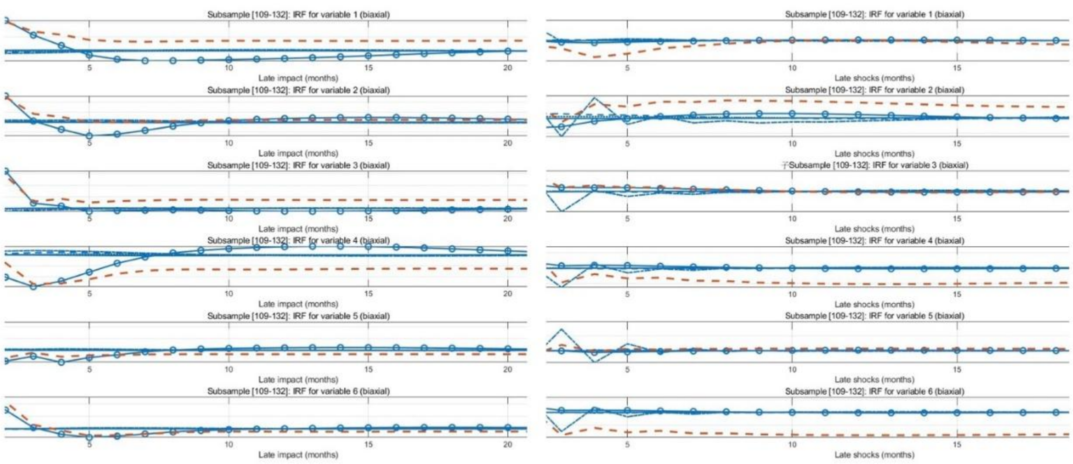
Figure 4.4 2016 – 2017 Impulse Response Analysis during the China- U.S. Crisis



Between 2016 and 2017, economic variables in China and the U.S. showed a markedly differentiated response to external shocks: the U.S. market responded quickly, stabilizing within five months of the shocks, while the Chinese market lagged in its response, showing significant changes only after about 17 months, after being relatively flat overall.

SBI_CN (left figure) increased its volatility during the crisis, suggesting that supply chain segments have become more sensitive to external uncertainties. During this period, Chinese economy faced downward pressure, and market risk appetite remained on the rise as business and consumer confidence weakened under the pressure to prevent and control systemic risks and capital outflows. In contrast, the U.S. economy has entered a recovery path, driven by a cycle of interest rate hikes and fiscal expansion, accompanied by rising inflation. USCCI (right figure) in the US is more sensitive to external shocks, reflecting the faster and more pronounced feedback of residents' expectations to policy and market signals against the backdrop of an economic rebound.

Figure 4.5 2020-2022 Impulse Response Analysis during the China- U.S. Crisis



Between 2020 and 2022, the economies of both China and the US were hit hard by the COVID-19. A sudden outbreak in the early stages of the epidemic leads to disruptions in global supply chains, production stagnation, and a sharp drop in consumption. Economic variables can be seen to respond immediately to the external shock, but the response is short-lived and quickly returns to a steady state. Unlike the response during the previous two crisis periods, China experienced a more pronounced and long-lasting negative response in economic variables during this crisis.

Chinese adherence to strict control and regulation during this period resulted in a longer period of restricted economic activity and a relative lag in the recovery of consumption, logistics and transport, and enterprise production. Pressured business expectations and lack of confidence led to a strong CNZEW response (left figure). The SBI_CN shown in the left panel exhibits obvious volatility characteristics, which suggests that supply chain system of China exhibits a high degree of sensitivity in the face of external shocks. This volatility is not only affected by disruptions to international transport but is exacerbated by internal logistics and production constraints imposed by frequent domestic closure and control policies. In contrast, although the US also experienced a large economic shock in the early 2020s, its relatively lax containment policies, coupled with timely and large-scale fiscal stimulus measures, led to a faster recovery in market confidence and business activity. The reaction of the US variables, while equally intense, was of shorter duration and was followed by a period of gradual repair.

4.4 Rolling regression analysis results and closed-loop display of infection paths

In this subsection, in order to capture the time-varying nature of the dynamic interactions among the banking industry, consumer behavior, and supply chain finance indicators in the Chinese and U.S. markets, we use a 24-period (i.e., 2-year) rolling-window methodology to estimate local regressions for each combination of variables. Considering that each industry contains two variables, a total of 2 × 2 × 2=8 combinations are constructed in this study. Due to the image size dimension problem, we will show some of the graphs and the rest will be put in the appendix. In addition, based on the results of the rolling regression analysis, we made a structural diagram of the crisis contagion loop in China and the United States during the so-called three crisis periods.

Figure 4.6 Closed-loop network diagram for China (crisis period 2013.1-2014.12)

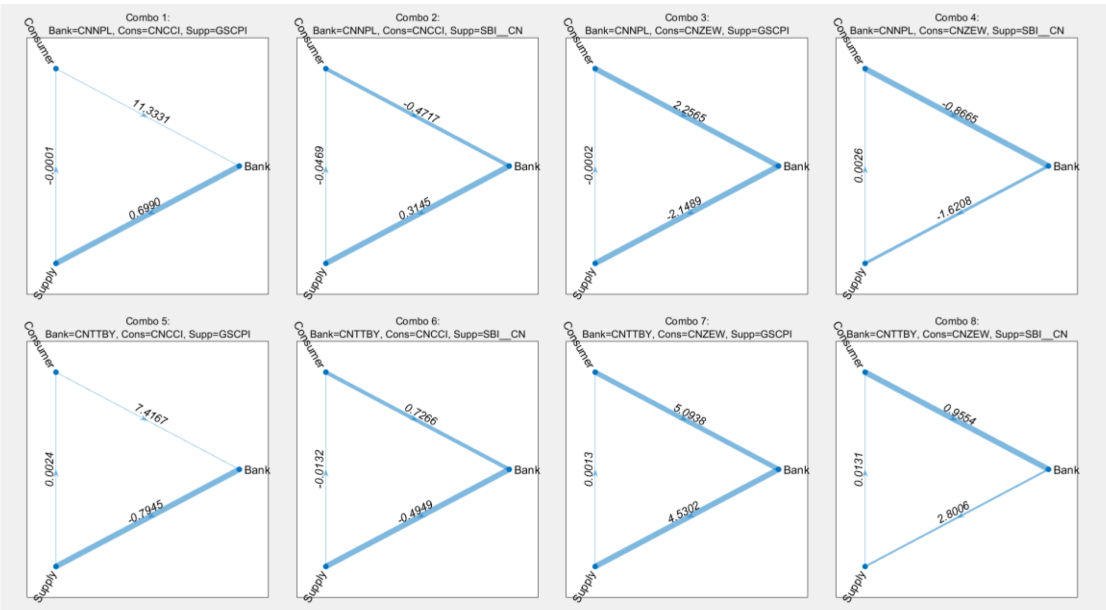


Figure 4.7 Closed-loop network diagram for China (crisis period 2016.1-2017.12)

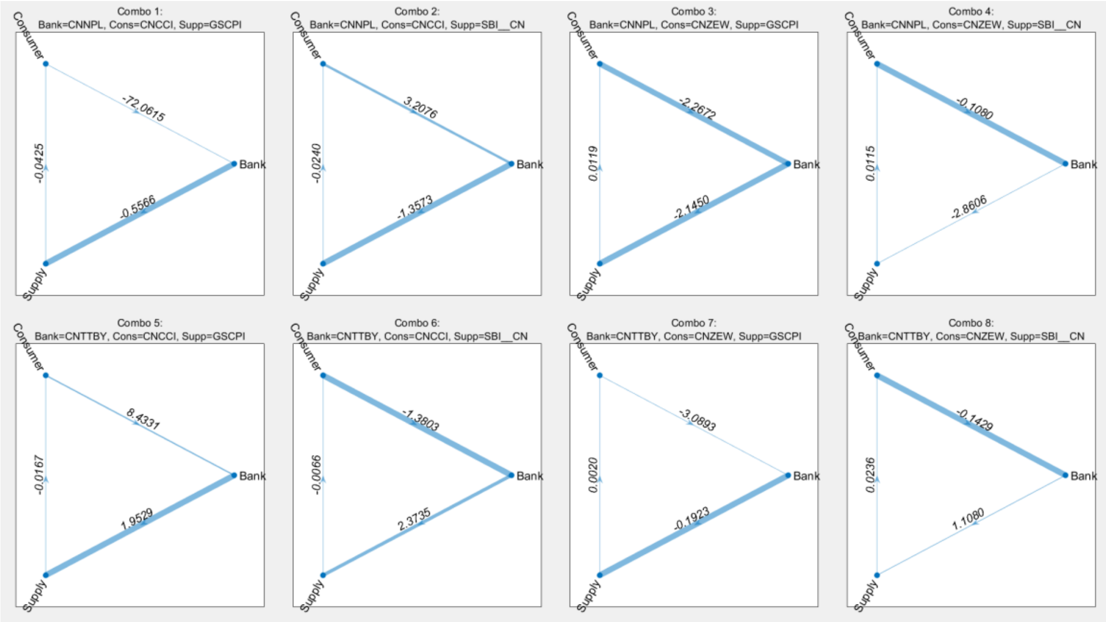
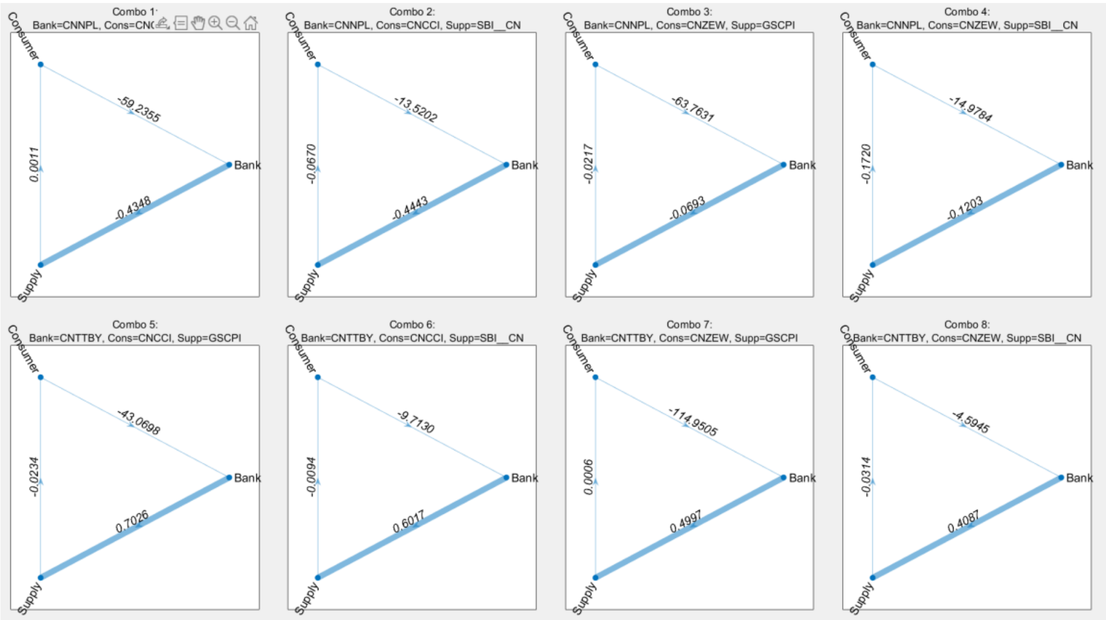


Figure 4.8 Closed-loop network diagram for China (crisis period 2020.1-2022.12)



Since there are many closed-loop results in the chart, we will not go into details here. After performing rolling regression analysis on eight variable combinations in the Chinese data, in Figure 4.6, we observed a group of combinations (10-year treasury bond yield, China's business climate index, and global supply chain pressure index) during the 2013-2014 Chinese economic crisis, which showed more consistent and significant dynamic transmission effects in the closed-loop network diagram during the crisis. The analysis of the figure shows that in the direction of consumer → bank: The average coefficient is 5.0938. This is an extremely thick line indicating that when the economic sentiment index (CNZEW) rises in the previous period, the current 10-year treasury bond yield (CNTTBY) rises significantly. In other words, an improvement in consumer sentiment or market expectations acted as an extremely strong positive driver of risk transmission to banks during that crisis. In the direction of Banks → Supply Chain: The average coefficient is 4.5302. This value suggests that a rise in banking indicators (e.g., increased risk or higher interest rates) also has a very significant transmission effect on Supply Chain Finance (GSCPI), indicating that a change in the state of the banks triggers a significant reaction at the supply chain level. In the supply chain → consumer direction: the average coefficient is only 0.0013, which is positive but so small that it can almost be considered as a "weak effect". This means that the feedback effect of changes in supply chain conditions on consumer indicators is almost negligible but there is a link between the two. This phenomenon suggests that there was a strong positive interaction between consumers and banks during the 2013-2014 crisis, and that fluctuations in banking indicators largely amplified positively on the supply chain; changes in the supply chain component fed back only marginally to the consumer level, and although the link between the two is weak, the data suggests that there is a link between the two. There is a link between the two.

In Figure 4.7, among the China closed-loop network diagrams we choose Combo 3 (Bank=CNNPL, Cons=CNZEW, Supply=GSCPI) closed-loop network diagram under the crisis period for detailed interpretation. Cons=CNZEW→CNNPL: The coefficient is -2.2672, the maximum value of this line is negative, which means that when the Cons=CNZEW rises by 1 unit in the last period, the CNNPL falls by 2.2672 units on average in the same period, which has a strong negative relationship with each other. The two have a very strong negative relationship. This strength implies that when enterprises are more optimistic about the future business environment, the pressure of bad loans in the banking system will be eased simultaneously, thus forming a reverse regulation effect. Bank Non-Performing Loan Ratio (CNNPL) → Global Supply Chain Stress Index (GSCPI): the coefficient is -2.1450, also negative and with a large absolute value, suggesting that the GSCPI instead goes down significantly when bank NPL ratio rises (or vice versa). When banks' risk rises, they may tighten capital controls and credit supply, thereby suppressing some outward-looking or risky supply chain activities, leading to a statistical decline in supply chain activity or “stress” indicators (Acemoglu et al., 2015). This result suggests a significant negative transmission of changes on the banking side to the supply chain side during the crisis period. The coefficient of the Global Supply Chain Pressure Index (GSCPI) → Corporate Sentiment Index (CNZEW) is 0.0119 This coefficient is very small and positive, indicating that a slight increase in supply chain pressure is accompanied by a slight increase in the Corporate Sentiment Index, which can be considered almost as a “weak positive effect”. From an economic perspective, this could mean that during 2016-2017, there was a slight isotropic linkage between fluctuations in certain segments of the supply chain and domestic business expectations, but the magnitude was very small, suggesting that the supply chain's feedback path on business sentiment was not very prominent during this period of crisis (Glasserman & Young, 2016).

In Figure 4.8, we provide a detailed interpretation of the closed-loop network graph formed for Combo 7 (Bank=CNTTBY, Consumer=CNZEW, Supply=GSCPI) for the 2020-2022 crisis period. The coefficient in the direction of the bank 10-year treasury bond yield (CNTTBY) → Global Supply Chain Stress Index (GSCPI) is 0.4997 This is the thickest edge in the graph, indicating that when bank interest rates or the related risk indicator (CNTTBY) increased in the previous period, the Global Supply Chain Stress (GSCPI) also showed a positive change in the current period. In other words, volatility at the bank level is effectively transmitted to the supply chain side, suggesting that changes in interest rates or bank-side stress have a more pronounced upward or “isotropic amplification” effect on GSCPI in the 2020-2022 timeframe (Acemoglu et al., 2015). In the Global Supply Chain Stress Index (GSMI) (Acemoglu et al. The average coefficient in the direction of the Global Supply Chain Stress Index (GSCPI) → Economic Sentiment Index (CNZEW) is 0.0006, which is a positive but very small value. It means that when the supply chain stress index is slightly upward, there is a small boost to the economic sentiment (CNZEW). In the enterprise sentiment index (CNZEW) → ten-year Treasury bond yields (CNTTBY) direction of the average coefficient of -114.9505 this line does not appear in the figure “thickest”, but numerically it is the largest negative coefficient of absolute value, indicating that when the previous period of enterprise sentiment index (CNZEW) This indicates that when the Economic Sentiment Index (CNZEW) rose in the previous period, the Bank Rate or Yield (CNTTBY) fell significantly in the current period (or vice versa). The large magnitude of the negative sign (-114.9505) suggests that firms' optimism about the future environment strongly inhibits the rise in interest rates or risk on the bank side, and that this counter-regulatory mechanism serves as a “buffer” in times of crisis (Acemoglu et al., 2015.);) As a whole, these three edges continue to form a closed loop in times of crisis.

Next, we will analyze the corresponding closed-loop network diagram for the United States.

Figure 4.9 Closed-loop network diagram for USA (crisis period 2013.1-2014.12)

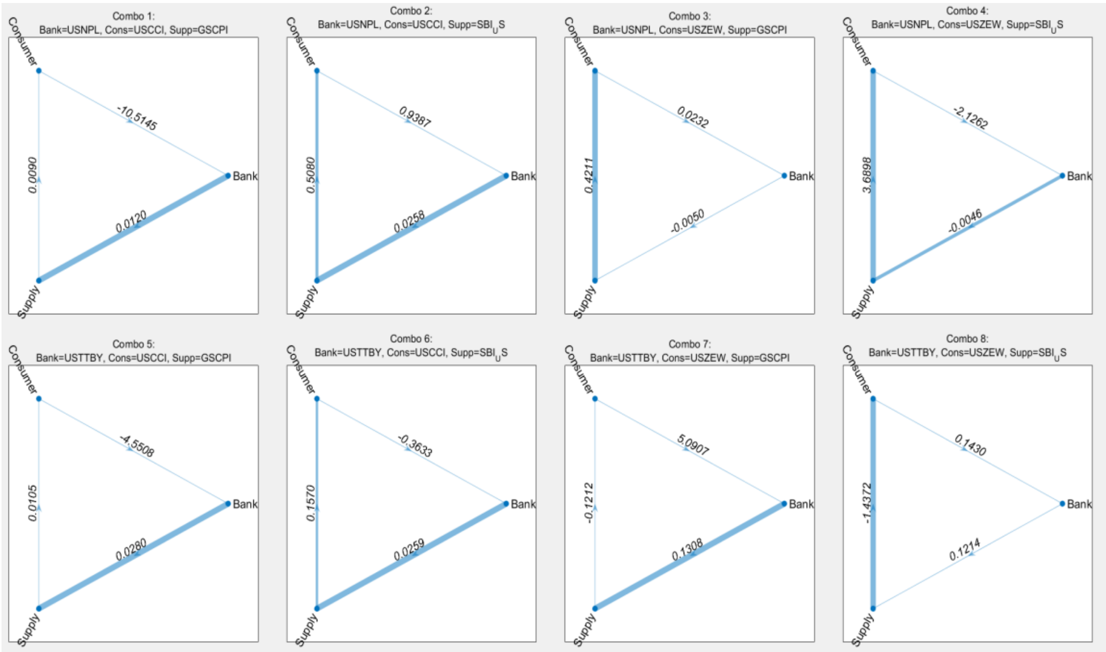


Figure 4.10 Closed-loop network diagram for USA (crisis period 2016.1-2017.12)

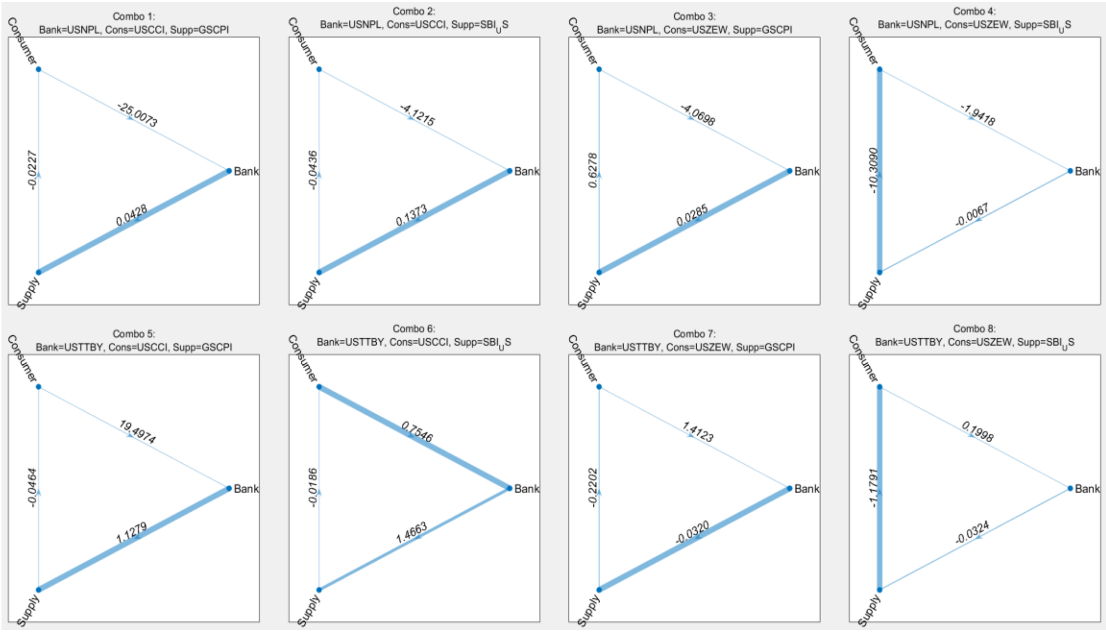
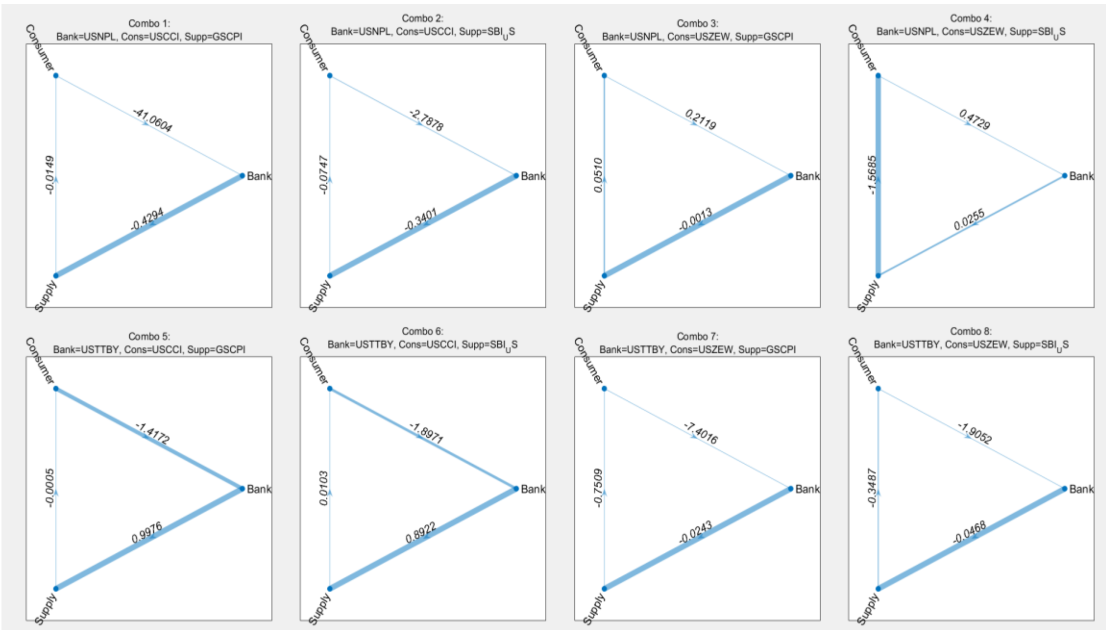


Figure 4.11 Closed-loop network diagram for USA (crisis period 2020.1-2022.12)



First of all, in Figure 4.9 is the closed-loop network diagram of the United States in 2013-2014, through the graphical analysis and computational analysis of Combo 4, we know that: the average coefficient in the direction of the U.S. Economic sentiment index (USZEW) → U.S. bank non-performing loan ratio (USNPL) is -2.1262 This connecting coefficient is negative, and the value is relatively large, which indicates that when the previous period of the business sentiment or the Consumer Indicators (USZEW) rises, when the current period bank non-performing loan ratio (USNPL) tends to show a significant decline. This can be intuitively explained by the fact that an improvement in business expectations or market sentiment reduces the level of risk on the bank side, resulting in a corresponding reduction in the NPL ratio (Hamilton, 1994). The average coefficient in the direction of the USNPL → Supply Chain Bottleneck Index (SBI_US) is -0.0046 The negative coefficient of this line and its very small value (-0.0046) indicate that the magnitude of the impact of the increase in the NPL ratio of the banks on the Supply Chain Bottleneck Index during this crisis was relatively small. The average coefficient in the direction of the Supply Chain Bottleneck Index (SBI_US) → U.S. Economic Sentiment (USZEW) is 3.6898, which is the thickest line in the figure, indicating that when the Supply Chain Bottleneck (SBI_US) rose in the previous period, the Consumer or Economic Sentiment indicator (USZEW) showed a relatively large positive increase. While the traditional economic intuition is that "rising bottlenecks → falling business sentiment" is more common, the data in the context of the crisis may reflect a different kind of isotropic fluctuation: shortages or bottlenecks in certain areas suggest instead that the market is full of orders, companies are full of orders, and business expectations are not pessimistic. As a whole, these three edges continue to form a closed loop in times of crisis.

In Figure 4.10, this closed-loop network diagram of Combo 6 (Bank=USTTBY, Consumer=USCCI, Supply=SBI_US) is analyzed for the 2016-2017 U.S. data. The average coefficient in the direction of Consumer Confidence Index (USCCI) → U.S. Ten-Year Treasury Yield (USTTBY) is 0.7546 This is the thickest connecting line in this graph, indicating that when the Consumer Confidence Index (USCCI) rises by 1 unit in the previous period, the U.S. Ten-Year Treasury Yield (USTTBY) rises by an average of 0.7546 units in the same period, showing a significant positive relationship (Bank=USTTBY). This is a significant positive relationship. In the 2016-2017 market environment, upward consumer optimism pushes up expectations for future economic growth and inflation, thus raising the level of long-term Treasury rates. It could also be because optimistic consumer demand leads to tighter funding conditions or a signal from the Federal Reserve to raise interest rates, which drives up Treasury yields (Glasserman & Young, 2016). The average coefficient in the direction of the U.S. 10-

year Treasury yield (USTBY) → Supply Chain Bottleneck Index (SBI_US) is 1.4663. This coefficient is positive and larger, indicating that when 10-year Treasury yields moved up in the previous period, the Supply Chain Bottleneck Index (SBI_US) experienced a larger climb in the same direction in the current period. In other words, higher interest rates tended to significantly push up the pressures and bottlenecks faced on the financing or logistics side of the supply chain during the 2016-2017 period. The average coefficient in the direction of the Supply Chain Bottleneck Index (SBI_US) → Consumer Confidence Index (USCCI) is -0.0186, which is a negative value, but the magnitude is extremely small, implying that there is a dampening effect on consumer confidence in the current period when there is an increase in bottlenecks on the supply chain side in the previous period. Problems in the supply chain can dampen confidence on the consumer side, but here the data show that this negative shock was not very significant during 2016-2017, which may indicate that the optimistic expectations of U.S. consumers depend more on macro factors such as employment and income than on local fluctuations in supply chain logistics that are directly determined by the supply chain. As a whole, these three edges continue to form a closed loop in times of crisis

In Figure 4.11, a closed-loop network diagram of Combo 5 (Bank=USTTBY, Cons=USCCI, Supply=GSCPI) is analyzed for the 2020-2022 U.S. data. The line with an average coefficient of -1.4172 in the direction of Consumers (USCCI) → Banks (USTTBY) is the second thickest, representing the fact that when the U.S. Consumer Confidence Index (USCCI) rises by 1 unit in the previous period, the U.S. 10-year Treasury rate (USTTBY) declines by an average of about 1.4172 units in the current period, showing a significant negative correlation. Consumers who are overly optimistic about future demand or the economic outlook may induce certain policies or market behaviors to lower long-term Treasury yields. This may also be due to the fact that the market does not believe that consumer optimism will necessarily lead to interest rate hikes or tightening in certain crisis situations, but rather there may be an interaction effect such as “optimism + return of safe-haven funds”. The average coefficient in the direction of Banks (USTBY) → Supply Chain (GSCPI) is 0.9976, which is the thickest line, implying that when US 10-year Treasury yields rise in the previous period, Global Supply Chain Pressure (GSCPI) will show a positive pass-through of nearly 1:1 in the current period. The average coefficient in the direction of Supply Chain (GSCPI) → Consumer (USCCI) is -0.0005 The value is negative but small, suggesting that when global supply chain pressure rises in the previous period, there is a weak dampening effect on U.S. consumer confidence in the current period. Taken as a whole, these three edges form a relatively specific closed-loop structure. In the U.S. market in 2020-2022, if consumer confidence strengthens, it will instead lead to lower long-term Treasury yields (or if Treasury rates are constrained by other factors and fail to rise in tandem with optimism on the consumer side), whereas the direction of interest rates has a greater impact on the supply chain; and changes in supply chain pressures have a weak dampening effect on consumer confidence. With the traditional impression of “consumer demand expansion → interest rates rise → supply chain tension → consumption decline” continuous logic is different, here shows the first two rings of strong interaction (negative + positive), and ultimately back to the consumer side will appear weaker.

By comparing the closed-loop network diagrams of the US and Chinese markets during the crisis, we find that there is significant heterogeneity in the intertransmission of the three main segments (banks, consumers, and supply chain) across countries during the three time periods, mainly in terms of the direction and magnitude of the transmission:

In the period 2013.1-2014.12, in China, the combination of variables mainly relies on the positive effects of “Consumer → Bank” and “Bank → Supply Chain” to drive the closed loop, while the feedback from the supply chain to the consumer is small and not particularly significant. The feedback from the supply chain to the consumer is smaller and not particularly significant. In contrast to China, the U.S. variable set and in the 2013-2014 timeframe, “Consumer → Bank” is negatively inhibited, while “Supply Chain → Consumer” is strongly positively incentivized, and “Bank → Supply Chain” is weakly incentivized, creating a closed loop that relies heavily on “Consumer → Bank” and “Bank → Supply Chain” to drive the closed loop. The role of banks → supply chain is relatively weak, creating a two-way mechanism that relies heavily on the interaction between consumers and supply chain. The combination of variables in both countries has a weak edge in this time period, which means that risk or sentiment is not necessarily transmitted smoothly between different nodes. In the case of China, the positive contagion of “upward corporate optimism → upward synchronization on the bank side → supply chain is also pushed up” during this time reflects a strong correlation between real demand and bank risk, and the lack of feedback from the supply chain to the consumer implies that crisis prevention and control should be more focused on the front-end interaction between the consumer or the enterprise and the bank. For the U.S., consumer optimism significantly reduces bank NPL ratios, while changes in supply chain stress significantly boosts consumer sentiment, suggesting that the supply chain is more critical in shaping “demand expectations” in the U.S. market at the macro-policy level, and that the impact of bank risk on the supply chain is weaker.

Overall, during the period 2016.1-2017.12, the closed loop in the Chinese market during this period relies on a strong negative transmission of “corporate sentiment → bank risk” and a negative transmission from banks to the supply chain, while the feedback from the supply chain to corporations appears to be somewhat weak. This suggests that risk transmission in the Chinese market is mainly reflected in the fact that improved business confidence significantly moderates bank risk and supply chain stress. The Chinese market relies mainly on the strong negative transmission of corporate sentiment to bank risk, forming a closed loop of regulation centered on corporate confidence. The closed-loop network in the U.S. market exhibits the following characteristics: first, the improvement of consumer confidence reduces bank risk through a more direct negative effect; second, the transmission effect of banks to the supply chain is very weak; and lastly, supply chain bottlenecks, however, have a very significant positive incentive effect on consumer confidence, forming a positive closed-loop with the feedback from the supply chain as the main driving force. This structure suggests that the U.S. market relied heavily on signals from the supply chain segment to inspire consumer enthusiasm during that period, and that the direct transmission of bank risk to the supply chain end would have been relatively small. The U.S. market, on the other hand, exhibits strong positive feedback from the supply chain to consumer confidence, allowing the main transmission path in the closed loop to be concentrated between the supply chain and the consumer. This difference not only reflects the inherent differences in the structure of the financial and real economies of the two countries, but also reveals that in times of crisis, policymakers should focus on regulating the key links to prevent risk spillovers according to the characteristics of their respective markets. For example, China could focus on stabilizing corporate expectations to reduce bank risk, while the United States needs to focus on the incentive effects of supply chain bottlenecks on consumer expectations in order to better target macro policies.

Over the 2020-2022 period, a significant upturn in business or consumer sentiment could significantly depress bank interest rates or risk; while an upturn in bank interest rates could moderately push up supply chain financial pressures; however, fluctuations in supply chain linkages would have less of an impact on business confidence. This structure suggests that the linkage between business vigor and bank risk (or interest rate levels) is extremely strong in the later stages of an epidemic shock, while the supply chain takes more of the impact from the bank side with limited feedback to business sentiment. For the U.S., rising consumer confidence moderately reduces long-term Treasury yields (or bank risk), while rising interest rates push up global supply chain pressures relatively significantly, but there is no significant reverse shock on the supply chain side to consumers. During the epidemic, the U.S. market's “bank→supply chain” became the main amplification path due to interest rate policy and global logistical stress, while consumer confidence played a somewhat negative moderating role in stabilizing or dampening interest rate rises. This suggests that the U.S. market in the latter part of the epidemic mainly amplified or suppressed risk through the “Banks ↔ Supply Chain” pathway, while consumer confidence played a somewhat negative regulatory role in depressing interest rates.

5. Conclusions and discussion

This study integrates multi-methodological tools such as VAR models, rolling regression analysis, time-varying causality tests, and closed-loop network diagrams in order to portray the dynamic relationships among the variables in the three domains of banks, consumers, and supply chains and to reveal the details of the risk transmission paths. The VAR models provide a holistic view of the dynamic correlations among the macro-variables and the response to shocks, while rolling regressions capture the coefficients evolution over time to identify the rolling regression captures the evolution of the coefficients over time to identify changes in the strength of the relationship across time, the time-varying causality test reveals the significance of the causal direction in different windows, and the rolling regression analysis and the closed-loop network diagram visualize the primary and secondary channels of cross-industry risk transmission among banks, consumers, and supply chains. The use of multiple methods corroborates each other, improves the accurate depiction and understanding of the cross-industry risk transmission mechanism, and shows obvious advantages in portraying complex financial transmission paths.

By analyzing and comparing the 2013-2014, 2016-2017, and 2020-2022 crisis periods, we find that the risk transmission paths among banks, consumers, and supply chains in China and the United States share commonalities as well as significant differences. Both countries show a closed-loop transmission chain of “supply chain pressure→consumer confidence→bank risk”, but the intensity and direction of the different links are different, reflecting the heterogeneity of the risk transmission mechanism under the differences in economic structure. The contagion chain in the Chinese market is mainly dominated by the interaction between consumer sentiment and bank risk: changes in consumer (corporate) confidence have a significant impact on bank credit risk, and even show a strong positive linkage effect during certain crisis phases (e.g., optimistic expectations are accompanied by an upward trend in bank interest rates, which exacerbates bank risk exposure), and the fluctuations in bank risk or interest rate levels will also be significantly transmitted to the supply chain finance. pressure, amplifying shocks in the real economic chain. However, the feedback effect of supply chain conditions on consumer confidence is weaker but positive over multiple crisis periods, implying that shocks in the supply chain are transmitted back to the consumer side in a slightly weaker form. In contrast, the risk transmission path in the U.S. market is more focused on the two-way coupling of consumer confidence and supply chain stress: on the one hand, changes in supply chain bottlenecks have become important signals affecting U.S. consumers' expectations, and the rise in supply chain stress in earlier crises (e.g., 2013-2014) had unexpectedly been accompanied by a significant increase in consumer confidence, suggesting that in particular contexts Supply chain shocks may boost demand expectations through factors such as full orders; on the other hand, fluctuations in consumer confidence also affect supply chain conditions through the interest rate and credit channels, with rising consumer optimism in mid- to late-crisis (e.g., 2016-2017 and epidemic-shocked 2020-2022) tending to push long-term interest rates upward and further exacerbate supply chain stress. Overall, risk contagion in the U.S. relies more on the interaction between the consumer and supply chain sides, with relatively limited direct impacts of banking factors on the supply chain, mainly indirectly through changes in the interest rate environment, while risk propagation in China relies more on the impact of consumer (business) confidence on the banking system and the transmission of risks from the banking side to the supply chain, with the supply chain forming only a weak feedback to the consumer side. This comparative result emphasizes the differences in the cross-industry risk transmission mechanisms between the two countries: the United States emphasizes more on the coupled feedback between real demand expectations and supply chain shocks, while China is dominated by the front-end interaction between the financial side (bank-credit) and the demand side (consumer-business confidence), with relatively weak feedback from the last link in the closed loop.

The above empirical analysis brings out a number of important findings and insights. First, there is a high degree of linkage between consumer confidence and bank risk, whether it is positive resonance (e.g., improved confidence leads to higher bank risk appetite) or negative moderation (e.g., declining confidence leads to higher bank delinquency), and the two often form a close and synchronized fluctuation relationship in crisis situations, which suggests that stabilizing the expectations of consumers and firms plays a key role in preventing banking sector risks. Second, the reverse impact of the supply chain on consumers is generally weak, and the asymmetry of transmission in the latter part of the chain means that pure supply chain shocks are not enough to shake the expectations of the consumer side; however, during certain periods in the U.S. market, supply chain bottlenecks and consumer confidence formed an obvious two-way coupling, and this coupling has become one of the core links in the transmission of risk in the U.S., which reflects the importance of supply chain stabilization in maintaining consumer confidence. Third, regardless of the United States and China, both countries have a closed-loop contagion channel between financial and real economic risks, but the closed-loop feedback in the United States is stronger and more concentrated, especially in the interaction between consumer confidence and the supply chain, while China's closed-loop is characterized by more unidirectional conduction dominance and weakened feedback. These differences reflect the inherent heterogeneity of risk contagion mechanisms under different economic structures.

The essential differences in risk transmission paths and feedback mechanisms between China and the United States reflect the different characteristics of the structure of their respective financial systems and real economies. In terms of policy, China should focus on stabilizing business and consumer confidence and mitigating bank risks, while the United States should focus on how to improve supply chain robustness and curb excessive supply chain transmission to consumer expectations. These findings provide strong empirical support for the formulation of differentiated macroeconomic control and financial stability policies.

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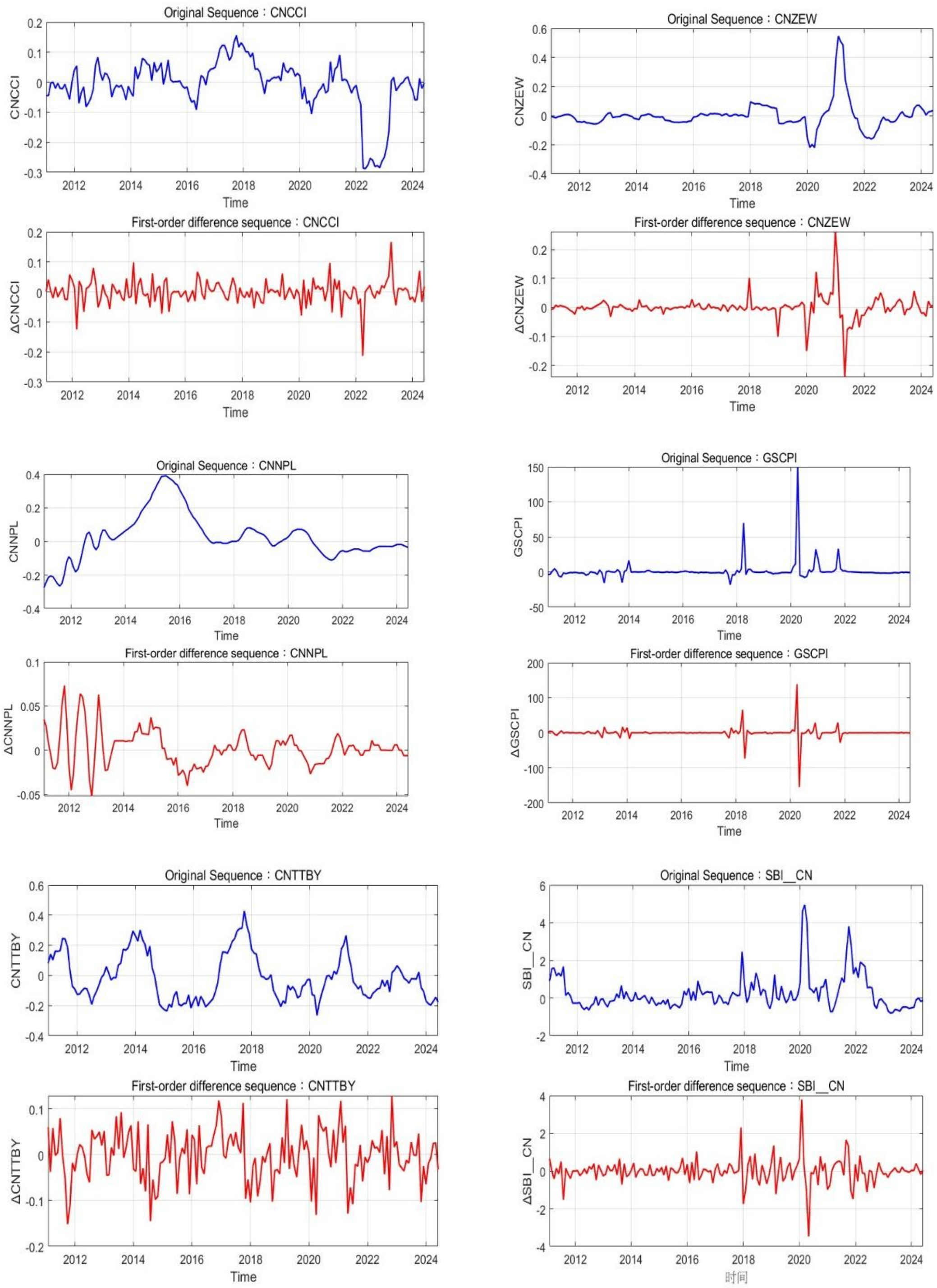
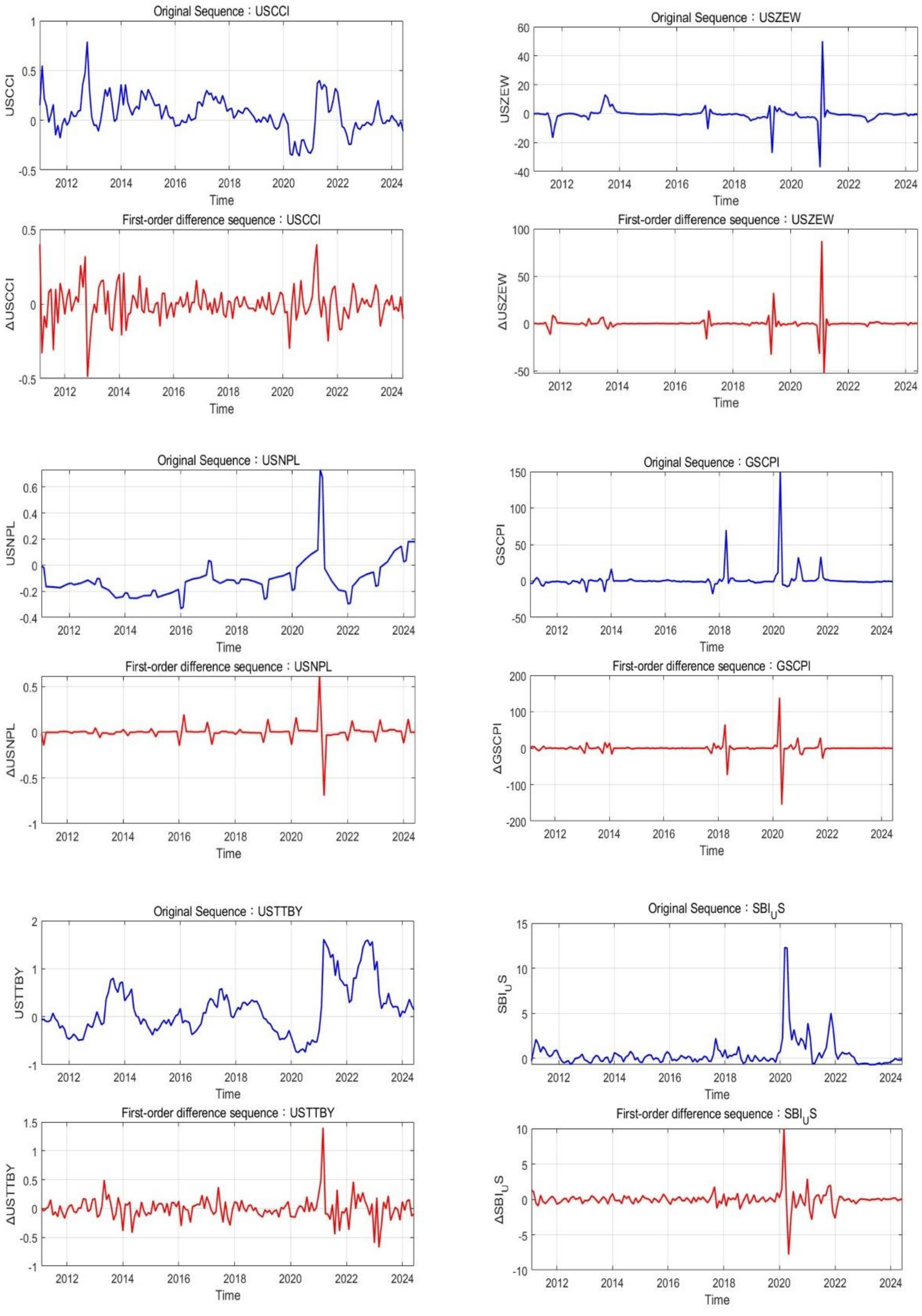
Appendix

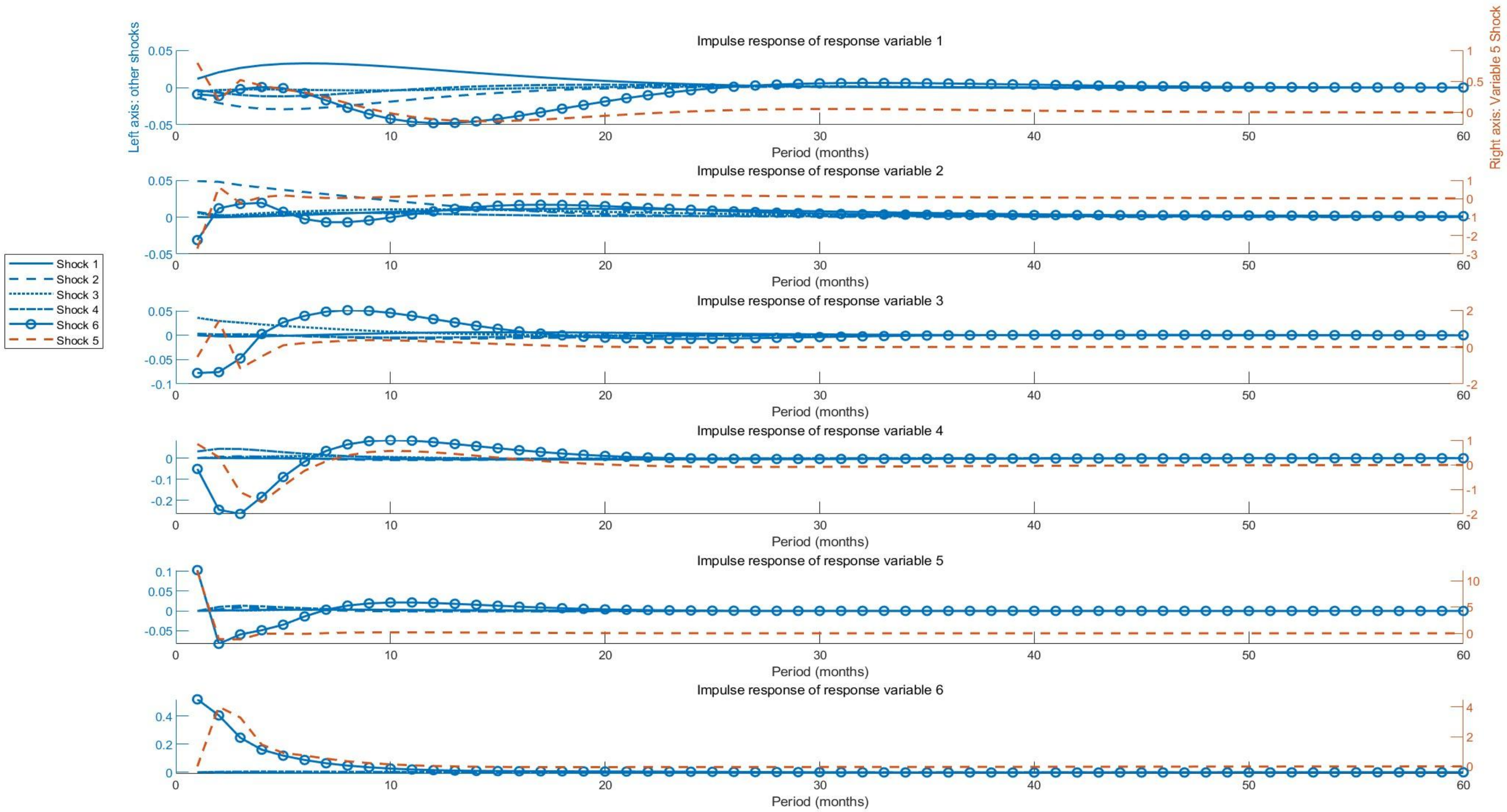
App. Figure 4.1: The data after Unit root test for China



App. Figure 4.2: The data after Unit root test for USA

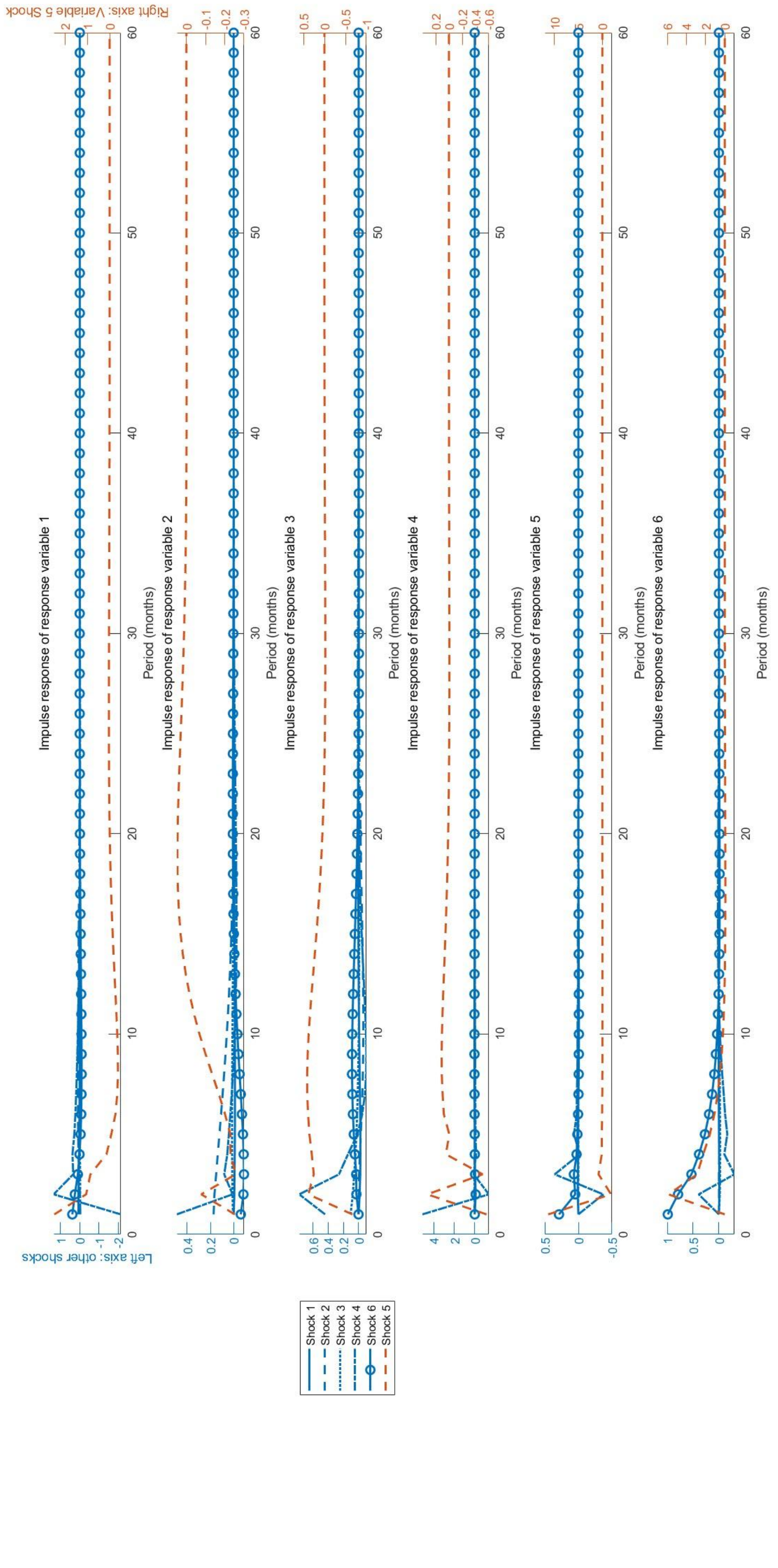


APP. Figure 4.3 Impulse Response Plots for Three Sectors in China

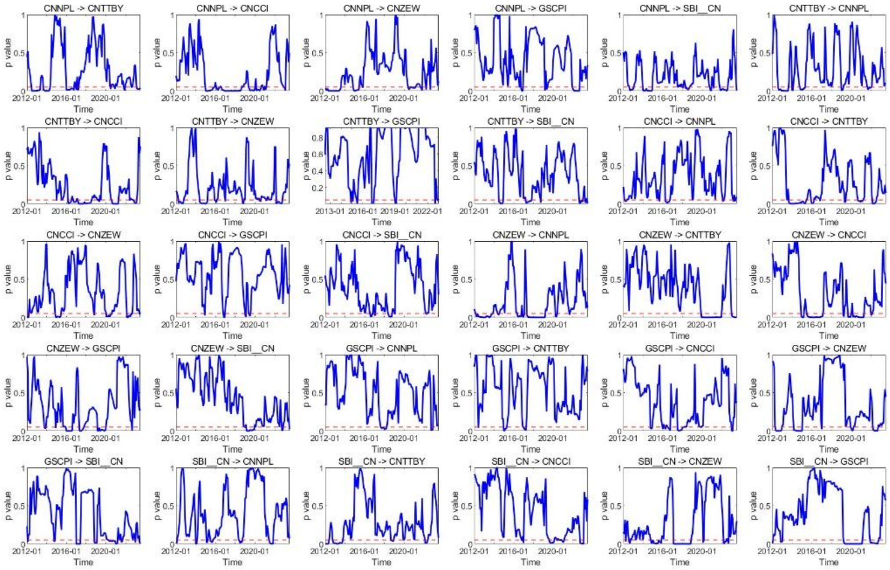


Impulse response of response variable 1
Impulse response of response variable 2
Impulse response of response variable 3
Impulse response of response variable 4
Impulse response of response variable 5
Impulse response of response variable 6
Period (months)
Left axis: other shocks
Right axis: Variable 5 Shock
Shock 1
Shock 2
Shock 3
Shock 4
Shock 6
Shock 5

APP. Figure 4.4 Impulse Response Plots for Three Sectors in America



APP. Figure 4.5 Results of causality tests in China



APP. Figure 4.6 Results of causality tests in USA